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Technological Forecasting by Artificial Asset Markets
- Utilizing market speculation to forecast New Technologies and Products
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Deutsche Kurzfassung der Dissertation

Fortschrittliche Technologie ist oft ein wesentlicher Erfolgsfaktor für Unternehmen und sogar ganze Nationen. Um den technologischen Fortschritt rechtzeitig zu erkennen, werden Technologieprognosen erstellt. Die Prognose von Technologien und technologischem Wandel zusammen mit dem verbundenen Aufwand für die Informationssammlung und -aggregation stellt eine große Herausforderung für Entscheider dar, sowohl in kommerziellen Unternehmen als auch in staatlichen Institutionen. Viele Prognosemethoden wurden entwickelt, um Entscheider mit Technologieprognosen zu unterstützen, jedoch versagen alle diese Methoden in jenen Phasen des Technologieentwicklungszykluses, in denen sich extreme Ungewissheit mit raschen Änderungen paart. Dies tritt vor allem in jenen strategisch entscheidenden Phasen auf, aus denen eine neue Technologie hervorgeht oder in denen eine Technologie von einer anderen durch Substitution "bedroht" wird.

Für diese Situationen gibt es daher den Bedarf nach einer Technologieprognosemethode, die sowohl in höchstem Grade anpassungsfähig (in der Auswahl und Verknüpfung relevanter Inputs mit gegebenen Dimensionen eines Outputs) als auch ohne Zeitverzögerung (durch Abgabe der Prognose in Quasi-Echtzeit ohne die Erfordernis nach Abwicklung einer zeitraubenden Prozedur) ist. Die Erfüllung dieses Bedarfs ist die zugrunde liegende Motivation dieser Arbeit für die Entwicklung einer neuen Technologieprognosemethode, die Technologieprognose mittels experimenteller Aktienmärkte. Zusätzlich ist diese Methode die erste, die auf den bereits lange im Bereich der Prognosemethodenforschung etablierten Grundsatz aufbaut, dass Prognosen durch effiziente Märkte optimal sind. Das heißt, dass die neue Methode die Aussicht in sich trägt, bessere Prognosen in Bezug auf Genauigkeit und Zuverlässigkeit zu liefern als alle Prognosen durch alternative Technologieprognosemethoden.

Mittels Literaturrecherche werden zunächst Belege gesammelt, dass experimentelle Aktienmärkte die Fähigkeit besitzen, verstreute Informationen zu sammeln, zu aggregieren und die Ergebnisse in Form von Preisen anzuzeigen. Während spekulative Finanzmärkte schon lange eingesetzt werden, um Risiken zu identifizieren und umzuverteilen, werden erst seit kurzem experimentelle Aktienmärkte eigens geschaffen, um Prognosen zu erstellen.

Durch empirische Untersuchungen mittels sekundärstatistischer Methoden wird im Rahmen dieser Forschungsarbeit der Beleg erbracht, dass experimentelle Aktienmärkte für Technologieprognosen den Ausgang technologischer Entwicklungen mit einer Wahrscheinlichkeit von >75% für etwa zwei Jahre im voraus bzw. für 59% des Prognosezeitraums voraussagen können. Außerdem wird durch einen indirekten Leistungsvergleich empirisch nachgewiesen, dass die Technologieprognosemethode mittels experimenteller Aktienmärkte besser, d.h. zuverlässiger, ist als alternative Prognosemethoden, die in denselben Kontext angewendet werden.

Da im Rahmen der Literaturrecherche die Erkenntnis gewonnen wird, dass die Leistungsfähigkeit der neuen Methode maßgeblich durch die konkrete Ausgestaltung der experimentellen Aktienmärkte bestimmt wird, werden konsequenterweise die verschiedenen Gestaltungsoptionen für experimentelle Aktienmärkte systematisch untersucht und auf ihre Eignung für die Anwendung in der Prognose von Technologien analysiert und bewertet.

Schließlich wird, motiviert durch die Anwendung des entwickelten Gestaltungsprozesses und der Gestaltungsrichtlinien und durch die Schaffung wertvoller empirischer Daten für die spätere Forschung, ein experimenteller Aktienmarkt für Technologieprognosen entworfen und implementiert.

Zusammenfassend kann der Forschungsinhalt dieser Dissertation sowohl den Disziplinen der Produktentwicklung, der Technologieprognose, und der experimentellen Ökonomie zugeordnet werden. Diese Forschungsarbeit erbringt den Beleg, dass die Methode Technologieprognose mittels experimenteller Aktienmärkte eine valide neue Methode für die Technologieprognose ist. Es werden Leistungsdaten für die absolute und relative Leistung der neuen Methode dokumentiert. Diese Belege werden durch eine Beschreibung und Analyse der wesentlichsten Charakteristika der neuen Prognosemethode ergänzt, um die Anwendung in kommerziellen Unternehmen oder staatlichen Institutionen zu erleichtern.

Zusätzlich werden in der vorliegenden Arbeit ein umfassender Entwicklungsprozess und eine Reihe von Entwicklungsrichtlinien für den Entwurf und die Implementierung von experimentellen Aktienmärkten für die Technologieprognose entwickelt.

Schlagwörter: Technologieprognose, S-Kurve, Prognosemethode, Prognosemärkte, Experimentelle Aktienmärkte, Experimentelle Ökonomie, Technology Futures Market, Austrian Electronic Markets, Iowa Electronic Markets, Hollywood Stock Exchange, Foresight Exchange

Abstract

Technological advancement can have a major impact on corporate profitability or the well-being of nations. For this reason technological forecasts are produced. The forecast of technologies and technological change along with the required information acquisition and processing is a major challenge for decision makers in both commercial enterprises and government. Many forecasting methods have been developed to assist decision makers in making technological forecasts, however, all of them fail in those phases of a technology's lifecycle, in which there is extreme uncertainty combined with rapid change. Most notably, these circumstances occur in the strategically most crucial technology lifecycle phases, as a technology emerges or is threatened by substitution from another technology.

For these situations there is a need for a technological forecasting (TF) method that is at the same time extremely adaptable (in relating relevant inputs to given dimensions of output) and instant (in delivering the current outlook in quasi-real-time without the requirement of going through a lengthy, time-consuming procedure). Addressing this need is the motivation for this thesis to develop a new TF method, technological forecasting by artificial asset markets (TF by AAM). Additionally, it is the first method to utilize an early established principle in forecasting, that is, forecasts provided by efficient markets are optimal. Thus, the new method holds no less than the prospect of delivering better forecasts in terms of forecast accuracy and reliability than forecasts provided by any alternative TF method.

By literature review, we establish that theory, empirical, and experimental evidence suggest that asset markets have the capacity to collect information that is dispersed, aggregate it like a statistician, and publish the findings in forms of prices. While speculative financial markets have long been used to identify and reallocate risk, only very recently have artificial asset markets been created primarily to make forecasts.

By empirical research using secondary statistics methodology, we establish that, on average, artificial asset markets for technological forecasting (AAM for TF) predict the eventual outcome of technological developments with a probability of >75% for approximately two years, or 59% of market duration, in advance of market maturation, that is, in advance of the technological event outcome. Furthermore, by indirect performance comparison, we establish empirical evidence to support AAM for TF as superior to alternative forecasting methods.

As we learn during the literature review that many potential pitfalls lie in the way of realizing information aggregation through artificial asset markets, that is, in their design, we consequently and systematically explore the design alternatives for artificial asset markets and evaluate these alternatives for their applicability to TF by AAM.

Finally, motivated by application of the developed design guidelines and the purpose of producing valuable empirical data for later research, we design and implement an artificial asset market for technological forecasting.

To conclude, the research presented in this thesis can be attributed to the disciplines of product development, technological forecasting, and to the discipline of experimental economics alike. This thesis produces evidence to support artificial assets markets as a new method of technological forecasting. Absolute and comparative performance data for the new method AAM for TF is established. This evidence is complemented by a description and analysis of the main characteristics of AAM for TF to facilitate its application in governmental institutions and commercial enterprises. Furthermore, this thesis proposes a comprehensive design process and a set of design guidelines for the design and implementation of AAM for TF.

Keywords: technological forecasting, s-curves, artificial asset markets, prediction markets, collective forecasts, probabilistic forecasts, combined forecasts, information aggregation, market microstructure, experimental economics, technology futures market, Austrian Electronic Markets, Iowa Electronic Markets, Hollywood Stock Exchange, Foresight Exchange

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Abbreviations

AAM	artificial asset market
ANN	artificial neural network
AEM	Austrian Electronic Markets
CalTech	California Institute of Technology
cu	currency units
EMH	Efficient Market Hypothesis
FX	Foresight Exchange
HP	Hewlett-Packard
HSX	Hollywood Stock Exchange
IEM	Iowa Electronics Markets
IPSM	Iowa Political Stock Market, a market of IEM
NN	neural network
PSM	Political Stock Market
R&D	research and development
RE	Theory of Rational Expectations
TF	technological forecasting
TFA	technology futures analysis
TU	Technische Universität

1. Introduction

In this chapter we identify the topic of this thesis and explain why it is important. As a starting point, a brief problem statement specifies the issue that needs to be resolved. Additionally, we present some further rationale for undertaking the research presented in this thesis. A concise section follows to outline the background and context of this piece of research.

Finally, we develop the research question, define the research objectives and reflect on the scope and contribution of this thesis. The chapter concludes with an overview of the thesis structure.

1.1 Problem statement

The forecast of technologies and technological change along with the required information acquisition and processing is a major challenge for decision makers in both commercial enterprises and government.¹ Many forecasting methods have been developed to assist decision makers in making technological forecasts (TF).²

However, the optimal TF method, that is, the best TF method in terms of forecast accuracy and reliability has not been developed yet: according to an early established principle in forecasting, forecasts provided by efficient markets are optimal.³ Consequently, an efficient market that is used for technological forecasting should provide the optimal technological forecast.

The work presented here aims to provide basic and original research on technological forecasting by efficient markets. As we will learn later on in this work, such markets for forecasting can be termed as speculative markets or artificial asset markets.

1.2 Additional rationale

In a technology's lifecycle there are phases of extreme uncertainty combined with rapid change in respect to the technology's further development, most notably, as the technology emerges – that is, from the point where scientific research reveals a

¹ see, e.g., (Martino 1993) or the Journal of Technological Forecasting and Social Change

² Ibid.

³ see (Armstrong 2001b), p.7

technological possibility to the point of commercialization of the technology in lead markets.⁴

For these phases there is a need for a TF method that is at the same time extremely adaptable (in relating relevant inputs to given dimensions of output) and instant (in delivering the current outlook in quasi-real-time without the requirement of going through a lengthy, time-consuming procedure). Currently, none of the existing TF methods satisfies this need.⁵

TF by artificial asset markets, however, inherently addresses this need.

1.3 Background and context

Technology is a key resource of profound importance for corporate profitability and growth.⁶ Public policy makers increasingly recognize that technological leadership has enormous significance for the well-being of national economies in the context of international competition.⁷ Accordingly, economic competition between corporations, between nations, and between international alliances is the main driver of technological innovation in an increasingly global economy.⁸

As economic competition continues to intensify and innovation cycles become increasingly compressed, anticipating and understanding the course of technological change is a growing challenge for decision makers in both corporations and government.⁹ Decisions that need to be well-informed concern setting priorities for research and development (R&D) efforts, understanding and managing the risks of technological innovation, exploiting intellectual property, and enhancing technological competitiveness of products, processes, and services.¹⁰

Many forms of analyzing future technology and its consequences coexist, for example: technology intelligence, forecasting, roadmapping, assessment, and foresight.¹¹ All of

⁴ see (Day, Schoemaker et al. 2000), p.2

⁵ see section 2.5.3

⁶ see, e.g., (Porter 1985), p.12, 28; (Porter 1998b), pp. 25-27; or (Roland Berger 2005), p.47

⁷ see (Porter 1998a) p.6, 19; and (Sachs 2000)

⁸ see, e.g., (Porter 1985), p.12, 28; (Porter 1998b), pp. 25-27; or (Roland Berger 2005), p.47

⁹ see (Porter 1998a) p.6, 19; and (Sachs 2000)

¹⁰ Ibid.

¹¹ see, e.g., (Martino 1993) or the Journal of Technological Forecasting and Social Change

these techniques fit into a field that has recently been termed as technology futures analysis (TFA).¹²

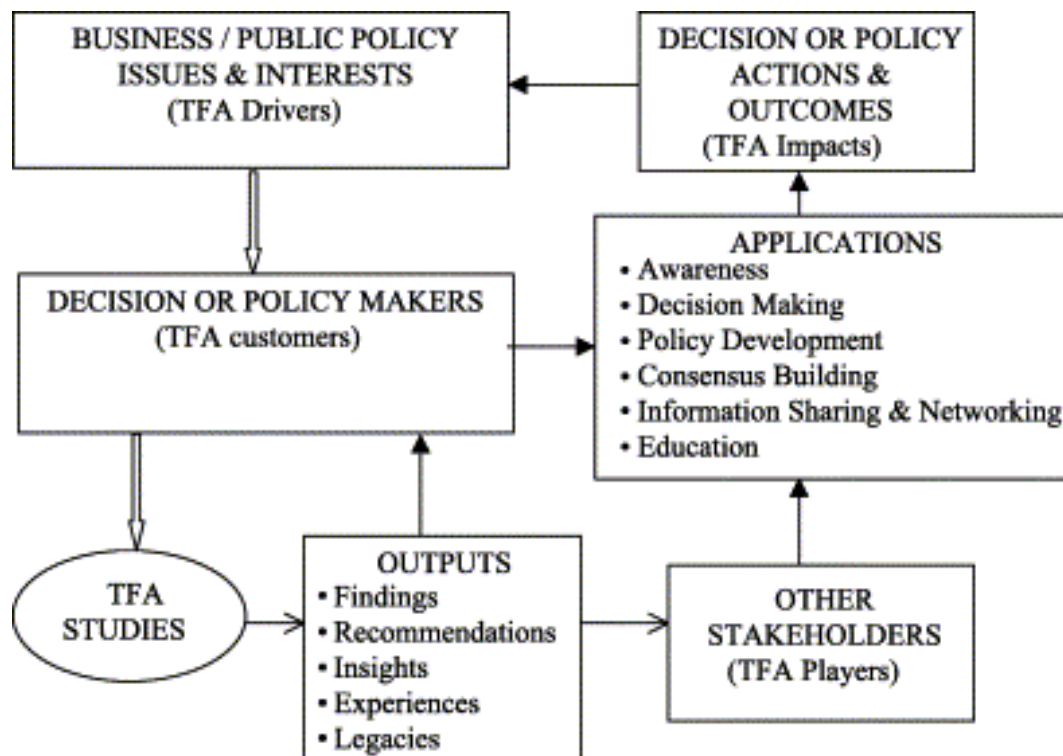


Figure 1: A framework for Technology Futures Analysis (Porter, Ashton et al. 2004), p.288

TFA represents any systematic process to produce judgments about emerging technology characteristics, development pathways, and potential impacts of a technology in the future.¹³ In this sense, TFA encompasses the broad technology foresight and assessment studies of the public sector and the technology forecasting and intelligence studies in private industry. A framework for TFA by Porter, Ashton et al. (2004) is illustrated by Figure 1.

Whereas the popularity and support for TF within the policymaking arena faltered during the late 1970s and 80s as it was realized that the uncertainties of technology development defied clear-cut “systems analysis” solutions, a change in the clientele of TF following the Cold War recasted its context significantly.¹⁴ Economic, not military or political, competition became the primary motive to undertake TF. The decade of the

¹² see (Porter, Ashton et al. 2004), p. 287

¹³ see (Porter, Ashton et al. 2004) , pp. 288-289

¹⁴ see (Coates, Farooque et al. 2001), pp.2-7

1990s has, therefore, initiated an upsurge in all forms of TF, using both old and new techniques and with much commonality of purpose.¹⁵

Today, phases of rapid change of competing and complementary technologies, increasing organizational complexity of corporations, and social forces – sometimes seemingly irrational – exacerbate the challenge to forecast technological developments correctly and timely.¹⁶

However, the information technology era has provided powerful new capabilities that can be exploited to advance TFA, both product and process. Given the complexity of innovation processes and competitive systems, understanding the diverse and increasingly sophisticated tools can elicit critical information from multiple sources. There is, therefore, much merit in revitalizing academic interest in TF, undertaking research to innovate and validate the tools, and providing training in their appropriate use.¹⁷

1.4 Research question, objectives, scope and contribution

In this section we develop the research question, define the research objectives and reflect on the scope and contribution of this thesis.

1.4.1 Research question

Based on the problem statement given in section 1.1 the overall research question for the investigation presented in this thesis is:

Can artificial asset markets forecast technological developments?

For the purpose of incremental validation, the overall research question can be split into the following sub-questions:

- a. Does the method TF by artificial asset markets work in principle?
- b. How does the method TF by artificial asset markets perform in terms of accuracy and reliability?
- c. How does the method TF by artificial asset markets perform in comparison to existing TF methods?

¹⁵ see (Coates, Farooque et al. 2001), pp.2-7; (Martino 2003); and (Porter, Ashton et al. 2004)

¹⁶ see (Day, Schoemaker et al. 2000), pp.5-6

¹⁷ see also, e.g., (Coates, Farooque et al. 2001), pp.2-7; and (Porter, Ashton et al. 2004)

- d. What is the theoretical, empirical and experimental foundation of artificial asset markets?
- e. How should artificial asset markets for TF be designed?

As we have established the research question(s) guiding this thesis, we define the research objectives next.

1.4.2 Research objectives

Based on the problem statement given in section 1.1 and the overall research question developed above in section 1.4.1, the research presented in this thesis aims to achieve the following primary objectives:

- I. to **validate** artificial asset markets as a tool for TF
- II. to **design and implement** an artificial asset market for TF

In the course of pursuing the primary objectives, we also strive to achieve some secondary objectives:

- to produce a **description and analysis** of artificial asset markets as an instrument of TF
- to produce a **set of design guidelines** of artificial asset markets for TF
- to establish **absolute and comparative performance data** on artificial asset markets for TF
- to perform an **experimental investigation** of artificial asset markets as instrument of TF

Next, as we have established the primary and secondary research objectives, we define the scope and the contribution of this thesis.

1.4.3 Scope and contribution of thesis

While much research has been done on technological forecasting¹⁸ and some basic research on the forecasting abilities of artificial asset markets is starting to accumulate¹⁹, this thesis is unique in exploring the use of artificial asset markets for

¹⁸ see, e.g., (Martino 1993), (Martino 2003), (Coates, Farooque et al. 2001) or (Porter, Ashton et al. 2004)

¹⁹ see chapter 3 for a comprehensive overview

technological forecasting. Furthermore, the work presented here is to provide a comprehensive set of design guidelines for conceptual and system-level design of artificial asset markets for (technological) forecasting. Thus, we can summarize the contribution of this thesis as follows:

- To provide original evidence on the performance of artificial asset markets as instrument of technological forecasting
- To contribute to the growing evidence on the performance of artificial asset markets as forecasting tool – especially in respect to field performance
- To provide insight on how artificial asset markets for TF is different to artificial asset markets for other forecasting fields
- To provide a comprehensive set of design guidelines for conceptual and system-level design of artificial asset markets for (technological) forecasting

The scope of this thesis limits itself to a basic but thorough research of TF by artificial asset markets. This includes the establishment of the new TF method's absolute forecasting performance in terms of forecast accuracy and reliability. Other performance measures, including cost, are not covered by this research.

This basic research includes the new TF method's comparative performance as well, however, limited to available forecasts based on alternative TF methods that are used in the same application context. That is, we do not produce forecasts based on alternative TF methods for comparison.

The range of technologies covered by the new TF method has not been limited by intention, thus, we include technologies defined in a broader sense. Covered technologies encompass mechanical assemblies, biomedical technology, electronics and software.

Finally, the scope of this thesis includes the development of a set of design guidelines. These design guidelines include top-level conceptual design as well as system-level design, but not detail design.

As we have established the contribution and the scope of this thesis, we turn to the thesis structure next.

1.5 Thesis structure

Based on the research question, objectives, thesis scope and contribution defined in the previous section, we organize this thesis as illustrated in Figure 2. Subsequently, we give a brief description of the content and rationale for each thesis part.

Chapter 1 – Introduction. In this chapter we identify the topic of this thesis and explain why it is important. As a starting point, a brief problem statement specifies the issue that needs to be resolved. Additionally, we present some further rationale for undertaking the research presented in this thesis. A concise section follows that gives the background and context for this piece of research.

1	Introduction
2	Technological forecasting: review and hypotheses development
3	Theoretical, empirical and experimental foundation of artificial asset markets applied to forecasting
4	Empirical investigation of artificial asset markets for technological forecasting
5	Design of artificial asset markets for technological forecasting
6	Implementation of an artificial asset market for technological forecasting
7	Conclusion

Figure 2: Thesis structure

Finally, we develop the research question, define the research objectives and reflect on the scope and contribution of this thesis. The first chapter concludes with an overview of the thesis structure.

Chapter 2 – Technological forecasting: review and hypothesis development. In this chapter we review the literature on technological forecasting, briefly conceptualize a new TF method and eventually develop hypotheses to test the new method.

After a brief introduction that discusses the basic motivation for technological forecasting, and a section on the basic definition of technological forecasting, we give a brief overview of TF methods. Subsequently, we discuss the motivation for developing a new TF method, TF by artificial asset markets, and explore its potential advantages and disadvantages of application.

Finally, we develop our hypotheses to test the new method's validity and application in the domain of technological forecasting. We conclude the chapter with a brief summary and conclusions.

Chapter 3 – Theoretical, empirical and experimental foundation of artificial asset markets applied to forecasting. After a brief introduction that discusses how market prices represent all available information, we give a brief review on the vast amount of literature on the corresponding efficient market hypothesis and its critique.

Subsequently, we establish the principle of artificial asset markets as information aggregation and forecasting tool and go on to review the experimental evidence produced by laboratory experiments. We additionally review the evidence produced by first field experiments, both in a private and public setting.

Finally, we review the literature on selected focus issues of market performance that are motivated by forecast accuracy.

We conclude the chapter with a brief summary and an examination of the support provided by the reviewed literature for the hypotheses developed in the previous chapter.

Chapter 4 – Empirical investigation of artificial asset markets for technological forecasting. In this chapter we present the empirical evidence produced in the course of this thesis. First, we develop a research concept for the empirical investigation of the hypotheses developed in chapter 2; and, subsequently, we establish the data that is used for analysis.

Next, we operationalize each of both hypotheses by developing sub-hypotheses; we then perform the corresponding analysis on the empirical data, examine and discuss the support for the sub-hypotheses and the original hypotheses.

We conclude the chapter with a brief summary of the support provided by the empirical research of the hypotheses developed in this thesis.

Chapter 5 – Design of artificial asset markets for technological forecasting.

Earlier in chapter 2, we learned that many potential pitfalls lie *in the way of realizing* good TF-relevant information aggregation through speculative markets.

Consequently, in this chapter we systematically explore the different possible design alternatives for an artificial asset market for TF and we evaluate the different design options for their applicability to the domain of technological forecasting.

After a brief introduction to financial instruments and financial markets, we start by establishing a design process for artificial asset markets. Subsequently, for each of the key steps in market design we identify a market's major elements in design and discuss for each the various design alternatives from a general viewpoint. These general discussions are followed by specific discussions of how these design choices apply to TF and which of these choices are more preferable for AAM for TF than others. The chapter is concluded with a brief summary.

Chapter 6 – Implementation of an artificial asset market for technological forecasting. Motivated by application of the design guidelines developed in the previous chapter and the two-stream empirical research approach proposed in chapter 4, we design an artificial asset market for technological forecasting and document its implementation.

First, we establish the project concept which documents the project resources and scope. Next, we establish the design of the AAM for TF based on the design guidelines developed in the previous chapter and limited by the constraints given by the project concept.

Finally, we document the design of the implemented AAM for TF. We conclude the chapter with a brief summary and a section on lessons learned during implementation.

Chapter 7 – Conclusion. This final chapter summarizes the main findings of this thesis. The results developed and presented in the course of each chapter are revisited. Based on these results, the research goals initially set in chapter 1 are reviewed and evaluated for fulfillment. This final chapter is concluded by an outlook of the field of study and suggestions for further research.

As we reflect on the described thesis structure and the defined research questions, we can point out which research question is addressed by which chapter, as shown by Table 1 below.

Table 1: Research questions and corresponding thesis chapters

Research questions	Corresponding thesis chapter
Does the method TF by artificial asset markets work in principle?	chapter 3, chapter 4
How does the method TF by artificial asset markets perform in terms of accuracy and reliability?	chapter 4
How does the method TF by artificial asset markets perform in comparison to existing TF methods?	chapter 4
What is the theoretical, empirical and experimental foundation of artificial asset markets?	chapter 3
How should artificial asset markets for TF be designed?	chapter 5

Next, we review the literature on technological forecasting, explore the need for a new TF method, conceptualize a new TF method and eventually develop hypotheses to test the validity of the new technique.

2. Technological forecasting: review and hypotheses development

In this chapter we review the literature on technological forecasting, explore the need for a new TF method, briefly conceptualize a new TF method and eventually develop hypotheses to test the new method.

After a brief introduction that discusses the basic motivation for technological forecasting, and a section on the obligate definition of technological forecasting, we give an overview of the state-of-the-art in TF methods.

Subsequently, we discuss the motivation for developing a new TF method, TF by speculative markets, and explore its potential advantages and disadvantages of application.

Finally, we develop our hypotheses to test the new method's validity and application in the domain of technological forecasting. We conclude the chapter with a brief summary and conclusions.

2.1 Introduction

Widespread interest and attention for the future development of technologies is a recent phenomenon in human history²⁰, as illustrated by Figure 3. Although few exceptional individuals, such as Robert Bacon in 1260 a.D. or Leonardo da Vinci in 1500 a.D., already anticipated flying machines and carlike devices, they had no broad or lasting impact on society's thinking about technological developments and they did not lead to the practice of systematic technological foresight.²¹

Only as late as in the 17th and 18th centuries, as scientific discoveries led to major innovations, which in turn inspired science fiction, did society's interest in technological developments emerge.²² Inventions such as the hot-air balloon signaled that air and perhaps even space travel was possible; the steam engine showed that sources of power were not restricted to animals, wind, and water.

Science fiction then spawned science prediction, "Futurology", which incorporates predictions of technological progress in visions of future society. Finally, in the 1950s, technological innovation increased substantially with the introduction of the computer, laser, transistor, television, space travel, commercial nuclear energy, and many other

²⁰ see (Sherden 1998), p.159

²¹ Ibid., p.160

²² Ibid., p.160

technological achievements. Technological forecasting emerged soon after as a specialized field in the 1960s.²³

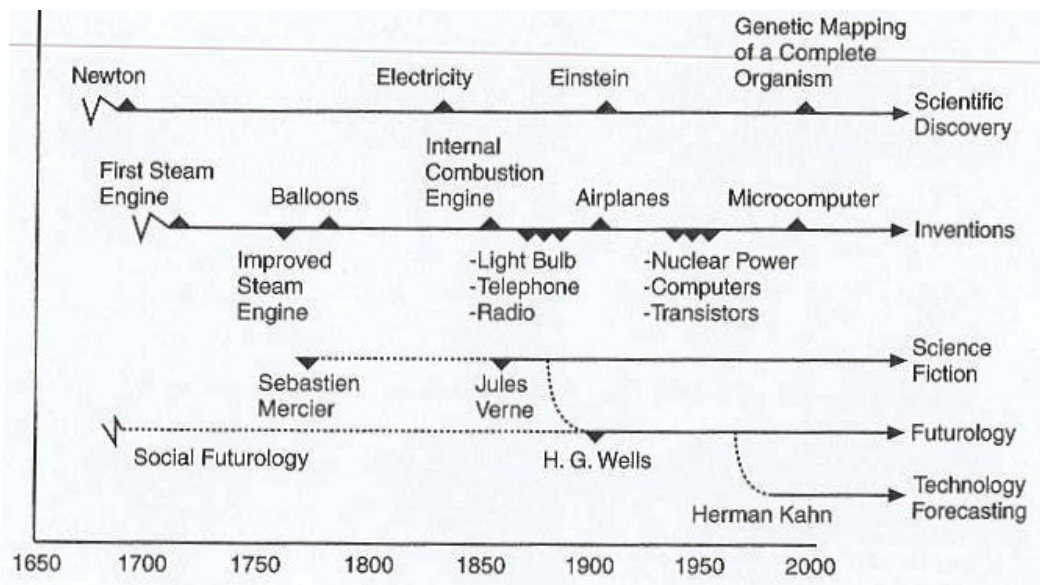


Figure 3: A history of major technological innovations and the dawn of technological forecasting (Sherden 1998), p.160

Today, technological forecasting draws ever more importance from business and society's ever increasing reliance on technology.²⁴ As outlined earlier in the introduction, technology is a key resource of profound importance for corporate profitability and growth.²⁵ It also has enormous significance for the well-being of national economies as well as international competitiveness.²⁶

Table 2: Reasons for technological forecasting (Martino 1993), p.4

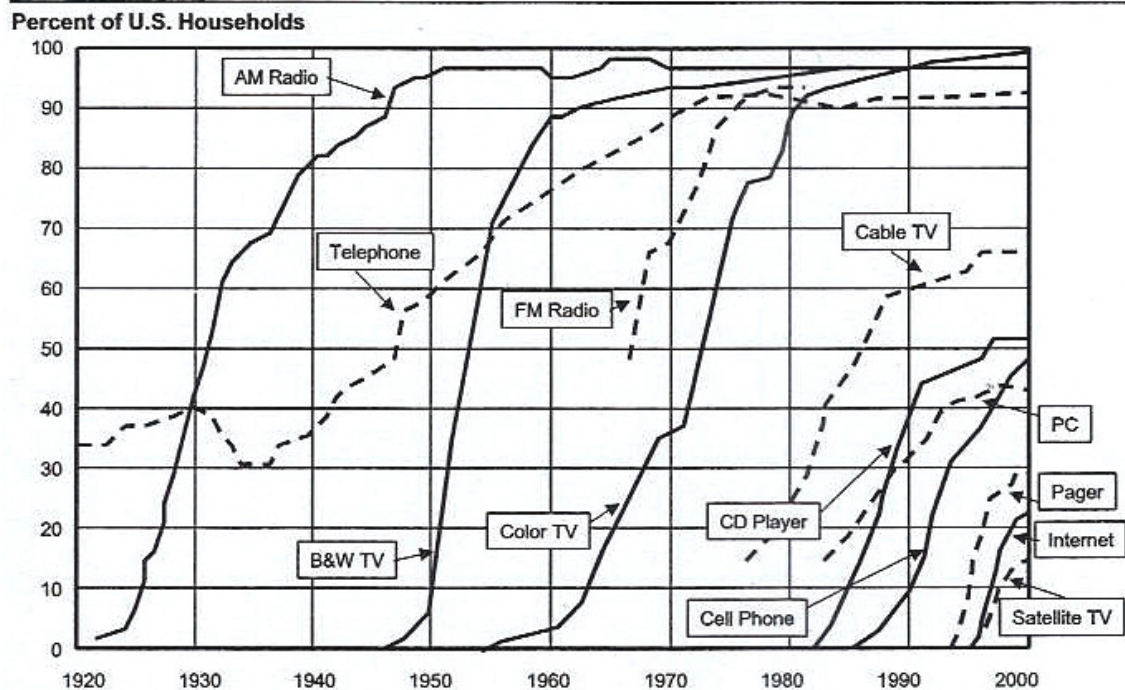
1.	To maximize gain from events external to the organization
2.	To maximize gains from events that are the result of actions taken by the organization
3.	To minimize loss associated with uncontrollable events external to the organization
4.	To offset the actions of competitive or hostile organizations
5.	To forecast demand for purposes of production and/or inventory control
6.	To forecast demand for facilities and for capital planning
7.	To forecast demand to assure adequate staffing
8.	To develop administrative plans and policy internal to an organization (e.g. budget)
9.	To develop policies that apply to people who are not part of the organization

²³ (Sherden 1998), p.160

²⁴ Ibid.

²⁵ see, e.g., (Porter 1985), p.12, 28; (Porter 1998b), pp. 25-27; or (Roland Berger 2005), p.47

²⁶ see (Porter 1998a) p.6, 19; and (Sachs 2000)



Source: *The Wall Street Journal Classroom* edition, 1998

Figure 4: Adoption rates of various communication technologies in the USA (Day, Schoemaker et al. 2000), p.7

Effective management of technology combines the disciplines of science, engineering, and management to address the issues involved in the planning, development, and implementation of technological capabilities to shape and accomplish the strategic and operational objectives of organizations and nations.²⁷ Obviously, this includes the task of technological forecasting. Thus, technological forecasting is done as means to an end – a set of motivations or reasons for TF is given by Martino (1993), see also Table 2.

As we have established the basic motivation for technological forecasting, we review and discuss the precise definition of TF in the next section.

2.2 Definition of Technological Forecasting (TF)

Technological forecasting is the set of activities that are performed in purpose of producing a technological forecast. We use the definition of a technological forecast provided by Martino (1993). A technological forecast has four elements:

²⁷ (Badawy 1993), p.1

1. the technology being forecast
2. the time of the forecast
3. a statement of the technology characteristics in terms of functional capability
4. a statement of the probability associated with the forecast

Subsequently, we discuss the elements of a technological forecast in more detail.

Technology being forecast.²⁸ The forecast must state whether it is for a single technical approach or for a more general technology. If it is for a technical approach, the forecast must be clear about how that approach is different from other technological approaches in the same general technology.

If the forecast is for a technology, the forecast must be clear about how that technology is to be distinguished from other technologies that may be used for the same function.

Time of the forecast.²⁹ The second element of the forecast is the time when the statement of the forecast is to be realized. This may be a single point in time or a time span. In either case the time of the forecast should be stated clearly.

Technology characteristics in terms of functional capability.³⁰ The third element of the forecast is the characteristics of the technology given in terms of functional capability. Functional capability is a quantitative measure of a technology's ability to carry out some function. The specific measures of functional capability chosen to characterize the given technology in the forecast depend on the forecast user's needs.

Probability.³¹ The last element of the forecast is the probability associated with it, which may be stated in several ways. The forecast may give the probability of achieving at all a given level of functional capability; it may state the probability of achieving a given level by a certain time; or it may state the probability distribution over the levels that might be achieved by a specific time. When the probability is not stated, it is assumed to be 100%.

²⁸ The following section is based on the definition given by (Martino 1993), pp.2-4

²⁹ Ibid.

³⁰ Ibid.

³¹ Ibid.

As we have established the definition of technological forecasting, we review the application of technological forecasting in the context of product development.

2.3 Application of TF in the context of product development

To better understand the application of technological forecasting, we explore its use in the context of product development at a commercial enterprise. Although there are many different organizations, including governmental agencies, which may produce technological forecasts for different purposes, we believe that these forecasts are ultimately used by commercial enterprises which develop products.³²

Product development. Commercial enterprises which develop products typically do so by following a product development process. This process is the sequence of steps or activities which an enterprise employs to conceive, design, and commercialize a product.³³ Some organizations define and follow a precise and detailed development process, while other organizations may not even be able to describe their processes; furthermore, every organization employs a process at least slightly different from that of every organization.³⁴

However, as a basis for our discussion we can use the generic process and associated best practices assembled and described by Ulrich and Eppinger (2000). Figure 5 illustrates the generic product development process.

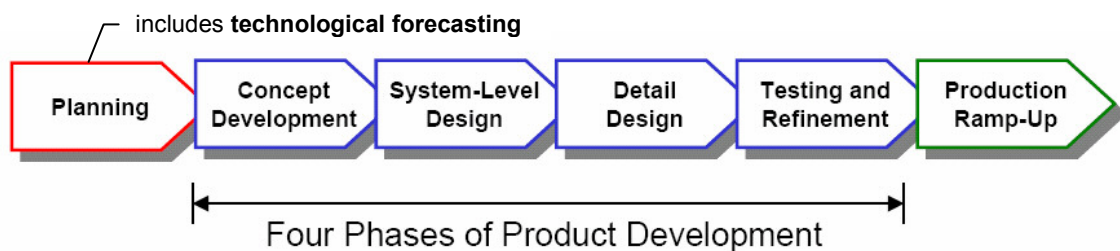


Figure 5: The generic product development process (Ulrich and Eppinger 2000), p.16

The generic product development process consists of four phases, concept development, system-level design, detail design, and testing and refinement. The development process is preceded by a planning phase, which also includes the activity

³² see, e.g., (Ulrich and Eppinger 2000), (V. Krishnan 2001), the Journal of Product Innovation Management, or the Journal of Technological Forecasting and Social Change

³³ see (Ulrich and Eppinger 2000), p.16

³⁴ see, e.g., (Ulrich and Eppinger 2000), (V. Krishnan 2001), or Journal of Product Innovation Management

of technological forecasting. The conclusion of the product development process is the production ramp-up at which the product is made using the intended production system. The transition from production ramp-up to ongoing production is gradual. As some point in this transition, the product is launched and becomes available for purchase in the marketplace.³⁵

The phase of planning precedes the project approval and launch of the actual product development process. The phase begins with corporate strategy and includes assessment of technology developments and market objectives. The output of the planning phase is the project mission statement, which specifies the target market for the product, business goals, key assumptions, and constraints.³⁶

Subsequently, we explore the "planning" phase in more detail to better understand the involvement of technological forecasting.

Product planning. The product planning process takes place before a product development project is formally approved, and before substantial resources are applied. Product planning is an activity that considers the portfolio of product development projects that an organization may pursue and determines what subset of these projects will be pursued over what time period.³⁷ Ulrich and Eppinger (2000) present a four-step planning process that is illustrated by Figure 6.

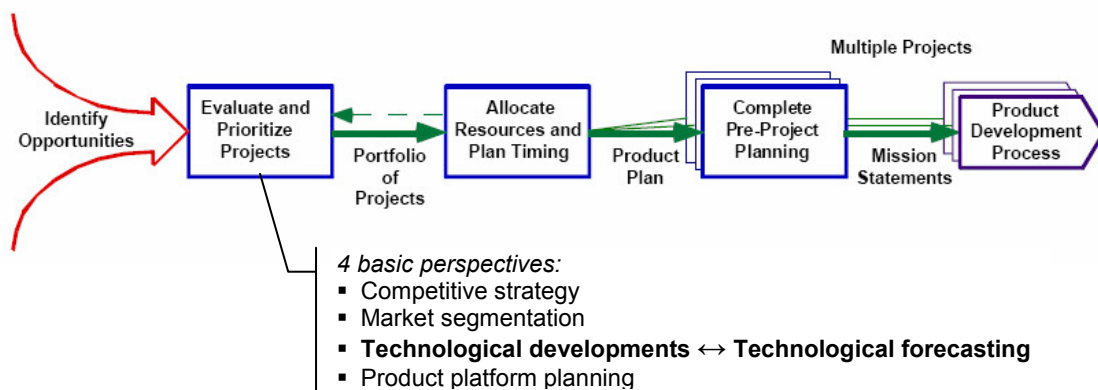


Figure 6: The generic product planning process (Ulrich and Eppinger 2000), p.39

First, multiple opportunities are prioritized and a set of promising projects is selected. Resources are allocated to these projects and they are scheduled. Once projects have been selected and resources allocated, pre-project planning is completed by producing a mission statement for each product. At this stage product planning connects to the

³⁵ see (Ulrich and Eppinger 2000), pp.38-43

³⁶ Ibid.

³⁷ Ibid.

product development process described earlier, as product development projects are approved, resources dedicated and development initiated.³⁸

Evaluating and prioritizing projects. The second step in the product planning process is to select the most promising projects to pursue. Because many opportunities may present themselves for development, some of these opportunities do not make sense in the context of the company's other activities, and in most cases, there are simply too many opportunities to pursue at once.³⁹

Thus, four basic perspectives are useful in evaluating and prioritizing opportunities for new product development projects: competitive strategy, market segmentation, product platforms, and technological developments⁴⁰ – the last perspective **based on technological forecasts.**

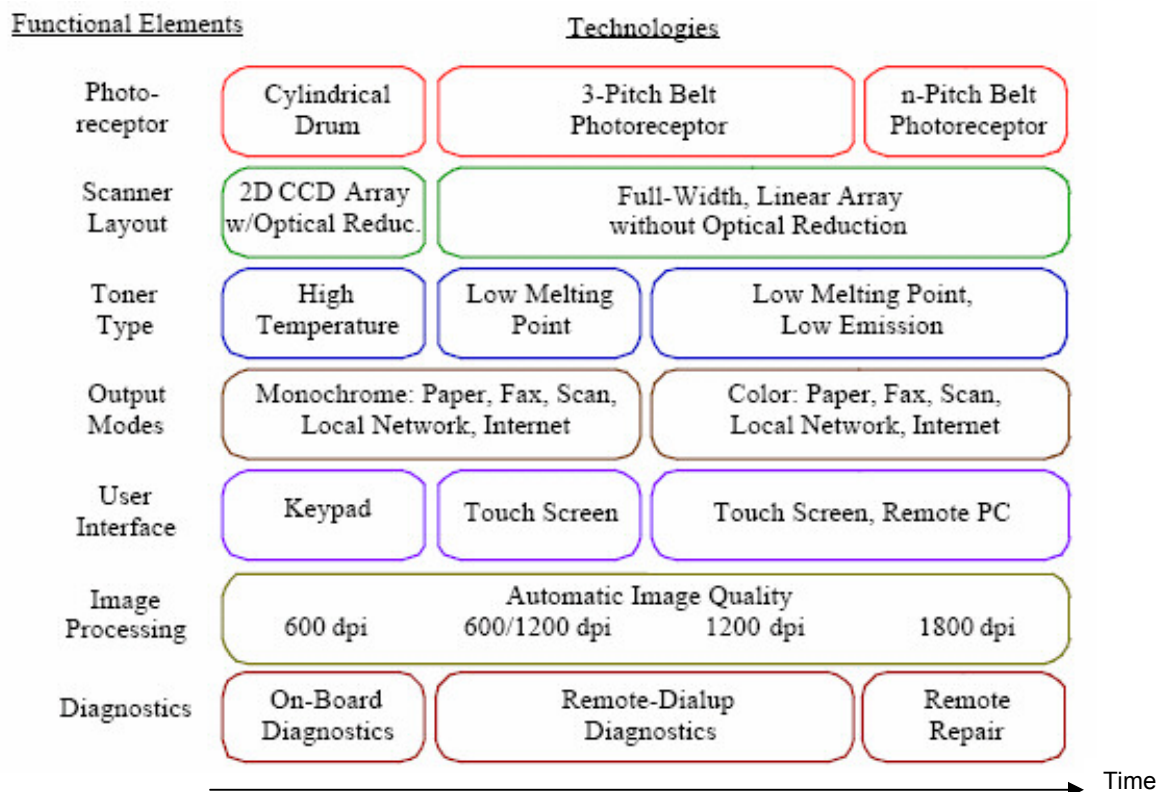


Figure 7: A technology roadmap for digital copy machines in 1999 (Xerox); (Ulrich and Eppinger 2000), p.39

³⁸ see (Ulrich and Eppinger 2000), pp.38-43

³⁹ Ibid.

⁴⁰ Ibid.

Technological developments. In technology-intensive businesses, a key product planning decision is when to adopt a new basic technology in a product line. For example, for the copy machine company Xerox, the key technological issue around 1996 was the shift to digital image processing and printing.⁴¹ In this case, the product planning decision was when to develop digital technology-based products, as opposed to developing another product based on light-lens technology.⁴²

The range of technological developments that needs to be considered is illustrated by technology roadmaps. Such maps serve as a planning tool to coordinate technology development and product planning and development.⁴³ It is a diagram that shows a product's key functional elements and the sequence of technologies expected to implement these elements over a given period of time – see Figure 7 for an illustration.

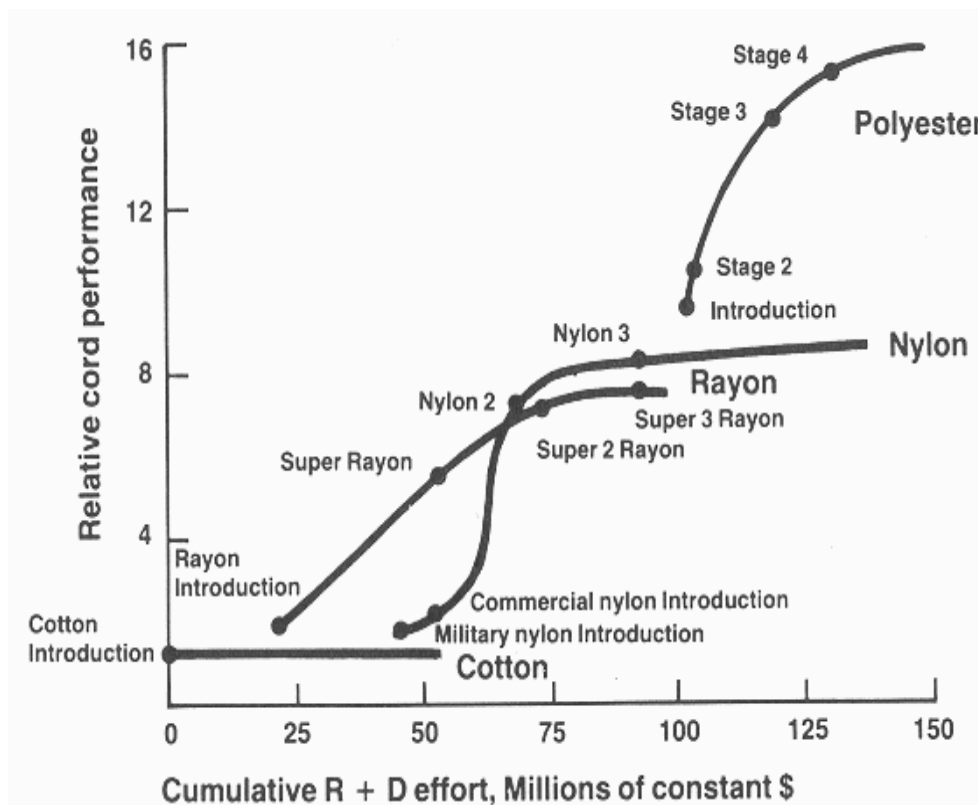


Figure 8: The technology s-curves for fabric technologies;
(Foster 1986), p.43

Thus, a technology roadmap is a way to represent the expected availability and future use of various technologies relevant to the product being considered for development. However, as such roadmaps address *when* to use *which* technology for *which*

⁴¹ Ibid.

⁴² Ibid.

⁴³ see, e.g., (Ulrich and Eppinger 2000), or the Journal of Product Innovation Management

functional element, they need as input an evaluation of technological developments in terms of technology readiness. A useful framework for evaluating such technological developments is Technology S-curves.

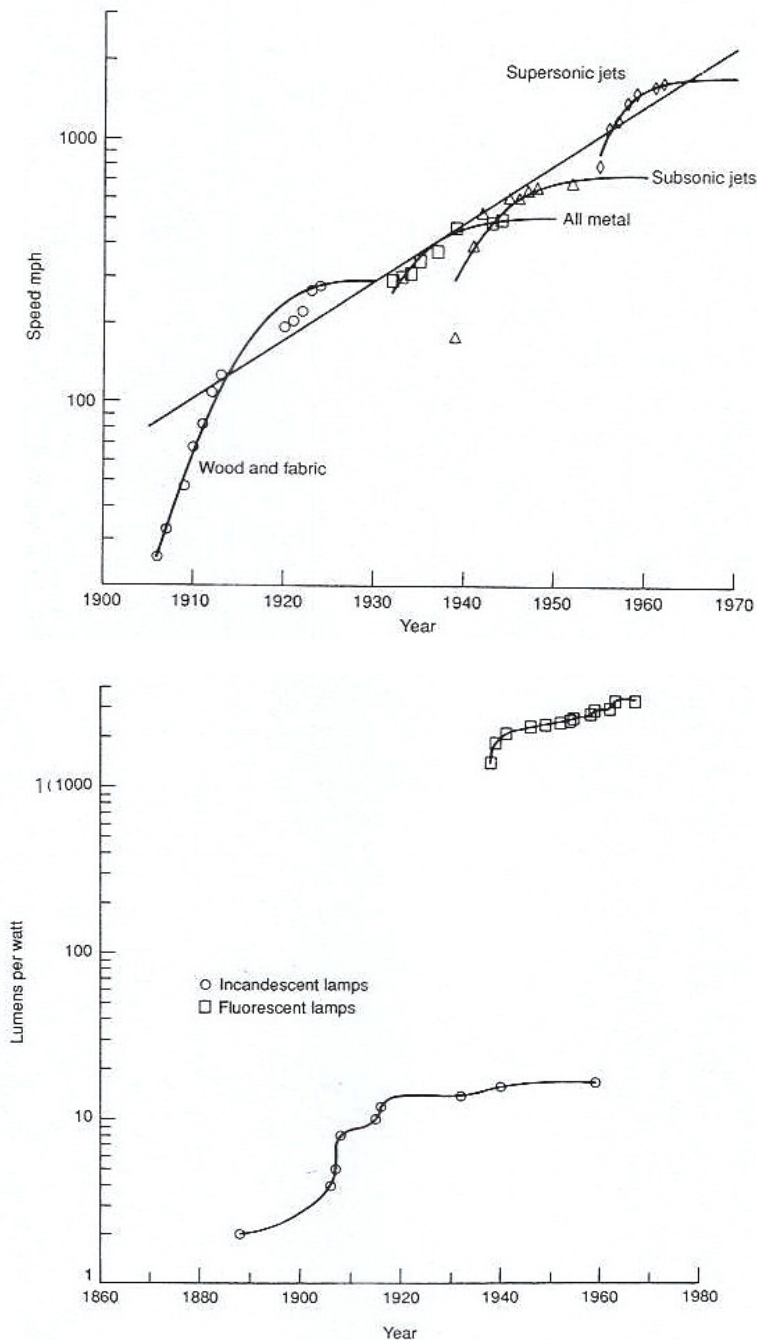


Figure 9: The technology s-curves for aircraft material technologies (top) and lighting technologies (bottom); (Martino 1993), pp. 210, 58

Technology S-curves. The technology S-curve displays the performance of the products in a product category over time, usually with respect to a single performance

variable such as resolution, speed, or reliability.⁴⁴ The S-curve illustrates a basic but important concept: Technologies evolve from initial emergence when performance is relatively low, through rapid growth in performance based on increasing experience per cumulative development effort, and finally approach maturity where some natural technological limit is reached and the technology may become obsolete.⁴⁵ The S-shaped trajectory captures this general dynamic, as shown in Figure 8.

The horizontal axis may be cumulative research and development effort or time; the vertical axis may be a performance-to-cost ratio or any important performance dimension.⁴⁶

While S-curves characterize technological change remarkably well in a wide variety of industries, it is often difficult to predict the future trajectory of the performance curve, for example, how near or far is the ultimate performance limit.⁴⁷ It is the task of technological forecasting to provide these predictions.

As we have reviewed the role of technological forecasting in product development, we advance to the next section that explores the available range of TF methods.

2.4 Overview of TF methods

In this section we review the current state of the art in TF methodology. Armstrong (2004) presents a methodology tree for forecasting methods in general, see Figure 10. The methods are classified by properties of the information base or knowledge source.

First, the methods are divided by those based primarily on judgment and those based on statistical sources. Whereas statistical forecasting methods require the availability of relevant numerical data, judgmental forecasting methods may be used if available data are inadequate for quantitative analysis or qualitative information is likely to increase accuracy, relevance, or acceptability of forecasts.⁴⁸

⁴⁴ see, e.g., (Martino 1993), p.57-59; (Foster 1986), p.; or (Christensen 1992)

⁴⁵ Ibid.

⁴⁶ Ibid.

⁴⁷ Ibid.

⁴⁸ see (Armstrong 2001b), pp.9-11

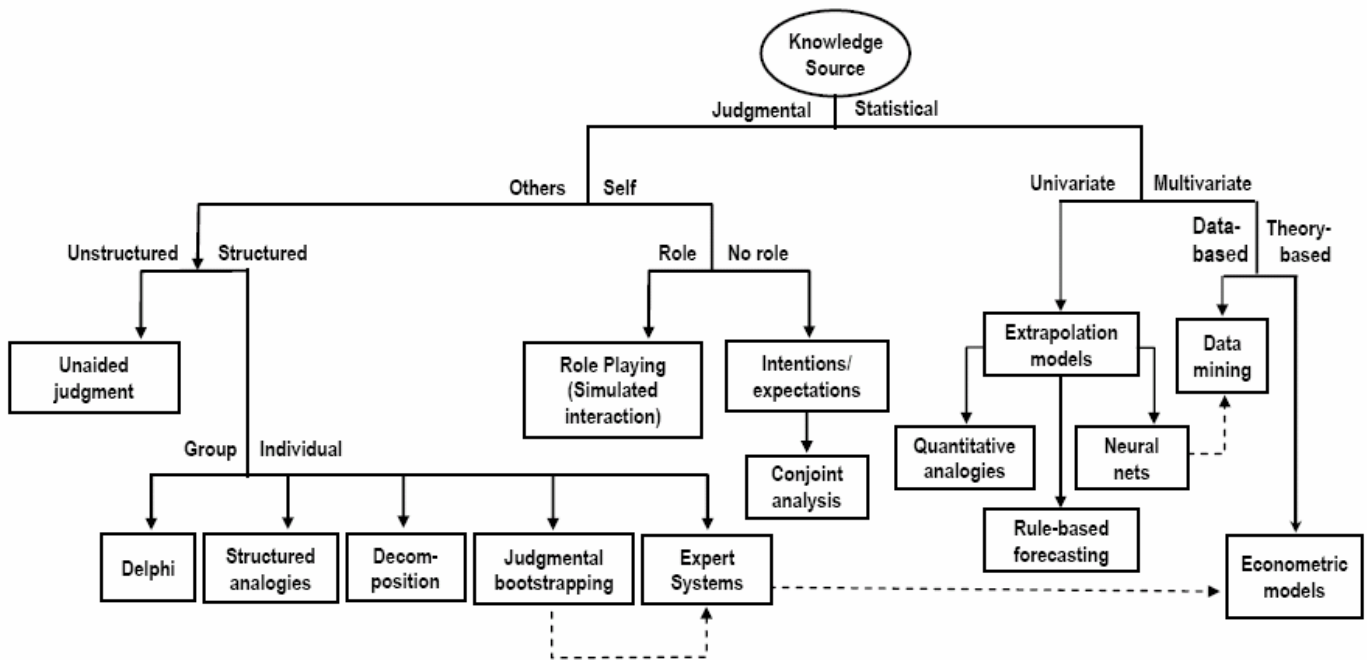


Figure 10: Methodology tree for forecasting methods; adapted from (Armstrong 2004)

Next, judgmental methods can be split into methods that predict one's own behavior versus methods which predict how others will behave.⁴⁹ The latter class of methods applies, if knowledge exists about the expected behavior of other people or organizations. Forecasting methods that predict one's own behavior apply, if people have valid intentions or expectations about their behavior.⁵⁰

Forecasting methods based on own behavior can again be separated into methods in which people's roles influence their behavior and there is knowledge about these roles, and in methods in which roles are not expected to influence behavior, or knowledge about the roles is lacking, or there are many actors with different roles.⁵¹ Role-based methods include role playing or simulated interaction; non-role-based methods include intentions or expectations methods, one of them which is conjoint analysis.⁵²

Role playing (Simulated interaction).⁵³ In role playing, people are expected to think in ways consistent with the role and situation described to them. If this involves

⁴⁹ see Figure 10

⁵⁰ Ibid.

⁵¹ see Figure 10

⁵² see (Armstrong 2001b), pp.9-11

⁵³ The following section is based on (Armstrong 2001b), pp.15-30

interacting with people with different roles for the purpose of predicting the behavior of actual protagonists, it is called simulated interaction. That is, people act out prospective interactions in a realistic manner. The role-players' decisions are then used as forecasts of the actual decision.

Intentions/expectations forecasting methods survey people about their intentions or expectations regarding their future behavior or those of their organization. The forecast is then derived from analysis of the survey data.

Conjoint analysis.⁵⁴ As a subset of Intentions/expectations forecasting methods, the conjoint analysis method elicits preferences from consumers (or other actors) for various offerings (e.g. for alternative computer designs or for different political platforms) by using combinations of features (e.g. power and weight for a laptop computer.) Regression-like analyses are then used to predict the most desirable design.

Methods which predict how others will behave can again be separated into methods that are structured and those that are unstructured.⁵⁵ The former class of methods uses formal methods to analyze the information. This means that the rules for analysis are determined in advance and they are rigorously adhered to.⁵⁶ Unstructured methods use the information in an informal manner. Unaided judgment belongs to this class of methods.

Unaided judgment.⁵⁷ In this forecasting method, experts think about a situation and predict how people will behave. They might have access to data and advice, but their forecasts are not aided by formal forecasting methods. This is the most commonly used method. It is fast, inexpensive when only a few forecasts are needed, and can be used in cases where small changes are expected. It is most likely to be useful when the forecaster gets good feedback about the accuracy of his forecasts, e.g., weather forecasting, betting on sports, and bidding in bridge games.

Structured, formal forecasting methods may again be separated into individual and group methods.⁵⁸ In individual methods, formal procedures are used to help individuals

⁵⁴ Ibid., pp.147-167

⁵⁵ see Figure 10

⁵⁶ see (Armstrong 2001b), pp.9-11

⁵⁷ Ibid.

⁵⁸ see Figure 10

to retrieve and organize their information about a forecasting situation. This information is then analyzed using pre-established rules.⁵⁹ Individual forecasting methods include structured analogies, decomposition, judgmental bootstrapping, and expert systems.⁶⁰ In group methods, formal procedures are used to solicit, weight, and combine forecasts from multiple individuals.⁶¹ Group forecasting methods include Delphi, and artificial asset markets, recently termed as "Prediction markets".⁶²

Structured analogies.⁶³ In this method, an expert lists analogies to a target, describes similarities and differences, rates similarity, and matches each analogy's decision (or outcome) with a potential target situation decision (or outcome). The outcome implied by the top-rated analogy is then used as a forecast.

Decomposition.⁶⁴ In this method, the forecasting problem is addressed in parts. The parts may either be multiplicative (e.g., to forecast a brand's sales, one could estimate total market sales and market share) or additive (estimates could be made for each type of item when forecasting new product sales for a division).

Expert systems use rules to represent experts' reasoning in solving problems.⁶⁵ The rules are based on knowledge about methods and the problem domain. More specifically, expert systems need to be provided with from a variety of sources, such as textbooks, research papers, interviews, surveys, and protocol analysis. In forecasting, the most promising applications of expert systems are to replace unaided judgment in cases requiring many forecasts, to model complex problems where data on the dependent variable are of poor quality, and to handle semi-structured problems.

Judgmental bootstrapping is a type of expert system.⁶⁶ It translates an expert's rules into a quantitative model by regressing the expert's forecasts against the information that he used. Bootstrapping models apply an expert's rules consistently, thus, such forecasts are typically more accurate than forecasts made by experts using unaided

⁵⁹ see (Armstrong 2001b), pp.9-11

⁶⁰ Ibid.

⁶¹ Ibid.

⁶² Ibid.

⁶³ The following section is based on (Armstrong 2001b), pp.195-213

⁶⁴ Ibid., pp. 107-123

⁶⁵ see (Armstrong 2001b), pp.285-300

⁶⁶ The following section is based on (Armstrong 2001b), pp.171-192

judgment. Bootstrapping can be useful when historical data on the variable to be forecast are lacking or of poor quality; otherwise, econometric models should be used. Furthermore, this method is most appropriate for complex situations, where judgments are unreliable, and where expert judgments have some validity.⁶⁷

Delphi technique.⁶⁸ In this method, predictions and reasoning from experts are collected and summarized by a moderator to provide anonymous feedback over at least two rounds. Experts revise as they see fit and forecasts are combined. Delphi groups are substantially more accurate than individual experts and traditional groups, and somewhat more accurate than statistical groups (which are made up of non-interacting individuals whose judgments are aggregated).⁶⁹

Despite its benefits, few firms currently use Delphi.⁷⁰ Perhaps this is because it involves procedures that conflict with the intuitions of most managers. They tend to prefer unstructured discussions to Delphi.⁷¹

As we return to statistical forecasting methods which require the availability of relevant numerical data, these methods may be separated into univariate and multivariate methods.⁷² Univariate forecasting methods comprise extrapolation methods, including quantitative analogies, rule-based forecasting, and neural nets. Multivariate forecasting methods include data mining methods and econometric models.

Extrapolation models use time-series data, or similar cross-sectional data, to predict.⁷³ For example, exponential smoothing is used to extrapolate over time, and diffusion models are used for innovations. Extrapolation methods are reliable, objective, inexpensive, quick, and easily automated. As a result, they are widely used, especially for inventory and production forecasts, for operational planning for up to two years ahead, and for long-term forecasts in some situations, such as population forecasting.

⁶⁷ Ibid.

⁶⁸ The following section is based on (Armstrong 2001b), pp. 125-144

⁶⁹ see (Rowe 2001), pp.125-144

⁷⁰ see (Armstrong 2002), p.2

⁷¹ Ibid.

⁷² see Figure 10

⁷³ The following section is based on (Armstrong 2001b), pp. 217-243

Quantitative analogies.⁷⁴ In this method, experts identify analogous situations for which time-series or cross-sectional data are available, and rate the similarity of each analogy to the data-poor target situation. These inputs are used to derive a forecast; for example, to forecast demand for cinema seats in a new suburb, average data from cinemas in suburbs identified by experts as similar to the target could be used.

Rule-based forecasting.⁷⁵ In this method, expert domain knowledge and statistical techniques are combined using an expert system to extrapolate time series. Most series features are identified by automated analysis, but experts identify some factors. In particular they identify the causal forces acting on trends.

Neural networks, or rather an artificial neural networks (ANN), involve a network of simple processing elements (neurons) which can exhibit complex global behaviour, determined by the connections between the processing elements and element parameters.⁷⁶ The original inspiration for the technique was from examination of the central nervous system and the neurons (and their axons, dendrites and synapses) which constitute one of its most significant information processing elements. In a neural network model, simple nodes (called variously "neurons", "neurodes", "PEs" ("processing elements") or "units") are connected together to form a network of nodes — hence the term "neural network".⁷⁷

While a neural network does not have to be adaptive per se, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.⁷⁸

These networks are also similar to the biological neural networks in the sense that functions are performed collectively and in parallel by the units, rather than there being a clear delineation of sub-tasks to which various units are assigned (see also connectionism).⁷⁹

In this sense, an ANN is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through

⁷⁴ Ibid., pp. 195-213

⁷⁵ Ibid., pp. 259-282

⁷⁶ see (Gurney 1997), Chapter 1

⁷⁷ Ibid.

⁷⁸ Ibid.

⁷⁹ Ibid.

the network. In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.⁸⁰

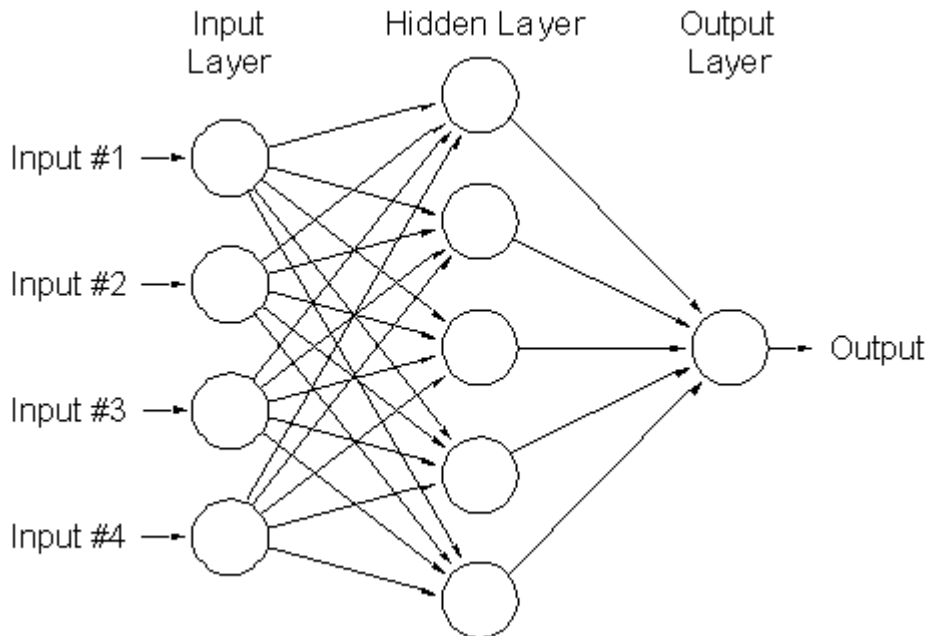


Figure 11: Illustration of the principle of neural networking: an interconnected group of nodes (Rounds 2002)

Thus, the utility of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particularly useful in those domains of forecasting, such as technological forecasting, where the complexity of the data or task makes the design of such a function by hand impractical.

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism which learns from observed data. However, there are practical limitations in using them and a relatively good understanding of the underlying theory is essential:

Choice of model: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.

Learning algorithm: There are numerous tradeoffs between learning algorithms. Almost any algorithm will work well with the correct hyperparameters for training on a particular

⁸⁰ see, e.g., (Rehkugler and Zimmermann 1994) or (Lange 2003)

fixed dataset. However selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.

Robustness: If the model, cost function and learning algorithm are selected appropriately the resulting ANN can be extremely robust.

As neural networks are relatively new to the forecasting domain; their application is still being explored.⁸¹

The multivariate forecasting methods may again be separated into data-based and theory-based methods.⁸² Whereas data-based methods rely on data mining, theory-based methods employ econometric models.

Data mining.⁸³ In this method, data mining, the nontrivial extraction of implicit, previously unknown, and potentially useful information from data, is used to generate forecasts. . This method uses machine learning, statistical and visualization techniques to discover and present knowledge in a form which is easily comprehensible. For example, bibliographic analysis searches literature databases to identify events that may foretell significant later developments.

Econometric methods.⁸⁴ Prior research and expert domain knowledge are used to specify relationships between a variable to be forecast and explanatory variables. Regression analysis is used to estimate model coefficients such that they are consistent with prior knowledge. Thus, in this method, theory, not the data, is used as a guide to selecting causal variables.

As we have reviewed the current state of the art in TF methods, in the next section we discuss the motivation for developing a new TF method and examine its potential for application to the field of technological development.

⁸¹ Ibid., pp. 245-256

⁸² see Figure 10

⁸³ The following section is based on (Armstrong 2001b), pp. 9-11

⁸⁴ The following section is based on (Armstrong 2001b), pp. 303-362

2.5 Motivation and potential of a new TF method

In this section we review the need for TF for emerging and disruptive technologies and identify a need not addressed yet. Furthermore, we review an early-established fundamental principle of forecasting, that is, forecasts by markets are optimal, and learn that this principle has not been utilized for TF yet. Finally, we conclude that artificial asset markets present an original opportunity for development as a new TF method – and we investigate its prospective potential.

2.5.1 The need for instant forecasts of emerging and disruptive technologies

In the previous section we have given an overview of the state of the art of TF methodology. There remains, however, a TF need currently not adequately served by available TF methods. To illustrate this need we start by reviewing the technology development cycle (or, rather, the technology maturation cycle).

We referred to the technology development cycle in section 2.3 by introducing the concept of the technology S-curve, illustrated in Figure 8. Technologies evolve from initial emergence when performance is relatively low, through rapid growth in performance based on increasing experience per cumulative development effort, and finally approach maturity where some natural technological limit is reached and the technology may become obsolete.

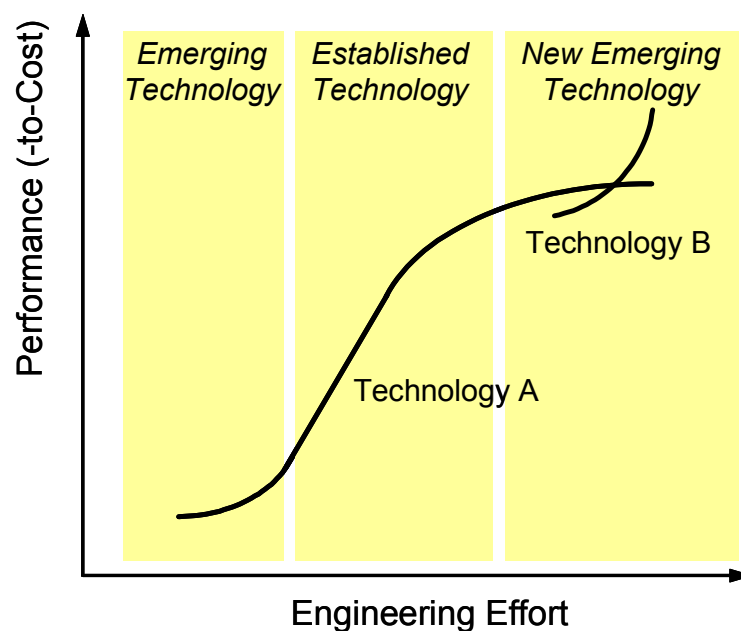


Figure 12: Illustration of the technology maturation cycle based on the S-curve framework; based on (Foster 1986), (Christensen 1992), and (Martino 1993)

Thus, we can broadly segment a technology maturation cycle into three phases, as illustrated in Figure 12:

1. Technology emerges → Technology establishes
2. Established technology evolves → Technology reaches performance plateau
3. Technology is substituted → New technology has emerged

Whereas the first and the last phase show great similarity, both are very different from the second technology maturation phase. While the technology, infrastructure, customers, and industry are relatively well defined for established technologies (Phase 2), considerable ambiguity surrounds emerging technologies (Phase 1, 3).⁸⁵ Table 3 contrasts the development environment for established and emerging technologies.

Table 3: Contrasting emerging and established technologies (Day, Schoemaker et al. 2000), p.5

	Established	Emerging
Technology		
• Science basis and applications	Established	Uncertain
• Architecture or standards	Evolutionary	Emergent
• Functions or benefits	Evolutionary	Unknown
Infrastructure		
• Value network of suppliers, channels	Established	Formative
• Regulation/standards	Established	Emergent
Market/Customers		
• Usage patterns/behavior	Well-defined	Formative
• Market knowledge	Thorough	Speculative
Industry		
• Structure	Established	Embryonic
• Rivals	Well-known	New players
• Rules of the game	Known	Emergent
Change characteristics of above	incremental change over long horizon	significant change over short horizon

⁸⁵ see (Day, Schoemaker et al. 2000), pp. 4-13

Indeed, one of the most confusing aspects of emerging technologies is that consumer usage patterns and behavior are exploratory and formative, while market knowledge is scant and the structure of competition is embryonic.⁸⁶

The uncertainty present in a technology's emerging phase is very different from the uncertainty that is present in a technology's established phase, even the most stable and predictable. Uncertainty in a stable environment is manageable, because there are usually only a few discrete outcomes that define the future and robust strategies can be devised to adapt to these possibilities.⁸⁷

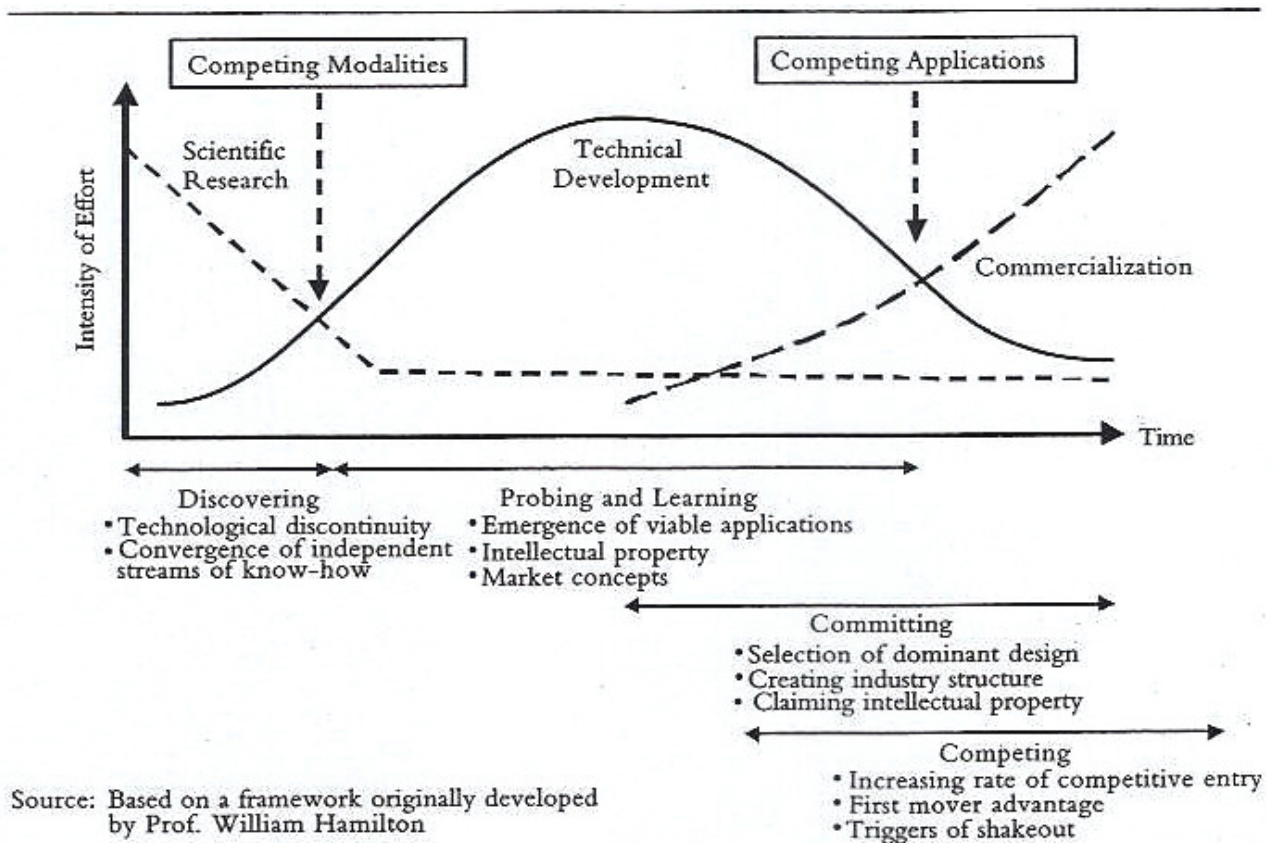


Figure 13: Characterization of the technology maturity phase for emerging technologies (Day, Schoemaker et al. 2000), p. viii

The character of uncertainty created by an emerging technology is profoundly different. The risks are not just external but also internal, relating to the biases and limitations of people's thinking frameworks.⁸⁸ There are so many unpredictable and volatile conditions interacting in unanticipated ways in the early stages that there appears to be

⁸⁶ see (Day, Schoemaker et al. 2000), p.5-7

⁸⁷ Ibid.

no sound way to predict the future.⁸⁹ See also Figure 13 for an illustration and characterization of the technology maturity phase.

Thus, the phases in the technology maturity cycle in which a technology emerges and in which it has established are very different – and, consequently, each present a very different operating environment to TF.

Next, we attempt to deduce the main needs to TF for each of both technology maturity phases. The deduction of both sets of needs is based on the primary forecasting question, the management action cycle needs, and on the implications for representation of the actual development. The result of this analysis is summarized by Table 4.

Table 4: Deduction of TF needs and methodological approach

	Established	Emerging
1 Primary forecasting questions (required forecast output)	<ul style="list-style-type: none"> • When will a given technology reach a specific performance? (rate of perf. development) • When will a given technology reach its performance plateau? At what performance? 	<ul style="list-style-type: none"> • When will a given technology establish? • Which of the given technologies will establish? When? • Will a given technology become substituted? When?
2 Management action cycle needs	<ul style="list-style-type: none"> • Measured/periodic delivery of forecast is sufficient • increased accuracy is important 	<ul style="list-style-type: none"> • instant delivery of forecast (current outlook) • instant adaptation to rapidly changing situations
3 Implications for representation of the actual development	<ul style="list-style-type: none"> • comprehensible number of variables • comprehensible relationships between variables <p>→ approximable by mathematical / structured model</p>	<ul style="list-style-type: none"> • quasi-infinite number of variables • Quasi-incomprehensible relationships between variables (non-linear!) <p>→ Practically NOT approximable by mathematical / structured model</p>
Deduced methodological approach for TF	<p>Modeling</p> <p>→ focus on constructing a model that is valid over long time horizon</p>	<p>Sampling</p> <p>→ focus on very frequent info collection, analysis and aggregation</p>

⁸⁸ see (Day, Schoemaker et al. 2000), p.5-7; Jürgen Habermas, a German philosopher, refers to this as epistemic risk, i.e., the risk of not knowing what one does not know.

⁸⁹ Ibid.

Next, we develop a two-dimensional application/needs-matrix – based on the dimension of the technology maturity phase and the dimension of management action cycle needs. The result is displayed by Figure 14. In segmenting the technology maturity phases, we introduce the segment "Disruptive". This segment does not actually represent a separate maturity stage, but indicates that there may be a situation in which an established technology is displaced rapidly and unexpectedly – such a development is referred to in the literature as disruptive.⁹⁰ If an established technology is disrupted, it is because any of the characteristics describing the development environment in Table 3 has changed fundamentally.⁹¹

The dimension management action cycle needs is segmented into an instant marginal forecast need and a delayed marginal forecast need. It refers to whether a measured delivery of a current forecast is sufficient or an (near-)instant delivery of a current forecast is necessary to manage the business related to the forecasted technology.

Within the two-dimensional space of the application/needs-matrix, we have positioned the currently available TF methods to indicate their coverage of the highlighted TF needs. Established technologies are well covered by the available statistical and structured methods. As this development phase features incremental change over a relatively long time horizon, there is no need for instant marginal forecast availability.

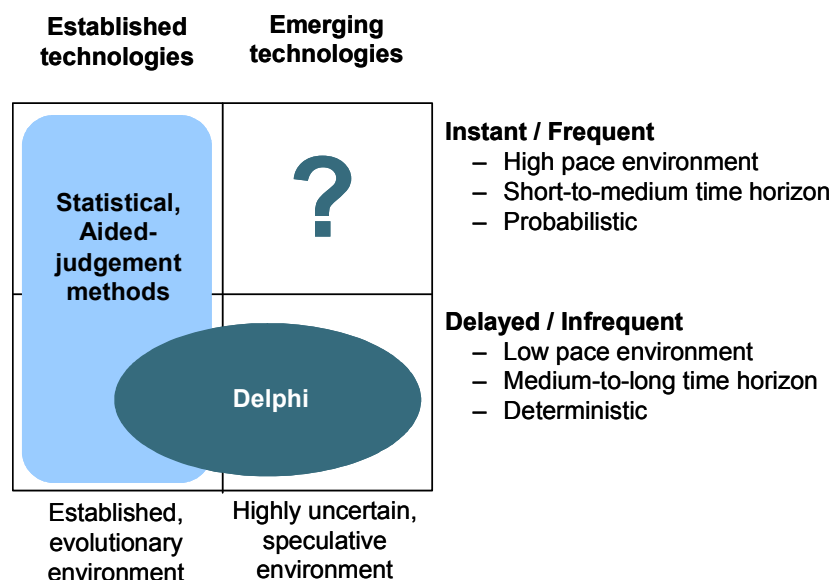


Figure 14: Application/needs-matrix for TF: illustration of a coverage gap by current TF methods

⁹⁰ see, e.g., (Christensen 1992; Christensen 1997; Day, Schoemaker et al. 2000; Burgelman 2004)

⁹¹ see (Christensen 1997)

For disruptive situations and in a technology's emerging phase, however, there is only partial needs coverage by existing TF methods. For example, the Delphi group method provides adequate forecasts in such phases, but only for a delayed marginal forecast availability need. This is sufficient for industries or product categories with a relatively low pace. Alternatively, forecasts based on Delphi are sufficient if technologies are forecasted for a very long time horizon, e.g. 5 to 30+ years.

Forecasts by scenario planning (or decomposition method) are of limited use for disruptive situations and especially in the emerging maturity stage. As noted earlier, in these situations there are so many unpredictable and volatile conditions interacting in unanticipated ways that the number of scenarios cannot be reduced to only a few discrete outcomes that define the future in order to develop robust strategies that can be devised to adapt to these reduced possibilities.

Thus, there is an unserved need for a TF method that is able to cope with the operating environment in the emerging maturity phase or in disruptive situations, and that supplies the management with an instant marginal forecast availability.

We conclude this section by developing the methodological approach to cover the identified unserved need – the approach is indicated by the deduced set of TF needs presented earlier in Table 4.

For an emerging technology's maturity phase a quasi-infinite number of variables would be needed to describe the driving development environment (characterized in Table 3). Moreover, in this phase the relationships between these variables are non-linear, to an extent that is quasi-incomprehensible.

Consequently, the driving forces in the emerging maturity phase are practically not approximable by a mathematical or structured model. We regard this insight as fundamental.

Thus, in developing a forecasting method for emerging technologies, instead of trying to model factors that drive technological development, the more appropriate approach is to sample the current development very frequently.

By sampling, we refer to collecting or screening the vast amount of information that might be relevant, analyzing its possible impact on the development and aggregating it into a comprehensible short-term outlook.

As we have identified the need for a new TF method and established the necessary methodological approach, we advance by reviewing an early-established fundamental principle in forecasting.

2.5.2 Forecasts by markets are optimal

Research in forecasting has established as an early foundation a collection of enduring principles. One of these fundamental principles is

"Forecasts provided by efficient markets are optimal" (Armstrong 2001b), p.7

Cowles (1933) concluded that forecasters could not improve the accuracy of forecasts derived from the actions of a market. Research findings have strengthened this conclusion (Sherden 1998). This applies to financial markets, betting on sporting events, and collectibles. Armstrong (2001b), p.7.

However, not until recently were markets artificially created for the prime purpose of forecasting. Whereas Plott and Sunder (1982, 1988) were among the first to demonstrate in laboratory experiments the ability of artificially created markets to collect and aggregate dispersed factual information (thus, the ability of markets to become informationally efficient), Forsythe, Nelson et al. (1992) demonstrated in a field experiment – the Iowa Electronic Markets (IEM) – the ability of artificially created markets to not only collect and aggregate factual information, but at the same time to collect and aggregate the evaluation of traders about the outcome of a U.S. Presidential election – thus, providing a forecast.

Artificial asset markets reassemble the logic and structure of real-world financial markets, i.e., stock markets. Individuals are offered the opportunity to invest in specific outcomes of selected uncertain events by buying contracts with prices that vary between x\$1 and x\$99 in the respective currency. While the outcome is undecided, supply and demand between traders determine the appropriate price for these contracts. Then, when the outcome is finally decided, the winning contracts are cashed in for x\$100 each, while the losing contracts are worthless. See Figure 15 for an illustration of the concept of AAMs.

In the end, the market price for each event will indicate an informed aggregation of the probabilities that informed speculators assign to that event. The market “sweeps up” the beliefs of the participants and aggregates them no matter how dispersed or how differentially informed those participants are.

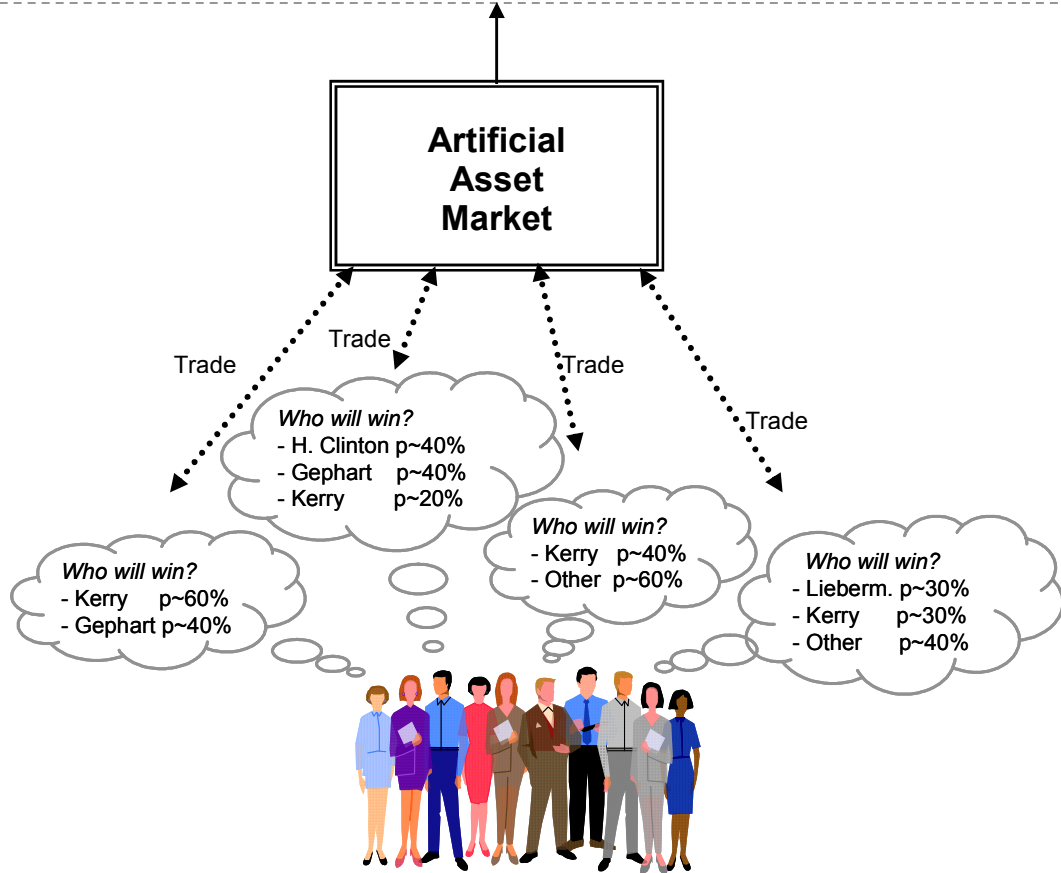
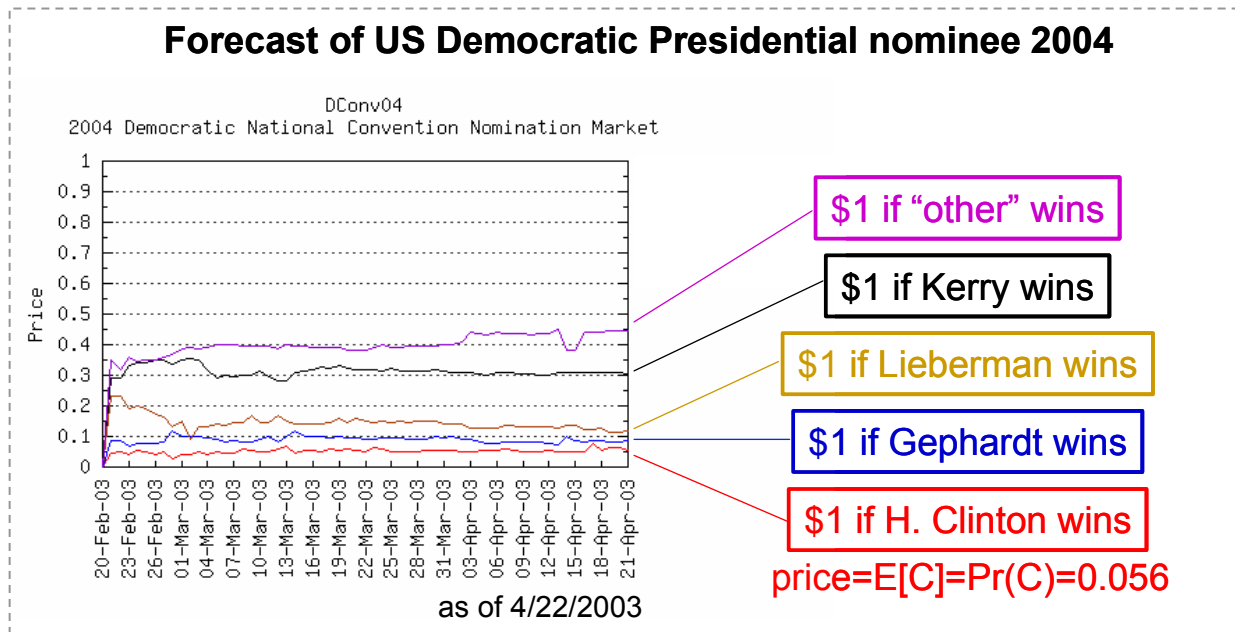


Figure 15: Illustration of the concept of artificial asset markets

Since the establishment of the IEM, little research has followed that further explored the ability of artificial asset markets to provide forecasts about future events.⁹² The classes of events covered by artificial asset markets created in the course of this research were almost entirely limited to political elections and sporting events.⁹³ The focus on such events was presumably motivated by their frequent occurrence, their short-term time horizon, and the ease of measuring and comparing outcomes to forecasts and forecasts to performance benchmarks (e.g., polls).⁹⁴

Events of technological development are, however, very different in many characteristics from those of events of political elections and sporting. Technological developments have relatively long time horizons, they occur relatively infrequently for a given technology, and the outcomes of technological developments are difficult to measure (instantly) and forecast performance benchmarks are scarce. Table 5 provides a comparison of the most important characteristics for both classes of events.

Table 5: Comparison of event context: Political elections and sporting events vs. technological developments

Political elections, Sports	Technological developments
<ul style="list-style-type: none"> • short-term events (<1 year horizon) • easy measurable outcomes • mainly high-frequency events (relatively) • generalist knowledge; increased interest of (groups of) broad public • potential trader base typically from local or national population • relatively little private information – more weight on opinion pooling than info collection 	<ul style="list-style-type: none"> • long-term events (multi-year horizon) • outcomes are ambiguous, difficult to measure (instantly) • mainly low-frequency events (relatively) • specialist knowledge; typically, only superficial interest of broad public • potential trader base typically globally dispersed • relatively lots of semi-private and unpopular information – balance of info collection and opinion pooling

In comparing these very different event types for forecasting, it appears unreasonable that the research results and the design of artificial asset markets in the context of political and sports events can be generalized, transferred and successfully applied to artificial asset markets in the context of technological developments. Thus, we can summarize:

⁹² see chapter 3 for a summary of this research

⁹³ Notable exceptions were the TU Vienna/Siemens 1997 market and the CalTech/HP Sales 1997 market. See chapter 3 for a review of the corresponding research.

⁹⁴ see, e.g., (Berg, Forsythe et al. 2000), p.1

There is still little evidence on the performance of artificial asset markets – especially on field performance

There is no evidence on the performance of artificial asset markets for TF

As the context of events for which some evidence has been produced is very different from the context of technology development, the evidence cannot be simply generalized as to apply for TF as well

2.5.3 Prospective potential of a new TF method: TF by artificial asset markets

In the previous sections of this chapter we reviewed the need for technological forecasting and its applications. In the course of this review we developed the insight, that there is an unserved need for a TF method that is able to cope with the operating environment in the **emerging** maturity phase or in **disruptive** situations, and that supplies the management with an **instant** marginal forecast availability. We concluded it reasonable to develop a TF method that addresses this need.

In search of a methodological approach we review two further insights developed and presented earlier:

1. As a TF method, instead of trying to model factors that drive technological development, the more appropriate approach for TF of emerging technologies is to sample the current development very frequently.
2. Forecasts by efficient markets are optimal – however, this principle has not been applied to TF yet. There is growing evidence that this principle can be utilized by artificial asset markets; though, there is no evidence in respect to TF and little of the evidence can be generalized to the context of TF.

We conclude from the above insights that artificial asset markets present an original opportunity for developing a new TF method.

Subsequently, we more specifically analyze the prospective potential for the new TF method based on artificial asset markets by two perspectives: performance and cost. The prospective characteristics for both perspectives are summarized by Table 6.

Table 6: Prospective potential of TF by artificial asset markets

Perspective	Prospective characteristics
Performance	<ul style="list-style-type: none"> • accuracy <ul style="list-style-type: none"> ○ theoretically, most accurate method ○ more accurate than comparable alternative methods (e.g. Delphi) ○ however, accuracy is a function of market efficiency! • forecast type <ul style="list-style-type: none"> ○ probabilistic forecasts (typically) ○ continuous forecast: continuously provides current "best estimate" instantly • dynamism <ul style="list-style-type: none"> ○ instantly adapts to "unforeseen" developments resulting from technology sales market dynamics, societal dynamics, etc. (= "environmental factors") ○ rather acts as a leading indicator of a dynamic development than as a static forecast of pre-determined events
Cost	<ul style="list-style-type: none"> • market platform (technical infrastructure) <ul style="list-style-type: none"> ○ one-time development and installation cost ○ ongoing operational cost ○ major cost drivers <ul style="list-style-type: none"> – implementation as highly automated electronic market OR as physical floor market – implementation as play money market OR as real money market that incurs considerable regulatory incl. consequential technical costs • per forecast (period) <ul style="list-style-type: none"> ○ Cost of active marketing to specialist knowledge traders ○ Cost of provision of trader incentives ○ Marginal cost for additional forecast of same event = ~0

In perspective of performance, the new method of TF by artificial asset markets offers no less than the prospect of being the most accurate forecasting method.⁹⁵ Consequently, forecasts by artificial asset markets (AAM) should perform better than comparable performance benchmarks set by other TF methods. However, as noted at the beginning of this section, only forecasts by *efficient* markets are optimal – thus, accuracy of forecasts by AAM is always a function of the degree of market efficiency achieved.

⁹⁵ see also section 2.5.2

Of the various forecast types, AAM typically produce probabilistic forecasts which provide a probability distribution over the possible event outcomes.⁹⁶ Furthermore, forecasts by the AAM method inherently provide a continuous forecast: the actual market price always reflects the markets consensus of the "best estimate" for the future outcome. Thus, the current forecast outlook is virtually instantly available.

Finally, the third notable aspect of performance addresses the dynamism of the new method. By providing a continuous forecast, the new method instantly adapts to "unforeseen" developments resulting from technology readiness and delivery dynamics, technology sales market dynamics, societal dynamics, and other "environmental factors".⁹⁷ Thus, the new method instantly updates the forecast in the face of dynamic developments. In this way, TF by AAM rather acts as a leading indicator of a dynamic development than as a static forecast of pre-determined events.

In perspective of the costs incurred by using the new TF method, there is a group of costs associated with setting up and maintaining the market platform as technical infrastructure and a group of costs on a per forecast-basis (marginal costs).

The cost of setting up and maintaining the technical infrastructure is strongly determined by the decision to implement the market platform as a highly automated, electronic market, and by the decision to implement the market platform as a real-money market which would incur considerable regulatory including consequential technical costs.

Once, the market platform has been set up, the marginal costs per forecast result from acquiring and maintaining the respective trader base, that is, the cost of active marketing to specialist knowledge traders, and the cost of providing incentives to traders.

However, the marginal costs for an additional forecast of the same event is ~0 (zero), as the same is true for an additional forecast of a related event for which the trader base has the appropriate specialist knowledge.

To relate the new TF method AAM to the other forecasting methods, we use the methodology tree presented in section 2.4. Figure 16 shows how the new method fits into this methodology tree.

⁹⁶ see also section 2.5.2 and chapter 3

⁹⁷ Many of the studies of past forecasts have concluded that a significant cause of error is the underestimation or omission of certain factors in the environment that could have an impact on the technology being forecast. See also (Martino 1993), p.308

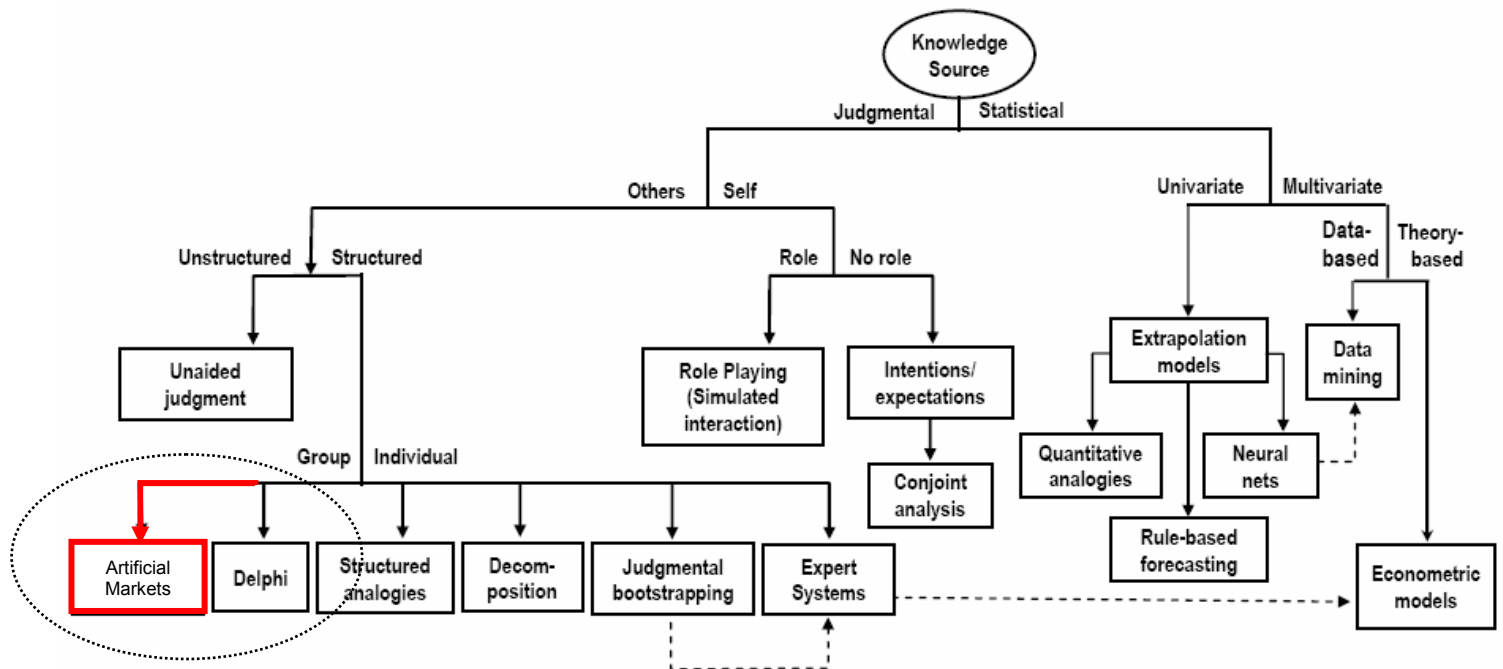


Figure 16: Fit of the new TF method <TF by Artificial Asset Markets> in the methodology tree of forecasting methods; adapted from (Armstrong 2004)

The knowledge source of the new TF method is judgmental, as it is not primarily based on statistical sources. Of the next subgroups, the new method belongs to the class of methods which predict how others will behave, as it primarily considers knowledge about the expected behavior of other people or organizations. Finally, it belongs the group of structured methods performed by groups, as the new method systematically collects and aggregates information from a group of "information traders". By this classification, the new method is a direct alternative to the Delphi method.

To conclude, from our view, the greatest prospective potential offered by TF by AAM results from

- high degree of accuracy, theoretically even better than alternative TF methods
- negligible marginal costs for additional forecasts in a specialist field once the infrastructure is set up and the trader base is established
- continuous delivery of the current forecast outlook
- instantly updates the forecast in the face of dynamic developments

2.6 Development of hypotheses

Based on the prospective potential of TF by artificial asset markets, as discussed in the previous section, we develop the following hypotheses as basis for further research presented in this work:

H1: Artificial asset markets can forecast technological developments (in principle)

Essentially, this hypothesis asserts that the concept of artificial asset markets, showing promising results in the various fields of forecasting, also "works" in the domain of technological forecasting: the forecast of long-term, low-frequency and difficult-to-measure events which result from very complex underlying business and social developments. Thus, the hypothesis refers to a minimum absolute performance in forecast capacity to acknowledge technological forecasts by artificial asset markets as reasonably accurate and reliable.⁹⁸

For empirical validation, the hypothesis needs to be operationalized in a way that it contains quantifiable properties that can be measured. This operationalization is done in chapter 4.

We develop a second hypothesis based on our discussion in the previous section:

H2: Artificial asset markets can forecast technological developments better than alternative TF methods used in a comparable application context

Essentially, this hypothesis asserts that, given a comparable application context, technological forecasts provided by artificial asset markets are more accurate and more reliable than those of alternative TF methods.⁹⁹

The application context, as described in the previous section 2.5.1, refers to situations in which the knowledge source is judgmental, that is, when expert opinion is needed to make a forecast. This includes situations in which no historical data exist (e.g., as new technologies emerge), the impact of external factors is more important than the factors that governed the previous development of the technology, or when ethical or moral

⁹⁸ Forecast accuracy and reliability are two quality attributes that are commonly used for forecast verification. See the appendix for an overview and description of forecast verification.

⁹⁹ Ibid.

considerations dominate the economic and technical considerations that usually govern the development of technology.¹⁰⁰

The TF methods appropriate in such an application context include – in first place – the group method Delphi and the Unaided Judgment, but also the individual methods Structured Analogies, Decomposition, Judgmental Bootstrapping and Expert Systems.¹⁰¹

Again, for empirical validation, the hypothesis needs to be operationalized in a way that it contains quantifiable properties that can be measured. This operationalization is done in chapter 3.

2.7 Summary and conclusions

In this chapter we reviewed the literature on technological forecasting, discussed the motivation for developing a new TF method, briefly conceptualized AAM as a new TF method, investigated its potential and eventually developed hypotheses to test the new method's validity and application in the domain of technological forecasting.

We established the importance of TF for businesses and policymakers alike, as innovation and technology development cycles are accelerating significantly, while the complexity underlying technological development is increasing rapidly.

Among the first insights of our review is that the phases in the technology maturity cycle in which a technology emerges and in which it has established are very different – both present a very different operating environment with a different set of requirements to TF.

Whereas the state of the art in TF methods cope well with the operating environment of established technologies, we have identified an unserved need for a TF method that is able to cope with the operating environment in the emerging maturity phase or in disruptive situations, and that supplies the management with an instant marginal forecast availability. We concluded it reasonable to develop a TF method that addresses this need.

¹⁰⁰ see (Day, Schoemaker et al. 2000), pp.4-12; and (Martino 1993), pp. 308-313

¹⁰¹ see section 2.4 for an overview and a description of the TF methods mentioned here

Most fundamentally, we assume the driving forces in the emerging maturity phase to be practically not approximable by a mathematical or structured model. Consequently, in search of a methodological approach for the new TF method, we conclude, instead of trying to model factors that drive technological development, the more appropriate approach for TF of emerging technologies is to sample the current development very frequently.

Artificial asset markets feature this characteristic. Furthermore, AAM are able to utilize an early-established principle of forecasting: that forecasts by markets are optimal. However, this principle has not been applied to TF yet. Although there is growing evidence that this principle can be successfully utilized by artificial asset markets, there is no evidence in respect to TF and little of the evidence can be generalized to the context of TF.

Thus, we conclude from the above insights that artificial asset markets present an original opportunity for developing a new TF method.

We analyzed the potential for the new TF method in terms of performance and cost and identified several prospects:

- a high degree of accuracy, theoretically even better than alternative TF methods
- negligible marginal costs for additional forecasts in a specialist field once the infrastructure is set up and the trader base is established
- continuous delivery of the current forecast outlook
- instant updates of the forecast in the face of dynamic developments

Based on the potential offered by TF by artificial asset markets, we developed two broad hypotheses as basis for further research presented in this work:

H1: Artificial asset markets can forecast technological developments (in principle)

H2: Artificial asset markets can forecast technological developments better than alternative TF methods used in a comparable application context

As we have established the motivation and hypotheses for research of a new TF method, in the next chapter we explore the theoretical, empirical, and experimental foundation of artificial asset markets applied to forecasting.

3. Theoretical, empirical and experimental foundation of artificial asset markets applied to forecasting

In this chapter we review the pieces of literature that have accumulated so far on artificial asset markets and we investigate the ability of AAMs to provide forecasts of any kind.

After a brief introduction that discusses how market prices represent all available information, we review the vast amount of literature on the corresponding efficient market hypothesis and its current critique.

Subsequently, we establish the principle of artificial asset markets as information aggregation and forecasting tool and go on to review the experimental evidence produced by laboratory experiments. We additionally review the evidence produced by first field experiments, both in a private and public setting.

Finally, we review the literature on selected focus issues of market performance that are motivated by forecast accuracy.

We conclude the chapter with a brief summary and an examination of the support provided by the reviewed literature for the hypotheses developed in the previous chapter.

3.1 Price as instant aggregated statistic of all available information

A market performs the dual role of allocation and price discovery among parties that are interested in the items exchanged through the market.¹⁰² In a seminal work Hayek (1945) suggested that prices in naturally occurring, free markets make important contributions to information transmission in economies. Prices, according to his theory, are a statistic that indicates the aggregation of information about underlying states of the economy.

Muth (1961), Samuelson (1965) and Fama (1965, 1970, 1991) more explicitly specified and operationalized Hayek's theory which resulted in the Efficient Market Hypothesis (EMH) and the theory of Rational Expectations (RE). The EMH essentially states that at any given time in a perfectly efficient market, security prices fully reflect all available information:

"An 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants.

¹⁰² see, e.g., (Sunder 1995), pp.445-447

In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value."
Fama (1965)

The EMH was complemented by the theory of rational expectations (RE), which posits that even when some market participants have exclusive access to inside information, prices equilibrate exactly as if everyone had access to all information.¹⁰³ The procedural explanation is that prices reveal to the ignorant participants any initially private information; that is, participants learn by observing prices.¹⁰⁴

The implications of the efficient market hypothesis and the theory of rational expectations are truly profound. Most individuals that buy and sell securities do so under the assumption that the securities they are buying are worth more than the price that they are paying, while securities that they are selling are worth less than the selling price.¹⁰⁵ But if markets are efficient and current prices fully reflect all information, then buying and selling securities in an attempt to outperform the market will effectively be a game of chance rather than skill.¹⁰⁶

The paradox of efficient markets is that if every investor believed a market was efficient, then the market would not be efficient because no one would analyze securities.¹⁰⁷ In effect, efficient markets depend on market participants who believe the market is inefficient and trade securities in an attempt to outperform the market.¹⁰⁸

The concept of fundamental value and market value is often used to explain why traders often differ in their opinions about prices as being efficient. According to this concept, a market price is informative (or "efficient") when it is near its fundamental value.¹⁰⁹ The market value of an instrument is the price at which traders can buy or sell the instrument. The fundamental value (or intrinsic value) is the "true value" of the instrument. In financial terms, fundamental value is the expected value of all present

¹⁰³ see, e.g. (Lo 1997)

¹⁰⁴ see (Lucas 1972), pp.103 and (Grossmann 1981), pp.541

¹⁰⁵ see, e.g. (Lo 1997)

¹⁰⁶ Ibid.

¹⁰⁷ Ibid.

¹⁰⁸ Ibid.

¹⁰⁹ see, e.g. (Harris 2002), pp.222-224

and future benefits and costs associated with holding the instrument.¹¹⁰ Everyone would agree upon this value if they all knew everything known about the instrument, if they all used the proper analyses to predict and discount all uncertain future cash flows, and if they all perceived the benefits and costs of holding the instrument equally. However, since these conditions never occur, traders often differ in their opinions about fundamental values.¹¹¹

Madhavan (2000) provides an illustration in mathematical terms¹¹²: let v_t denote the (log) true value of a risky asset at some point in time t ; thus, v_t represents the full-information expected present value of future benefits and costs of holding the asset. Fundamental value may change over time because of variation in expected future benefits and costs or in the discount rate. The conditional expectation of v_t given the set of public information H_t at time t is denoted by $\mu_t = E[v_t|H_t]$. Further, let p_t denote the (log) price of the risky asset at time t .

In the canonical model of (weakly) efficient markets, price reflects all public information. If agents are assumed to possess symmetric information and trade frictions are negligible – the simplest set of assumptions – then prices simply reflect expected values: $p_t = v_t$.

Taking log differences, we obtain the simplest model of stock returns:

$$r_t = p_t - p_{t-1} = \varepsilon_t.$$

$$\varepsilon_t \text{ is the change in beliefs: } \varepsilon_t = \mu_t - \mu_{t-1} = E[v_t|H_t] - E[v_{t-1}|H_{t-1}]$$

Since μ_t follows a martingale process, applying the Law of Iterated Expectations, returns are serially uncorrelated. Thus, markets are efficient in the sense that prices at all points in time reflect expected values.

To conclude, the informational efficiency of capital markets is a central theme in modern finance. The ability of markets to efficiently aggregate information is well known in the finance literature.¹¹³

¹¹⁰ Ibid.

¹¹¹ Ibid.

¹¹² see (Madhavan 2000), pp.208-209

¹¹³ see, e.g. (Lo 1997), (Lo 2000), and (Ackert and Church 1998)

We point out that the focus is especially on the capacities of asset markets. A definition is provided by Sunder (1995):

Capital or asset markets are distinguished from other markets by the informational role of prices and by the duality of traders' role: each trader may buy and sell asset(s) in exchange for money or some other numeraire commodity.

Although prices in other markets may inform the participants in the sense of making them aware of their opportunity sets, prices in capital markets inform the traders substantively as determinants of their endogenously formed demand and supply. Asymmetry of information among the traders is an essential ingredient for prices to have an informational role, and I use this as the defining characteristic of capital or asset markets [..].

Next, we examine the empirical research of capital markets' capacities in respect to market efficiency.

3.2 Empirical evidence

As identified in the preceding section, the EMH forms the foundation of a market's ability to collect and aggregate information by reflection of all information in security prices. The EMH and the theory of RE have been subject to three decades of intense debate among academics and financial professionals, which has resulted in hundreds and thousands of empirical studies attempting to determine whether specific markets are in fact "efficient" and if so to what degree security prices reflect available information.¹¹⁴

Price data gathered from stock and commodities exchanges made it possible for researchers to test the EMH, but most of the empirical testing of the EMH has centered on the observable *changes* of stock prices associated with private or public events.¹¹⁵ An overview of the results from a large number of studies which largely support the EMH for small price changes in financial markets is given in Fama (1970) and Fama (1991).

¹¹⁴ see, e.g. (Lo 1997)

¹¹⁵ see, e.g., (Sunder 1995), p.447 for a detailed description

The efficiency of large price changes and the efficiency of price levels have proven to be very difficult if not impossible to be examined by empirical research and remains to be tested.¹¹⁶ In fact, it appears that the general principle that it is possible for market prices to reflect information so the uninformed traders are able to act as they are informed cannot be conclusively tested by empirical research.¹¹⁷

Moreover, accumulating evidence challenges the efficient market view of prices representing rational valuation of fundamental factors due to psychological factors, social movements, "noise trading", and fashions or "fads" of irrational investors in a speculative market.¹¹⁸ For example, when individuals are faced with the complex task of assigning probabilities to uncertain outcomes, they often tend to use cognitive heuristics.¹¹⁹ While this behavior is useful in reducing the task to a manageable proportion, these heuristics often lead to systematic biases—and, thus, to not fully rational behavior.¹²⁰ Other research, for example, has challenged the notion of rational behavior by uncovering that sunshine is strongly correlated with daily stock returns, suggesting that sunshine biases investor behavior by putting people in a good mood.¹²¹

Thus, in conclusion, the empirical evidence suggests that, in reality, markets are neither perfectly efficient nor completely inefficient.¹²² All markets are efficient to a certain extent, some more so than others. Rather than being an issue of black or white, market efficiency is more a matter of shades of gray.

Thus, in markets with substantial impairments of efficiency, more knowledgeable investors can strive to outperform less knowledgeable ones. Government bond markets for instance, are considered to be extremely efficient.¹²³ Most researchers consider large capitalization stocks to also be very efficient, while small capitalization stocks and international stocks are considered by some to be less efficient.¹²⁴

¹¹⁶ see (Sunder 1995), p.447

¹¹⁷ see (Sunder 1995), p.447

¹¹⁸ see, e.g. (Russel and Torbey 2002)

¹¹⁹ see, e.g. (Kahneman and Tversky 1986)

¹²⁰ see, e.g. (Kahneman and Tversky 1986)

¹²¹ see (Hirshleifer and Shumway 2001)

¹²² see, e.g. (Lo 1997) and (Russel and Torbey 2002)

¹²³ see (InvestorHome 2004)

¹²⁴ see (InvestorHome 2004)

Real estate and venture capital, which don't have fluid and continuous markets, are considered to be less efficient because different participants may have varying amounts and quality of information.¹²⁵

As a result, a body of research in the theory of market microstructure has developed. Its central idea is that asset prices need not equal full-information expectations of value because of a variety of "frictions".¹²⁶

By theory, we recapitulate from section 3.1, price fluctuations reassemble a temporal (im-)balance of two driving forces: a rational incorporation of new information versus an incorporation of irrational expectations (speculation).

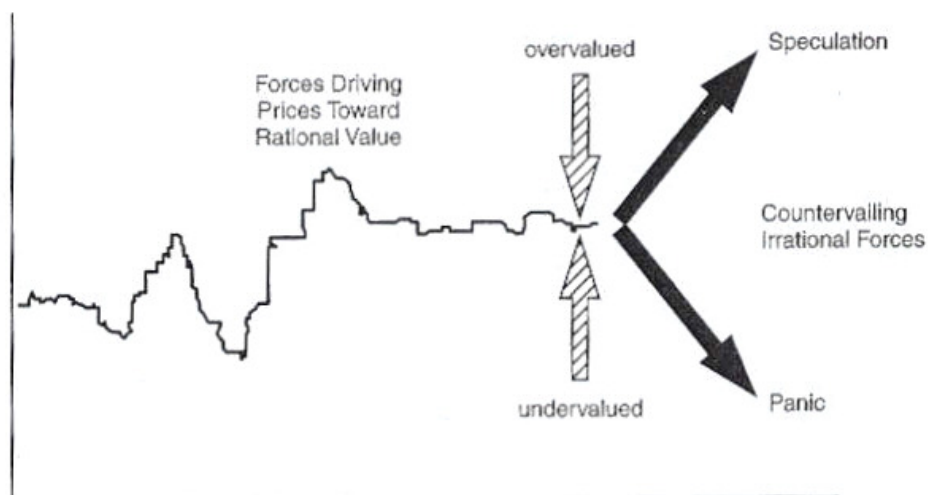


Figure 17: Stock market price as a result of rational and irrational forces (Sherden 1998), p.118

Sherden (1998) provides an interpretation of the empirical evidence on stock market price development in which the market is a complex system with rational and countervailing irrational forces at work, as illustrated in Figure 17. While rational forces drive the market toward its fair value, irrational forces of speculation and panic cause the market to diverge from rational value. These irrational forces give rise to significant nonlinearities that make the market unpredictable. Speculation and panic are nonlinear forces with positive feedback loops. The greater the surge in stock prices, the more

¹²⁵ see (InvestorHome 2004)

¹²⁶ see (Madhavan 2000), p.207

investors are tempted to buy shares, which causes the market to surge further-until price drops set off a run of panic selling, causing a huge market decline.

Next, we explore the capacity of capital markets in respect to information aggregation and forecasting.

3.3 Artificial asset markets as information aggregation and forecasting tool

In reference to the theory introduced in section 3.1, a financial security's value is the expected value of all present and future benefits and costs associated with holding the instrument. A security's market price reflects the market's consensus of what the security is worth at that point in time.¹²⁷

For example, a stock transaction is a bet on the future performance of the underlying firm. A commodities futures contract is a bet on the value of the underlying commodity at a specific date in the future. And a term contract between firms is a mutual bet on the merits of an ongoing business relationship.

However, most security trading is based on traders' differing expectations of future value rather than their knowledge of and need for current consumption, sales, or production.¹²⁸ As a result, transactions are often re-traded many times prior to their becoming current transactions.¹²⁹ Put differently, this turning over of the transactions is a result of changing expectations among the traders and highlights the role of asset markets as information lens, aggregating and focusing predictions of asset value.¹³⁰

Intentionally, speculative asset markets, such as futures markets, were created to reallocate risk.¹³¹ For example, a producer of wheat was trying to secure a selling price for next season's crop, while a bread maker was trying to secure a buying price to determine how much bread can be made and at what profit. So the farmer and the bread maker entered into a futures contract requiring the delivery of e.g. 5,000 bushels of grain to the buyer at a specific date in the next season at a price of e.g. \$4 per

¹²⁷ see section 3.1

¹²⁸ see section 3.1 or (NetExchange 2003a), p.25

¹²⁹ A stock transaction only becomes a current, rather than future, sale when the firm is bought out and its equity thus consumed. Term contracts between firms may not be directly re-traded, but they are hedged through a number of insurance and insurance-like transactions, which are then re-traded actively; see (NetExchange 2003a), p.25

¹³⁰ see (NetExchange 2003a), p.25

¹³¹ see, e.g., (Harris 2002), p.41

bushel. By entering into this futures contract, the farmer and the bread maker secured a price that both parties believed would be a fair price in the next season.¹³²

Table 7: Historical roots and development of AAM for forecasting (NetExchange 2003b)

Historical development stages	
Village market	prices indicate current distribution of values among villagers and impact future production.
Futures market	separate current pricing from forward pricing (thus, more effectively plan future production & investment)
Derivatives market	allow futures to be combined so that specific risks can be hedged (focus on the risks you can affect)
Iowa Electronic Market (IEM)	pure informative artificial asset market for forecasting political election outcomes
Economic derivatives market	Derivatives futures contracts written off trusted economic data indices, e.g. US employment, US retail sales, or industrial production
Decision support market	Firm-internal market to aid investment and risk management decisions

As a side effect, such speculative markets also provided accurate predictions of future prices and future events. Research has shown, for example, that the price of an orange juice future can be a better predictor of the probability of a freeze than the very best weather models can provide.¹³³

As a result, experimental, artificial asset markets have been created with the intention to produce forecasts in the first place. An early and well-documented example is the Iowa Electronic Market (IEM).¹³⁴ More recently, Goldman Sachs and Deutsche Bank, both financial institutions, have introduced a market that trades in derivatives on the development of economic data, such as US employment, allowing both, to allocate risk and to produce forecasts on economic development.¹³⁵

To understand how markets can be created to aggregate information into reliable predictions of events of interest, consider the following example. Suppose a decision maker is interested in whether technology A or technology B will become the dominant market standard beyond 2004. He could simply ask everyone, weigh the evidence and guess.

¹³² It is this contract—and not the grain per se—that can then be bought and sold in the futures market

¹³³ see (Roll 1984)

¹³⁴ see section 3.6.1 for a detailed description of the IEM and sections 3.5 and 3.6 for detailed description of other examples of informative artificial asset markets for forecasting

¹³⁵ see section 3.6

Alternatively the decision maker could create two contracts which will be bought and sold. Contract 1 states “I will pay \$1 if technology A dominates after 2004” Contract 2 states “I will pay \$1 if technology B dominates after 2004.” Letting participants trade these contracts among themselves will lead the prices of the contracts to reflect the information of the individuals.

Explained simply, if only one person knew for sure that technology A would become the dominant market standard beyond 2004 and if the price of contract 1 were less than \$1, then that person could make money for sure by buying as many units of contract 1 as possible until its price were driven up to \$1. The equilibrium price of contract 1 will be \$1 which signals that the probability of that event is 1.

It requires a bit more subtle argument when one person’s belief is, say, that the probability of technology A becoming the dominant market standard beyond 2004 is 85%, but the principle is similar. In the end, the market price for each event will indicate an informed aggregation of the probabilities that informed speculators assign to that event. The market “sweeps up” the beliefs of the participants and aggregates them no matter how dispersed or how differentially informed those participants are.

An algebraic illustration provided by Harris (2002) further exemplifies how the market aggregates information.¹³⁶ Suppose N traders each produce a different forecast of the true value of a security. Let f_i be the forecast of the i^{th} trader and assume that it is an unbiased estimate of V , the true value of the security. We can represent the forecast as $f_i = V + e_i$ where e_i is the error in the i^{th} trader's forecast.

The expected forecast error is 0, because the forecasts are unbiased. However, the individual forecast errors might be quite large in absolute value.

Let each trader's desired position in the security D_i be proportional to the difference between his forecast value and the market price P , that is, $D_i = a(f_i - P)$ where a is some constant of proportionality. This assumption assures that traders will want a long position if their forecast is greater than the market price and a short position otherwise. It also ensures that the more different their forecast is from the market price, the more they will want to hold.

Finally, assume that the security is in zero net supply; traders create such securities when they sell them short. This assumption simplifies the arithmetic but does not affect the qualitative result of this illustration.

¹³⁶ see (Harris 2002), p.225

We compute the market price by setting the sum of all desired positions equal to the net supply and solving the resulting equation for P :

$$\sum_{i=1}^N D_i = \sum_{i=1}^N a(f_i - P) = a \sum_{i=1}^N f_i - N \cdot a \cdot P = 0$$

The market price $P = \frac{1}{N} \sum_{i=1}^N f_i$ is an average of the individual forecasts. As we

substitute for $f_i = V + e_i$, the expression gives $P = V + e_m$, where $e_m = \frac{1}{N} \sum_{i=1}^N e_i$ is the

forecast error of the market price.

If the individual forecast errors are independent of each other, the Law of Large Numbers implies that the market error e_m will approach 0 as the number of traders N gets large.

Even if the number of traders is not large, the average market forecast error will be less than the average individual forecast error if the individual forecast errors are not identical.

Thus, the market price estimates the true value of the security better than any individual trader can estimate it. Apparently, prices are most informative when many informed traders collect information independently.

Subsequently, in the next sections we review experimental evidence on the ability of artificial asset markets to collect and aggregate information, and, more specifically, how it performs this task for the purpose of forecasting.

3.4 Experimental evidence: laboratory experiments

Laboratory asset market experiments in economics are an increasingly important tool in understanding markets.¹³⁷ These experiments usually comprise a number of participants, who are given a combination of one or more assets whose payouts are prescribed by the experimenters. While in early experiments, as in early exchanges, the participants arranged deals on their own or posted them on a blackboard, current experimental asset markets are usually executed through a computer network, using any one of numerous auction mechanisms.¹³⁸

¹³⁷ see, e.g., (Smith 1982), (Friedman and Sunder 1994), or (Kagel and Roth 1995)

¹³⁸ Ibid.

The laboratory markets are an important complement to studying market phenomena through field data, because hypotheses can be tested by defining appropriate rules of payout for the asset and then replicated.¹³⁹ In particular, the feasibility of trading across periods, during which the fundamental value of the asset may change, leads to the possibility of studying price dynamics in markets.¹⁴⁰

The first asset markets experiments were not conducted until the early 1980s. Plott and Sunder (1982, 1988) were first to demonstrate that the ability of markets to aggregate information is sensitive to the market architecture. In particular, this early work demonstrated that compound securities are not as reliable as indicators as a complete set of state dependent instruments. The conditions under which a single compound security is reliable are isolated in Forsythe and Lundholm (1990).

The need for selecting proper instruments is underlined by demonstrations of markets that can equilibrate at patterns that are not fully revealing of information such as cascades¹⁴¹ or misleading such as mirages¹⁴² or bubbles¹⁴³. In fact, some types of market organization facilitate no information aggregation at all as is the case of the winners curse in sealed bid auction markets.¹⁴⁴

The results of experimental studies so far can be summarized as follows Sunder (1995):

- information dissemination and aggregation can occur, but does not occur under all conditions
- when it does occur, it is rarely instantaneous or perfect; but both can be surprisingly small, given the complexity of the task facing the traders, and the limitations of human information processing
- statistical efficiency of a market (the absence of arbitrage opportunities) does not imply that the market is allocatively or informationally efficient – a trader may have the information and the incentives but not the means of doing so

¹³⁹ Ibid.

¹⁴⁰ Ibid.

¹⁴¹ see (Anderson and Holt 1997) and (Hung and Plott 2001)

¹⁴² (Plott and Chen 1998) cites (Camerer and Weigelt 1991)

¹⁴³ (Plott and Chen 1998) cites (Smith, Suchanek et al. 1988; King, Smith et al. 1993)

¹⁴⁴ (Plott and Chen 1998) cites (Kagel and Levin 1986; Lind and Plott 1991)

Thus, the results of the experiments suggest that the successful aggregation of information in markets depends on the features of these markets—rules, information distribution, common knowledge, experience of traders, number, nature and relationship of assets traded, etc.¹⁴⁵ A more precise understanding of factors that facilitate or retard information remains to be explored by further experimental research.¹⁴⁶

3.5 More experimental evidence: field tests of private artificial asset markets

Whereas the concept of information aggregation by markets was (and still is) tested in laboratory experiments, some researchers have collaborated with commercial enterprises and set up private artificial asset markets. Table 8 lists some of the most quoted examples of these field-deployed artificial information asset markets.

Table 8: Overview of most quoted private artificial asset markets

Market	Focus	Typical turnover characteristics
Siemens project completion forecast <i>Run by Siemens Austria and Vienna University of Technology in 1997</i> (Ortner 1997; Ortner 1998)	Internal market to forecast the amount of delay of completion of a software project Access limited to selected staff 1 market experiment	~50 active traders traders received a cash endowment of ~\$15 at a self-deposit of ~\$7
HP product sales forecast <i>Run by HP Labs and California Institute of Technology in 1996, 97 & 99</i> (Plott and Chen 1998)	Internal market to forecast sales of different products Access limited to selected staff 12 market experiments	7-26 active traders traders received a "small" endowment of shares and cash

Such markets occupy a niche between the stylized, tightly controlled markets in the laboratory and the information-rich environments of naturally occurring markets.¹⁴⁷ Moreover, these field deployed markets offer more data than available from typical financial markets.¹⁴⁸ This data includes transaction and order flow data associated with individual traders, complete queue information, portfolio positions of each trader and trader demographics.¹⁴⁹ The field markets can also be used to survey traders at any

¹⁴⁵ see (Sunder 1995), pp.445-446

¹⁴⁶ see (Plott 2006 (forthcoming))

¹⁴⁷ see (Berg, Forsythe et al. 2000)

¹⁴⁸ Ibid.

¹⁴⁹ Ibid.

time, recording survey responses and associating them with other data.¹⁵⁰ Thus, they provide an excellent complement to other existing research techniques.

Subsequently, the markets shown in Table 8 are briefly introduced and their performance is reviewed.

3.5.1 "TU Vienna/Siemens PSE Austria 1997" market¹⁵¹

Market description. In 1996 a joint research project between the Vienna University of Technology and Siemens PSE Austria led to the implementation of a very small-scale, real-money artificial asset market to forecast the timely completion of a project milestone (Ortner 1997; Ortner 1998). Market access was restricted to project team staff of Siemens.

The market's information task concerned a software project that involved 200 team members of Siemens PSE Austria and that was scheduled to run from April 1997 to September 1997 by which it should meet a completion deadline labeled "B500" and be handed over to the (Siemens-internal) customer. Specifically, the task was to predict whether the project would meet "B500" on time and if not, how much the delay would be.

The major rationale for such a market was to provide project management with a tool that would deliver a more accurate and reliable forecast of project progress than traditional tools. This should primarily be achieved by bypassing the remaining deficiency of traditional project controlling methods, in which project team members have a tendency to suppress "bad news", as they are afraid to suffer from negative consequences by providing such information.¹⁵²

In May 1997, the "Siemens PSE" market was initiated by the opening of two submarkets, named "B500" and "Verzug". The market mechanism employed was a web-based, automated continuous double auction market that was installed on the corporate intranet of Siemens PSE Austria. The market software was licensed from Kumo, Inc., which was affiliated with the research group that had developed the software of the Foresight Exchange. Trading hours were unrestricted, thus, trade was possible for 24 hours, 7 days a week.

¹⁵⁰ see, e.g. (Ortner 1997; Ortner 1998)

¹⁵¹ This section is based on a two-part report by (Ortner 1997; Ortner 1998)

¹⁵² see (Ortner 1997), p.2

Market participants were required to invest 100 ATS of own funds, but received a further 200 ATS as subsidy from Siemens. Of the 200 project team members eligible for market participation, 63 signed up for trade and about 50 of those became active traders.

In the first submarket, labeled "B500", a binary security set was offered for trade on if the software project would meet the milestone on time or not. Thus, same as for FX standard securities, traders could buy either "yes" or "no" coupons, effectively investing "for" or "against" the market claim. Contracts associated with the "winning" answer would pay off 1 ATS, all other contracts would pay 0 ATS. Thus, as market forces in an efficient market should let securities trade at their expected liquidation values, market prices would range from 0 to 1 ATS, and prices would equal an estimate of the probability of the underlying claim coming true.

In the second submarket, labeled "Verzug", another binary security set was offered for trade. The contract liquidation value for the security labeled "Early" was determined by the function $[\max((1 - 0,2 * \text{no. of weeks late}), 0)]$; and for the security labeled "Late" by the function $[\min((0,2 * \text{no. of weeks late}), 1)]$, see also Figure 18.

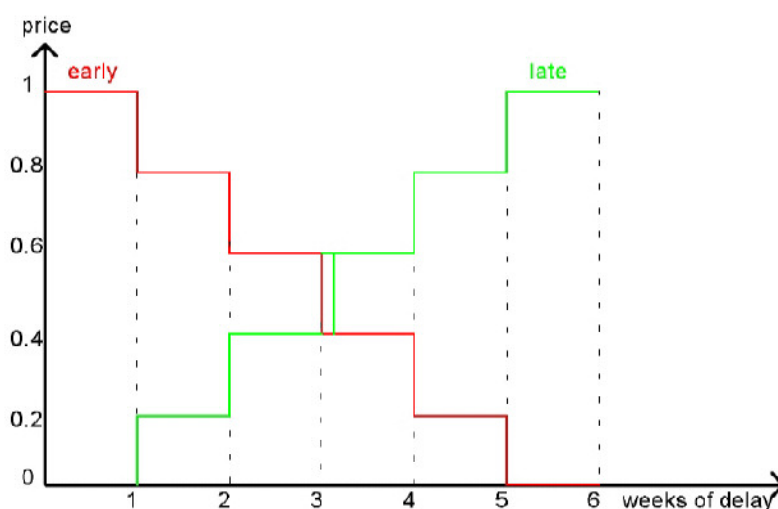


Figure 18: AAM "TU Vienna/Siemens PSE Austria 1997" – payoff rule for securities in the submarket "Verzug" (Ortner 1997)

Eventually, the software project met its "B500/M500" milestone in October 1997 with 13 days delay.

Market performance. Figure 19 and Figure 20 show the development of the average daily prices and the traded volume in both submarkets. After approximately a month of

trade prices in both submarkets stabilized; at around 0,45 ATS in the submarket "B500" representing a probability of 45% that the project will meet its milestone in time; at around 0,55 ATS in the submarket "Verzug" indicating a 2-3 week delay.

On August, 7th, the customer unexpectedly rescheduled the project delivery by one month to October 1997, and, subsequently, the "B500" milestone was rescheduled as well. As defined for such an unlikely event, market trading was suspended and contracts were liquidated; all "no" coupons paid 1 ATS, all "yes" coupons paid 0 ATS. Thereafter, the markets were restarted with securities adapted to the new milestone labeled "M500".

The right sides of Figure 19 and Figure 20 show the further development of the average daily prices and the traded volume in both submarkets after the milestone rescheduling. After the closing and reopening of the markets, prices quickly moved very close to the same level as before the market closure, although one could expect less delay due to the additional project time by a later milestone.

In general, the markets appear to have generated reliable forecasts after only one month of trading. Notably, after only one month of trading and more than three months before the scheduled deadline, the submarket "Verzug" predicted a delay of 2-3 weeks, which came very close to the actual outcome of 13 days delay.

Conclusion. The "TU Vienna/Siemens PSE Austria" market adds to the evidence that artificial asset markets can collect and aggregate information for the purpose of forecasting.

Whereas markets such as the IEM or HSX are "thick", with many participants operating over a long period of time, the TU/Siemens markets were "thin", featured relatively few participants and operated over very short periods. While the IEM is focused on events that are observable to a broad based population at large, such as election outcomes, traders in the TU/Siemens markets had specific, specialized and private information that is not available to other traders or to the general public. Finally, ensuring trader participation in the TU/Siemens market demands a comparatively higher level of incentivization and stimulation, as the opportunity costs of doing something other than participating in the forecasting exercise can be very high for the business people.

Thus, the "TU Vienna/Siemens PSE Austria" market supports, in particular, markets as information aggregation and forecasting tool under business environment conditions.

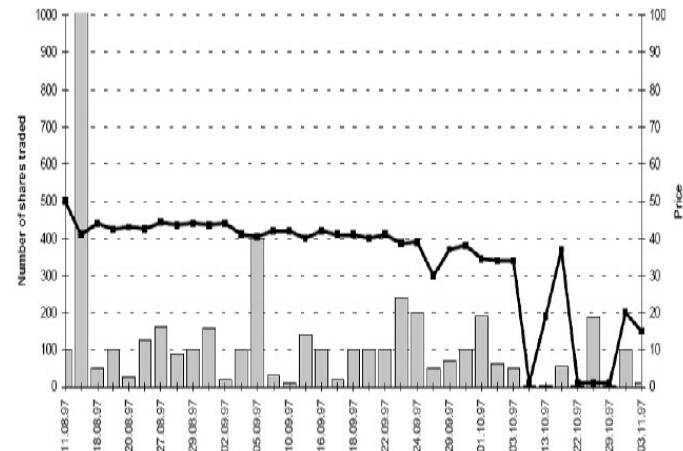
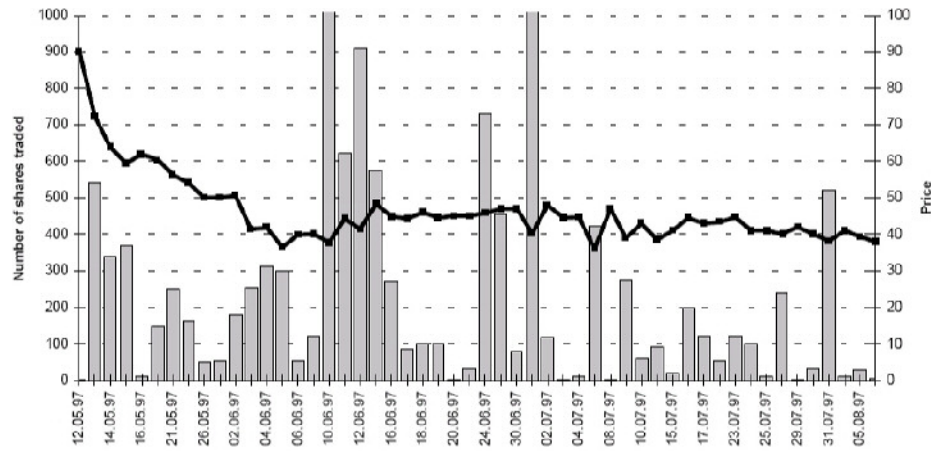


Figure 19: AAM "TU Vienna/Siemens PSE Austria 1997" – submarket B500/M500 before (left) and after (right) milestone rescheduling (Ortner 1997; Ortner 1998)

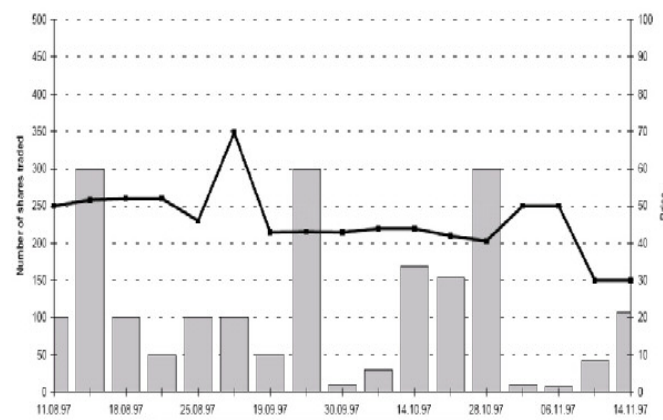
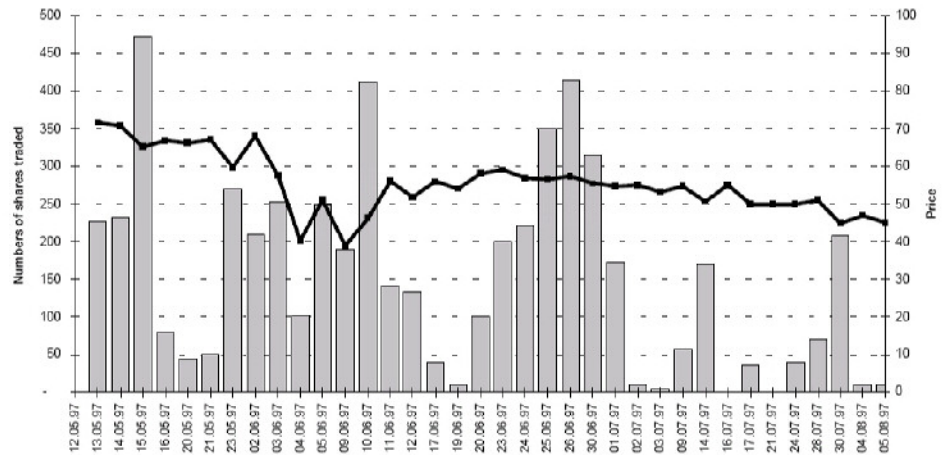


Figure 20: AAM "TU Vienna/Siemens PSE Austria 1997" – submarket "Verzug" before (left) and after (right) milestone rescheduling (Ortner 1997; Ortner 1998)

3.5.2 "CalTech/HP Sales 1997/1999" market¹⁵³

Market description. In 1996, a joint research project between the California Institute of Technology and Hewlett-Packard Laboratories led to the implementation of a very small-scale, real-money artificial asset market to forecast sales of HP products (Plott and Chen 1998). Market access was restricted to selected staff of HP.

From 1996 to 1999 a total of twelve predictions were performed, see also Table 9. Typically, the prediction was for monthly sales of a product three months in advance, with the exception being the first two exercises for which the predicted event was only one month ahead. Predictions were performed for eight different products, more than once for some of the products and only once on others. In some instances the predicted measure of sales was USD and in other instances it was units.

In all cases market duration was limited to a week with trading hours during lunch and in the evening. The latter was a constraint by the HP management, as they did not want HP staff to engage in trading during business hours when pressing, daily operational business issues needed their attention.

The experiments were conducted with three different HP divisions, but limited to the marketing and finance departments. Of those, typically, around 20-30 people signed up for the experiments. Additionally, around five subjects were recruited from HP Labs in each experiment to increase liquidity in the markets.

The "HP sales" market offered a set of state contingent contracts that were associated with intervals covering the entire space of possible outcomes. For example, the interval "Unit sales of 0-100" would be associated with a security named "0-100" that traded in a market named "0-100". Each contract liquidation value was determined by the outcome value lying within the contract's associated interval or not. The security corresponding to the interval in which the final outcome fell would pay a fixed amount of \$1, all other shares would pay \$0.

Consequently, the market prediction would be the interval in which the outcome is predicted to fall. Furthermore, the predicted interval would be sensitive to the probabilities attached to intervals and the interpretation attached to the highest interval.

¹⁵³ This section is based on a report by (Plott and Chen 1998)

Each participant was given a portfolio of shares in markets and cash. In some exercises all participants were endowed equal shares in all securities, in other exercises participants were endowed with shares in every other security, alternating which security was first across participants. The unequal distribution of endowments was used to encourage trading by attempting to make sure that the initial endowments of securities did not approximate the ultimate equilibrium.

The market mechanism employed was a double auction market.

Table 9: AAM "CalTech/HP Sales 1997/1999" – market overview and results; consolidated from (Plott and Chen 1998)

#	Subject	Date, duration traders	C / T	Outcome ¹⁾ [unit, %error]	HP Official forecast [unit, %error]	Market forecast ²⁾ [unit, %error]
1	Profit sharing percentage to be announced by upper Mgmt.	10/1996 1 week	8 / 16	8.770	N/A	9.100 3,7%
2	Next month sales (in \$) of product A	11/1996 1 week	9 / 26	220.000	249.000 13,2%	230.000 4,6%
3	Next month sales (in \$) of product B	01/1997 1 week	9 / 20	1152.000	1838.000 59,5%	1814.000 57,5%
4	Quarter ahead monthly sales (in units) of product C	05/1997 1 week	10 / 21	1840.000	1681.000 -8,6%	1696.000 -7,8%
5	Quarter ahead monthly sales (in units) of product D	05/1997 1 week	10 / 21	2210.000	1501.000 -32,1%	1526.000 -30,9%
6	Quarter ahead monthly sales (in units) of product B	05/1997 1 week	10 / 21	128.000	90.000 -29,7%	97.000 -24,2%
7	Quarter ahead monthly sales (in units) of product C	06/1997 1 week	10 / 24	2002.000	2084.000 4,1%	1855.000 -7,3%
8	Quarter ahead monthly sales (in units) of product D	06/1997 1 week	10 / 24	1788.000	1786.000 -0,1%	1752.000 -2,0%
9	Quarter ahead monthly sales (in units) of product E	06/1997 1 week	10 / 24	166.000	119.000 -28,3%	126.000 -23,9%
10	Quarter ahead monthly sales (in units) of product F	04/1999 1 week	8 / 12	30.000	N/A	15.000 -49,9%
11	Quarter ahead monthly sales (in units) of product G	04/1999 1 week	8 / 12	10.000	N/A	15.200 51,7%
12	Quarter ahead monthly sales (in units) of product H	05/1999 1 week	8 / 7	17.000	N/A	15.000 -11,8%

C / T: No. of intervals and contracts / No. of active traders

¹⁾ Unit undisclosed

²⁾ volume averaged price based on the last 60% of trades; rounded

Although the results of this field market were encouraging, the market was discontinued in 1999 for various operational reasons, ultimately indicating a lack of long-term management commitment. Plott and Chen (1998) report the encounter of numerous roadblocks in the course of experiments, such as scheduling conflicts and a lower than ideal level of participation.

Market performance. An overview of the markets, forecasts, and outcomes is given in Table 9. For example, for event 2 the outcome was a sales level of 220.000 as compared to the official HP forecast of 249.000 (13.182% error) and the market forecast of 234.000 (6,4% error).

As Plott and Chen (1998) report, the key issue in interpreting the results was to find a reasonable way to derive predictions from the market data. Theoretically, in an efficient market the security prices should equal their expected liquidation value, which in turn should be proportional to the probabilities of the states conditioned on the information in the market.

However, as the market experiments showed, security prices did not always sum to the total amount suggested by market efficiency, nor did prices stabilize in the final trading phase. Thus, some method needed to be developed to calculate states probabilities and the overall market forecast from security prices.

Plott and Chen (1998) chose, among other methods, the volume-averaged transaction price for the last 60% of trades (as displayed in Table 9).

The official HP forecasts were used as a benchmark. They were available for 8 out of 12 events, and they not revealed until the "Sales" markets closed. In fact, anecdotal evidence suggests that the market activities were used as inputs to HP official forecasts in more than one occasion.

The overall pattern of results indicates that the market forecasts are a considerable improvement over the HP official forecast as a benchmark Plott and Chen (1998).

In 6 out of 8 events for which official forecasts were available the IAM predictions were closer to the actual outcome than the official forecast. T-tests also showed that the absolute % errors of the official forecasts were higher than that of the IAM predictions.¹⁵⁴

As the used asset structure also produced probabilistic information about the likelihood of possible outcomes, (Plott and Chen 1998) examined and verified that the probability distributions derived from prices were consistent with actual outcomes.

¹⁵⁴ see (Plott & chen 1998) for details and results

Conclusion. The "HP Sales" market provides further evidence that artificial asset markets can collect and aggregate information for the purpose of forecasting.

Whereas markets such as the IEM or HSX are "thick", with many participants operating over a long period of time, the HP markets were "thin" and operated over very short periods. Whereas the IEM is focused on events that are observable to a broad based population at large, such as election outcomes, traders in the HP markets had specific, specialized and private information that is not available to other traders or the general public.

Whereas traders join the IEM purely by self-selection and appear to be primarily motivated by entertainment value and "bragging rights", traders in the HP were selected specifically from different parts of the business operation and ensuring their participation was difficult, as the opportunity costs of doing something other than participating in the forecasting exercise can be very high for the business people.

Thus, the "HP Sales" market specifically supports the notion of forecasting by AAM by the application as an internal enterprise information tool under challenging business environment conditions. Furthermore, the freshly introduced market forecasts managed to promptly outperform the well established official sales forecast of a leading global business enterprise.

3.6 Further experimental evidence: field tests of public artificial asset markets

As outlined in 3.5, whereas the concept of information aggregation by markets was (and still is) being tested in laboratory experiments, some researchers and even commercial enterprises have moved forward by setting up public artificial asset markets in the field. Table 10 lists some of the most quoted examples of these field-deployed artificial information asset markets.

Table 10: Overview of most quoted field artificial information asset markets; adapted from (Wolfers and Zitzewitz 2004)

Market	Focus	Typical turnover on an event [USD]
Iowa Electronic Markets < www.biz.uiowa.edu/iem > <i>Run by University of Iowa (est. 1988)</i>	Small-scale election markets. Similar markets are run by: UBC (Canada) < www.esm.buc.ca > and TU Vienna (Austria) < ebweb.tuwien.ac.at/apsm >	~10.000 USD (Traders limited to \$500 positions)
Hollywood Stock Exchange < www.hsx.com > <i>For profit company (est. 1996)</i>	Success of movies, movie stars, awards, including a related set of complex derivatives and futures Data used for market research	Virtual currency
Foresight Exchange < www.ideoshere.com > <i>By Non-profit research group (est. 1994)</i>	Political, finance, current events, science and technology events suggested by clients	Virtual currency
Newsfutures < www.newsfutures.com > <i>For profit company (est. 2000)</i>	Political, finance, current events, and sports markets. Also pharmaceutical futures for specific clients	Virtual currency redeemable for monthly prizes (such as a TV)
TradeSports < www.tradesports.com > <i>For profit company (est. 2002)</i>	Trade in a rich set of political futures, finance contracts, current events, sports and entertainment	~100.000 USD
Economic Derivatives < www.economicderivatives.com > <i>Run by Goldman Sachs and Deutsche Bank (est. 2002)</i>	Large-scale financial market trading in the likely outcome of future economic data releases	~100 mio. USD

Such markets occupy a niche between the stylized, tightly controlled markets in the laboratory and the information-rich environments of naturally occurring markets.¹⁵⁵ Moreover, these field deployed markets offer more data than available from typical

¹⁵⁵ see (Berg, Forsythe et al. 2000), p.1

financial markets.¹⁵⁶ This data includes transaction and order flow data associated with individual traders, complete queue information, portfolio positions of each trader and trader demographics.¹⁵⁷ The field markets can also be used to survey traders at any time, recording survey responses and associating them with other data.¹⁵⁸ Thus, they provide an excellent complement to other existing research techniques.

The numbers of successes in these markets, both within firms and with regard to public events like presidential elections, have generated substantial interest among both political and financial economists.¹⁵⁹

Subsequently, the markets of Table 10 are briefly introduced and their performance is reviewed.

3.6.1 Iowa Electronic Markets' (IEM) Iowa Political Stock Markets (IPSM)¹⁶⁰

Market description. The best known and most thoroughly validated case of an artificial information asset market may be the Iowa Political Stock Market (IPSM), run since 1988 by the University of Iowa for research and teaching purposes. The IPSM is a small-scale, real-money futures market in which contract payoffs depend on U.S. political events, such as the U.S. presidential or congressional elections. The market is open to the public and accessible through the Internet.¹⁶¹ Universities in other countries have followed and established similar markets of their own, most notably the Vienna University of Technology¹⁶² and the University of British Columbia¹⁶³.

IPSM features different types of markets, e.g. vote-share markets, seat-share markets, or winner-takes-all markets. In vote-share markets, the relative vote shares candidates receive in the election determine contract liquidation values. Typically, a particular contract will have a liquidation value equal to \$1 times the vote share received by the associated candidate. The market is designed such that the vote share of all

¹⁵⁶ see (Berg, Forsythe et al. 2000), p.1

¹⁵⁷ Ibid.

¹⁵⁸ Ibid., p.7

¹⁵⁹ see, e.g. (Wolfers and Zitzewitz 2004), p.24

¹⁶⁰ This section is primarily based on information provided by the IEM website

¹⁶¹ <www.biz.iowa.edu/iem> as of October 2004

¹⁶² <ebweb.tuwien.ac.at/apsm> as of October 2004

¹⁶³ <www.esm.buc.ca> as of October 2004

candidates sums to 100%. Thus, market forces let vote-share contracts trade at the expected liquidation values, which equals the expected vote shares.

Seat-share markets operate same as vote-shares markets, except that contracts liquidate at values determined by the congressional or parliamentary seats allocated to parties in an election.

In a winner-takes-all market, contract payoff is determined by which of the candidates receives the biggest (equal to the winning) vote share. Contracts associated with the candidate who does not receive the biggest number of votes in the election will pay off \$0. Contracts associated with the candidate that receives the biggest number of votes will pay off \$1. Thus, as market forces let winner-takes-all contracts trade at the expected liquidation values, these values equal an estimate of the probability of victory for the candidate associated with each contract.

Market performance. Research of the performance of the IPSM markets has established, that the ISPM markets both yielded very accurate predictions (see Figure 21, Figure 22, and Figure 24), and also outperformed comparable benchmark performance set by large-scale polling organizations (see Figure 23).¹⁶⁴

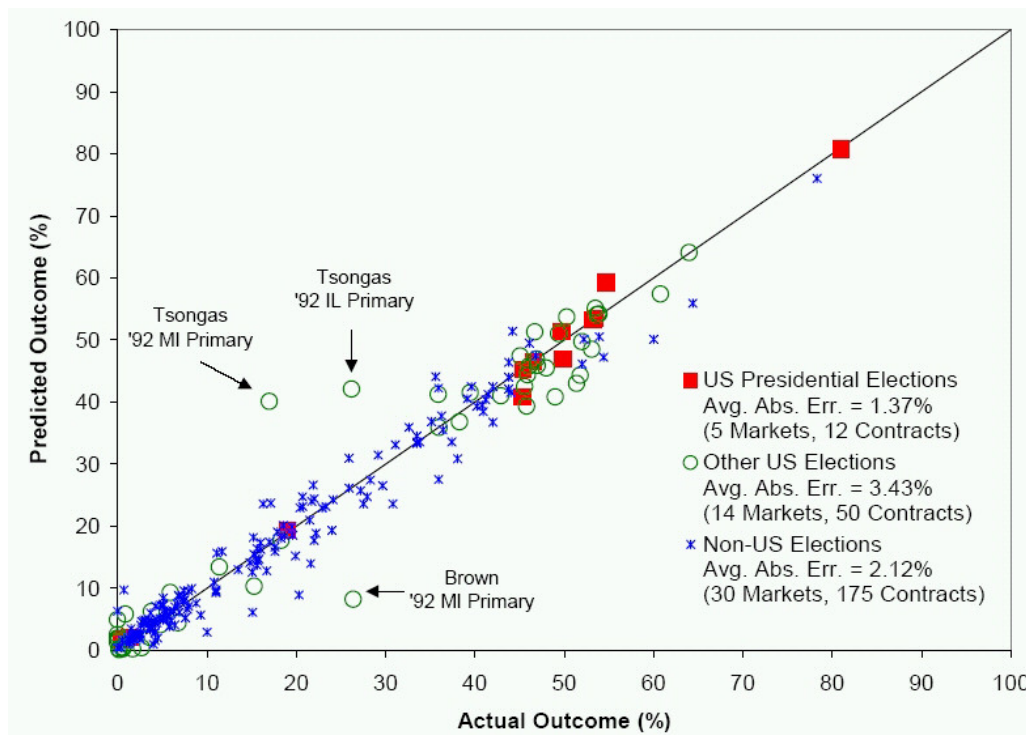


Figure 21: IEM accuracy: predicted outcome (last-trade prices before election) vs. actual outcome for various IPSM markets (Berg, Forsythe et al. 2000)

¹⁶⁴ see (Berg, Forsythe et al. 2000)

Figure 21 shows the absolute accuracy of 237 contract predictions in 49 vote-share and seat-share markets run in 13 countries.¹⁶⁵ It compares the predicted outcome by the market based on final, last-trade prices to the actual outcome of the elections. Thus, all points of the diagonal would reflect perfect accuracy.

On average, the IPSM markets show good accuracy. Presidential election markets perform better than congressional, state and local election markets. Markets with more volume near the election perform better than those with less. And markets with fewer contracts (e.g. due to fewer candidates or parties) predict better than those with more.

¹⁶⁶

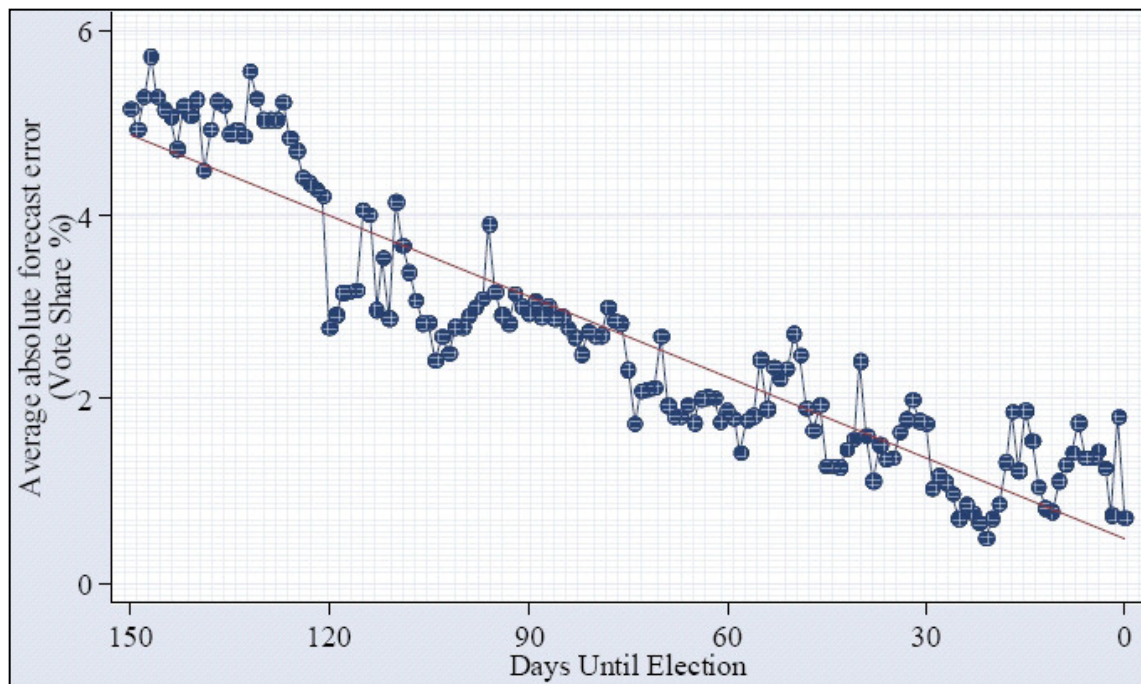


Figure 22: IEM accuracy: mean absolute error (MAE) of vote share markets for four U.S. presidential elections of 1988-2000 (Wolfers and Zitzewitz 2004)

Figure 22 shows over time the development of the mean absolute error (MAE) against the election outcome for IPSM two-party vote shares of the four U.S. presidential elections from 1988-2000. The graph shows how the MAE of the market prediction improves considerably as the election draws closer. Finally, in the week leading up to the election, the IPSM markets predicted vote shares for the Democratic and Republican candidates with an average absolute error of around 1,5 percentage

¹⁶⁵ see (Berg, Forsythe et al. 2000), p.4

¹⁶⁶ Ibid.

points.¹⁶⁷ By comparison, over the same four elections, the final Gallup poll yielded forecasts that erred by 2,1 percentage points.¹⁶⁸

Figure 23 shows how the IPSM markets compare to polls (for those markets for which poll data was available for comparison). Since market prices vary continuously, two price measures were selected as predictions by the market: the final, last-trade market prices as of midnight on election eve and the volume weighted average price of all transactions over the week before the election.¹⁶⁹

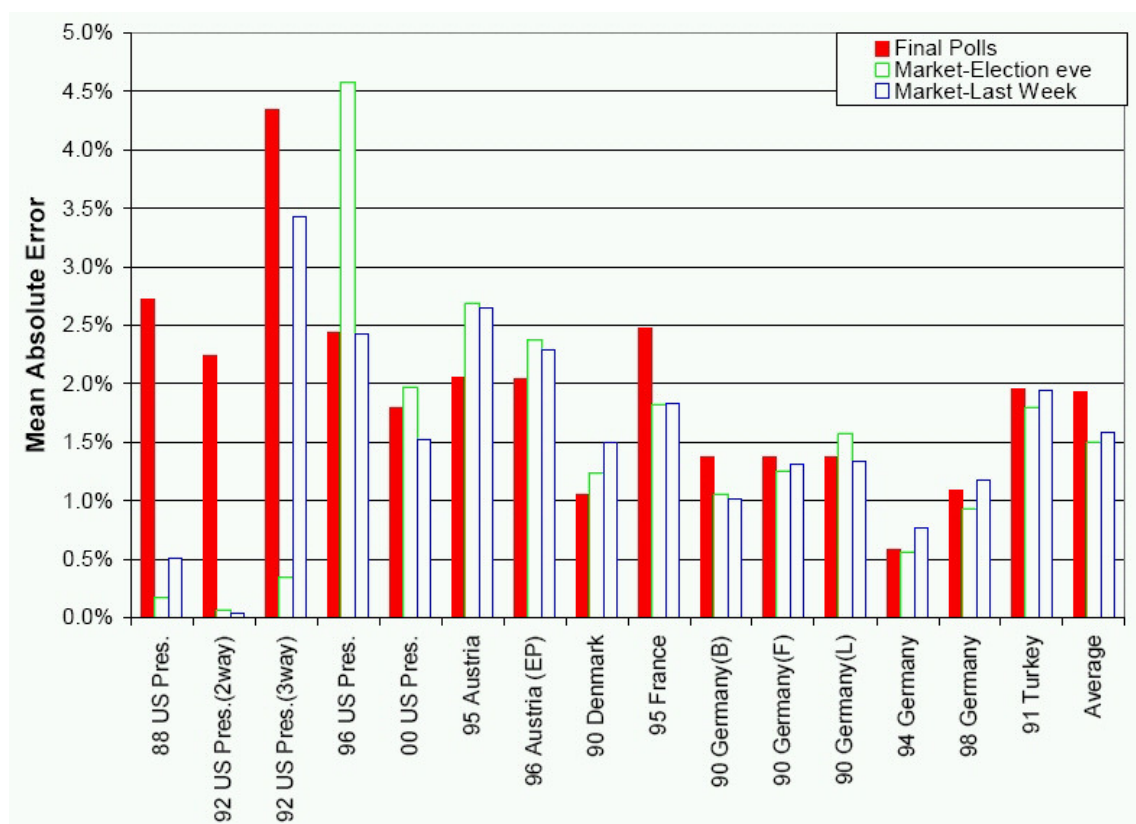


Figure 23: IEM accuracy: mean absolute error (MAE) against election outcome of selected IPSM vote share markets and corresponding final polls (Berg, Forsythe et al. 2000)

The market outperformed polls in 9 out of 15 cases according to both measures.¹⁷⁰ Across all elections, the average poll error was 1,93% while the average market error

¹⁶⁷ see (Wolfers and Zitzewitz 2004), p.7

¹⁶⁸ Ibid.

¹⁶⁹ see (Berg, Forsythe et al. 2000), p.4

¹⁷⁰ Ibid.

was 1,49% and 1,58% by the two measures.¹⁷¹ In general, the market does about as well as the average poll, sometime worse but often better, even if by a small margin.¹⁷²

Table 11 presents further evidence of whether the IPSM market or polls predict the election outcome more closely—with more focus on long-term performance. Binomial tests compare IPSM markets for the four presidential elections from 1988-2000 with the corresponding poll predictions for relative predictive accuracy.

Table 11: IEM accuracy: Binomial tests for relative accuracy of the market and contemporaneous poll predictions (Berg, Nelson et al. 2003)

Days included in sample	Item	1988	1992	1996	2000	all years
All (from the beginning of the market)	Number of polls	59	151	157	229	596
	poll "wins"	25	43	21	56	145
	market "wins"	34	108	136	173	451
	% market	58%	72%	87%	76%	76%
	p-value (1sided)	0.148	0.000	0.000	0.000	0.000
Last 100	Number of polls	45	82	124	180	431
	poll "wins"	24	23	18	54	119
	market "wins"	21	59	106	126	312
	% market	47%	72%	85%	70%	72%
	p-value (1sided)	0.724	0.000	0.000	0.000	0.000
Last 65	Number of polls	34	62	91	141	328
	poll "wins"	19	15	15	52	101
	market "wins"	15	47	76	89	227
	% market	44%	76%	84%	63%	69%
	p-value (1sided)	0.804	0.000	0.000	0.001	0.000
Last 31	Number of polls	21	40	58	84	203
	poll "wins"	7	7	13	26	53
	market "wins"	14	33	45	58	150
	% market	67%	83%	78%	69%	74%
	p-value (1sided)	0.094	0.000	0.000	0.000	0.000
Last 5	Number of polls	6	6	11	25	48
	poll "wins"	0	1	4	8	13
	market "wins"	6	5	7	17	35
	% market	100%	83%	64%	68%	73%
	p-value (1sided)	0.016	0.109	0.274	0.054	0.001

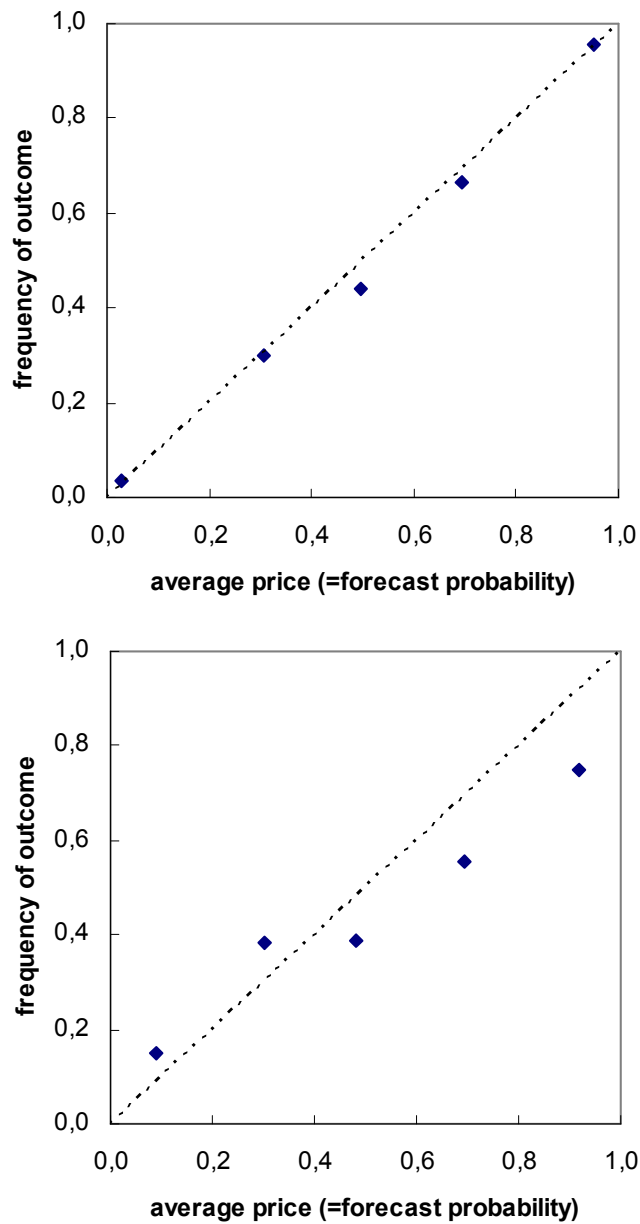
The market predictions are the normalized two-party vote share predictions on the last day each poll was in the field collecting data. Poll predictions come from major polls taken during the election and are the normalized two-party vote shares. The binomial

¹⁷¹ see (Berg, Forsythe et al. 2000), p.5

¹⁷² Ibid.

variable is assigned a value of 1 if the market prediction is closer to the actual outcome than the poll prediction and 0 otherwise. The number of observations is the number of polls in the sample period. If multiple polls are released on the same day, the same market price is compared to each poll.¹⁷³

Figure 24: IEM accuracy: Reliability diagrams showing the correlation of price group averages and corresponding observed outcome frequency of two monthly series of IEM winner-takes-all markets; top: prices collected at market closure; bottom: prices collected 21 days prior market closure; diagonal represents perfect accuracy; calculations based on data in (Berg and Rietz 2002)



¹⁷³ see (Berg, Nelson et al. 2003), p.13

As the results of this test show, market predictions are closer to the final outcomes than poll predictions for most of periods of each election. Thus, this evidence suggests that the markets are accurate months in advance and are better than polls at longer horizons.

Whereas the performance reviews to this point were based on share markets, both vote-shares and seat-shares, a performance review of IEM winner-takes-all markets is presented below. Figure 23 shows how price group averages of prices collected at market closure (left) and 21 days prior to market closure (right) correlate with their corresponding observed outcome frequencies for two monthly series of IEM winner-takes-all markets.¹⁷⁴ If market prices are accurate, then among all contracts with a price of 0,1 about one in ten should end up "winning".¹⁷⁵

Prices collected at market closure (Figure 23, left) correlate very well with the observed frequencies of their outcome, as all data points are very close to the diagonal of perfect accuracy.

Although prices collected 21 days prior to market closure (Figure 23, right) show some variance in their correlation to the observed frequencies of their outcome, as all data points have some distance to the diagonal of perfect accuracy, the correlation still supports the general trend that markets predict uncertain outcomes rather well (even if not perfectly well at all times).¹⁷⁶

As noted in the introduction to this section, the Vienna University of Technology conducted artificial asset markets very similar to the IPSM.¹⁷⁷ Table 12 summarizes the absolute accuracy of these Austrian PSMs and compares market performance to polls. Market error as the mean average error in percentage points of the final, last-trade market prices is compared to the same error measure for the average of polls of major institutions. The Austrian markets outperformed polls in 3 out of 10 cases, but otherwise lags polls by a small margin.

¹⁷⁴ The IEM markets considered are "Microsoft Stock Price Level" and "Computer Industry Returns"

¹⁷⁵ see section 4.3.2 for details on this forecast verification method

¹⁷⁶ Notably, the lower price groups have a lower outcome frequency than it's price suggests, whereas the opposite is true for the higher price groups; this inaccuracy appears to reflect a systematic bias, see section 3.7.2 for a detailed discussion

¹⁷⁷ initially, these markets were conducted by the Vienna University of Technology. Later Austrian media were induced to continue conducting such markets; see <ebweb.tuwien.ac.at/apsm>

Table 12: Absolute and relative accuracy of political stock markets in Austria for various Austrian elections from 1994-2002 (Filzmaier, Beyrl et al. 2003)

Austrian election	Market error [MAE in %pts]	Poll error [MAE in %pts]
Nationalratswahlen 1994	1,2	1,3
Nationalratswahlen 1995	2,7	2,2
Landtagswahl Steiermark 1995	3,0	2,3
Gemeinderatswahl Wien 1996	1,2	1,3
Wahl zum EU-Parlament 1996	2,3	2,0
Bundespräsidentenwahl 1998	1,7	2,2
Wahl zum EU-Parlament 1999	2,3	1,7
Nationalratswahlen 1999	0,9	0,6
Gemeinderatswahl Wien 2001	3,1	2,1
Nationalratswahlen 2002	2,4	2,2

In general, the same conclusion holds true for the Austrian PSM as for the IPSM: the market does about as well as the average poll, sometimes better, sometimes worse, both by a small margin.

Conclusion. The evidence presented so far reflects only a tiny fraction of the ample evidence documenting the remarkable performance of the IEM markets in absolute and in relative terms. These markets have impressively demonstrated their ability to collect and aggregate information. Given this evidence alone, it is no longer defensible to argue that artificial asset markets cannot serve as tools of forecasting.

3.6.2 Hollywood Stock Exchange (HSX)¹⁷⁸

Market description. The Hollywood Stock Exchange (HSX) is an artificial asset market on the internet. It allows people to use virtual currency to speculate on movie-related questions like opening-weekend performance, total box office returns, and who will win Oscars. The market was established by a for-profit company in 1996 and has ever since been open to the public and accessible through the Internet.¹⁷⁹

¹⁷⁸ This section is based on information provided by the HSX website

¹⁷⁹ <www.hsx.com> as of October 2004

HSX operates multiple, different types of artificial asset markets, e.g. "MovieStocks", "StarBonds", "TVStocks", event-related options, funds, and warrants. For example, "MovieStocks" represent films (both in the process of being made and that are currently in theaters) that are traded on the HSX. The liquidation value of a MovieStock security is determined by the movie's gross revenue in its first four weeks at the box office in the U.S. Thus, if a MovieStock is priced at \$80 of HSX currency, it means that traders expect the film to make \$80 million in its first four weeks in release.

HSX lists MovieStocks for trade long before the corresponding movies debut at U.S. theatres. In fact, MovieStocks are offered sometimes as soon as rumors of a movie surface based on pitches or ideas which are not in active development. To indicate the development stage of movies, HSX attributes five distinct maturity stages: concept, development, production, wrap, and release.

A HSX "StarBond" represents actors and directors traded on HSX. The price of a StarBond reflects overall star power as determined by HSX traders, as well as how much money their films make at the box office as determined by their trailing average gross (TAG).¹⁸⁰ Beginning with their second film, StarBond prices are adjusted to match the TAG when credited MovieStocks cash out. If a celebrity should happen to meet the end of his or her career (death, retirement, etc.), the StarBond is cashed out at TAG value.

Also available for trade are HSX options, which are short-term investment securities based around a specific entertainment event, such as a film's opening weekend, award ceremonies, or TV shows. For example, "call" and "put" options are released on the opening weekend of a particular MovieStock. Each option has a "strike price" that is set according to what the market expects the film to gross in its opening weekend. The value of an option is determined by the supply and demand of the market. Trading is halted on the respective film's opening weekend. Options are cashed out on the Monday following the opening weekend at a price equal to the opening weekend box-office gross (in millions) minus the strike price.

¹⁸⁰ This term represents a star's average box-office performance over their last five credited films. Each time a MovieStock featuring a particular star cashes out from the Movie Market, the box-office gross of the film is calculated into the star's TAG, and the bond price is adjusted to match. A maximum of five films are used in the TAG calculation divided by a minimum of three. Box-office gross for any one film is capped at \$250 million.

Thus, for a call option to be worth more than an investor paid for it the film must gross more than the strike price PLUS the price the investor paid for the option. If the film makes less money than the strike price, call options cash out at H\$0. For a put option to be worth more than an investor paid for it, the film must gross less than the strike price MINUS the price the investor paid for the option. If the film makes more money than the strike price, put options cash out at H\$0.

Market performance. HSX performance has been examined by Pennock, Lawrence et al. (2001) and Wolfers and Zitzewitz (2004), who both conclude that MovieStock prices are good indicators of actual box office returns and that prices of HSX securities in Oscar, Emmy, and Grammy awards correlate well with observed frequencies of winning.

Figure 25 shows the absolute accuracy of 489 contract predictions for movies aired from 2000-2003. It compares the predicted outcome by the market based on final, last-trade prices to the actual outcome of the movie box office sales for the opening weekend. Thus, all points of the diagonal would reflect perfect accuracy.

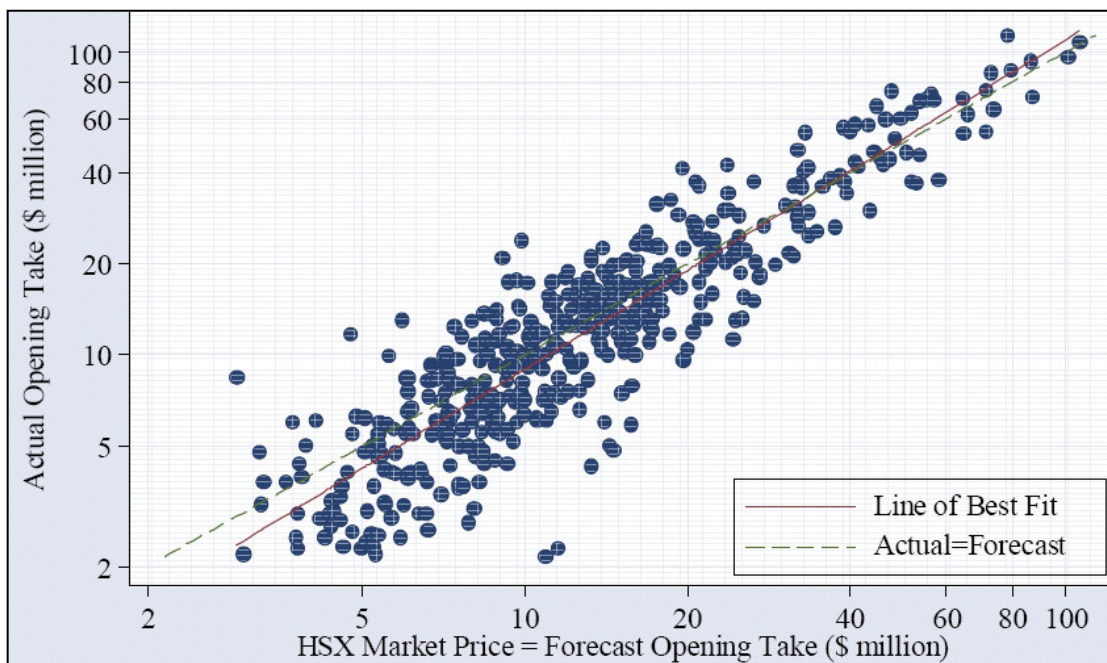


Figure 25: HSX accuracy: predicted vs. actual movie box office sales for the opening weekend of 489 movies from 2000-2003 (Wolfers and Zitzewitz 2004)

As indicated by the figure above, the HSX MovieStock markets are remarkably accurate. A correlation of 0,940 between market estimate and actual outcome, an

average absolute error of 3,57 and an average percent error of 31,5% is reported for an examination of 50 movie openings in 2000.¹⁸¹ Collectively, HSX market participants appear to be knowledgeable about the prospects of upcoming movies and sufficiently motivated to reveal their information in the context of the market game, even without much prospect for tangible compensation.¹⁸²

Figure 26 shows how price group averages of option prices collected at market closure correlate with their corresponding observed outcome frequencies for 135 Oscar, Grammy, and Emmy awards in 2000. If market prices are accurate, then among all options with a price of H\$0,1 about one in ten should end up "winning". As the figure shows, prices collected correlate very well with the observed frequencies of their outcome, as all data points are very close to the diagonal of perfect accuracy.¹⁸³

Figure 27 and Figure 28 compares HSX prices of Oscar options to the reported probability assessments from five experts for the Oscar awards in 2000. Whereas Figure 27 shows a snapshot comparison as of February 18, 2000, Figure 28 compares the probability assessments over time – from February 15, 2000 to market closure on March 26 and the Oscar award ceremony on March 27.

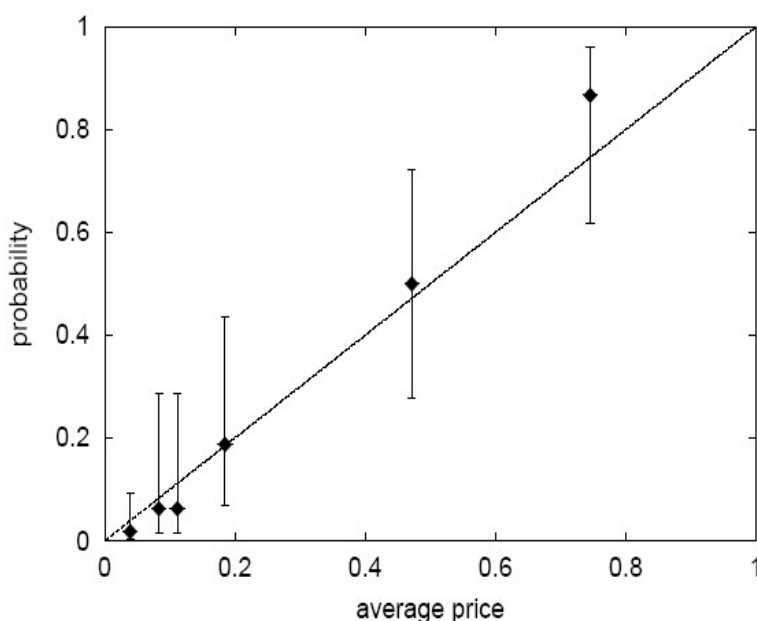


Figure 26: HSX accuracy: Correlation of option price group averages at market closure and corresponding observed outcome frequency for 135 Oscar, Grammy, and Emmy awards in 2000 (Pennock, Lawrence et al. 2001)

¹⁸¹ see (Pennock, Lawrence et al. 2001), p.4

¹⁸² Ibid., p.9

¹⁸³ Notably, the price group with the highest average price has a higher outcome frequency than its price suggests; this inaccuracy appears to reflect a systematic bias, see section 3.7.2 for a detailed discussion

forecast source	avg log score
Feb 18 HSX prices	-1.08
Feb 19 HSX prices	-0.854
Tom	-1.08
Jen	-1.25
John	-1.22
Fielding	-1.04
DPRoberts	-0.874
columnist consensus	-1.05

Figure 27: HSX accuracy: Comparison of Average Logarithmic Score (ALS) for HSX prices and expert forecasts for Oscar awards as of Feb, 18th, 2000; Less negative scores are better (Pennock, Lawrence et al. 2001)

The comparison uses the average logarithmic scoring (ALS) rule to rate the market and the columnists.¹⁸⁴ Higher (less negative) scores are better, with 0 being the maximum (best) score and negative infinity being the minimum (worst) score.

As Figure 28 displays, shortly after the HSX market opened, it rapidly improved from inferior to superior accuracy swiftly outperforming expert forecasts. On February, 18, only one of the five experts scored appreciably better than the market (see Figure 27 for numeric values). By the next day, the market's score had surpassed all of the scores for all five experts and their consensus.

Apart from this notable performance demonstration, it becomes apparent that markets as information tool inherit an outstanding characteristic: they are dynamic and informationally adaptive by nature. Whereas expert forecasts are in principle rather static and remain unrevised for some time, especially in the case of expert panels or Delphi surveys which are based on a consensus forecast, markets as information tool continuously adapt their current forecast to new information, and, so, serve as a leading indicator for the uncertain outcome.¹⁸⁵

¹⁸⁴ see section 4.3.3 for details of this forecast verification method

¹⁸⁵ see section 2.5.1 for a detailed discussion of this matter

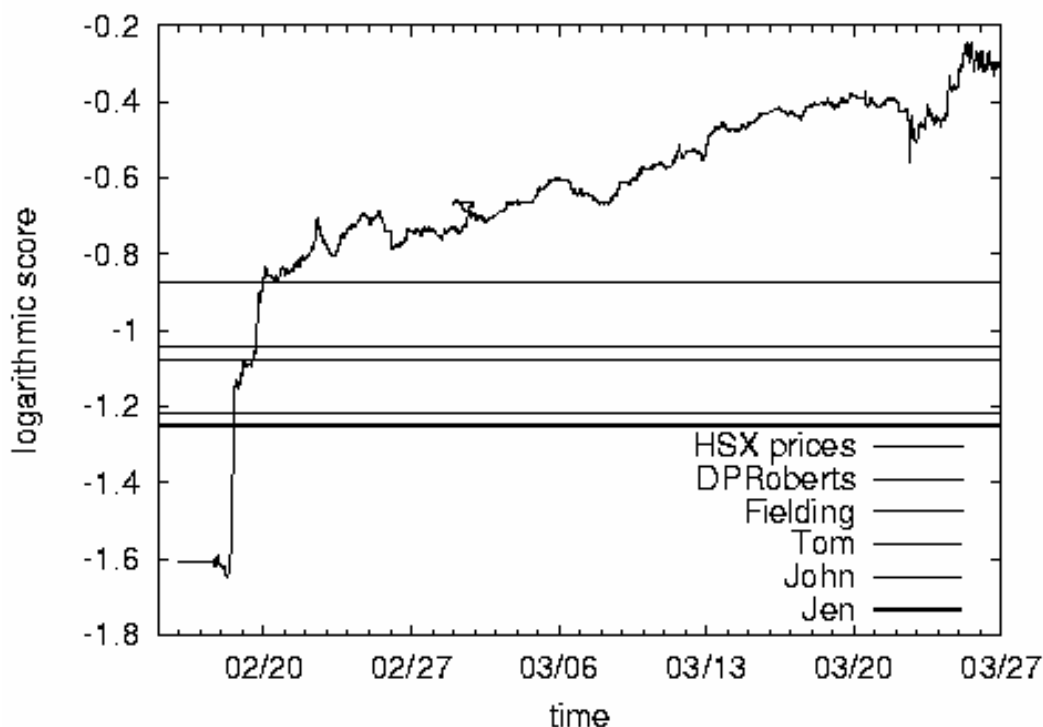


Figure 28: HSX accuracy: Comparison of Average Logarithmic Score (ALS) development for HSX prices and expert forecasts for Oscar awards in 2000 from February, 20 to March 26; Less negative scores are better; legend order corresponds to closing price order (Pennock, Lawrence et al. 2001)

Conclusion. HSX performance convincingly adds to the evidence that markets are able to collect and aggregate information, and that markets can produce remarkably accurate forecasts in absolute terms and in comparison with expert forecasts. This performance is even more impressive, when considering that these results are achieved with markets participants who are motivated by no tangible incentives.

3.6.3 Foresight Exchange (FX)¹⁸⁶

Market description. The Foresight Exchange (FX) is a play-money market in which the commodities traded are mid- and long-term claims about future events¹⁸⁷; initially with a focus on the development of science and technology, later with a broader scope including various subjects of public interest, such as politics, disasters, world finance, and arts and entertainment. The market was established by a US/Canadian research group in 1994 and was distinctively motivated by Robin Hanson's Idea Futures concept

¹⁸⁶ This section is primarily based on information provided by the FX website

Kittlitz, Hewitt et al. (1995). The market has ever since been open to the public and accessible through the Internet.¹⁸⁸

The major rationale for such a market was to provide what Hanson, writing on the subject of scientific research, calls an "honest consensus".¹⁸⁹ In science, as in other areas, the attention an idea receives sometimes has less to do with its merit than with how well it meshes with conventional wisdom or pleases those in positions of power. Research funding is difficult to allocate objectively, but only partly because of the uncertainty inherent in evaluating any prospectus. Scientists are people, and their judgment is subject to self-interest and other biases, just like the rest of us. Putting ideas into a marketplace recognizes this and gives people incentive to overcome it. Someone spending real money on an Idea Futures claim share has good reason to consider the claim's likelihood objectively, regardless of how they feel about it personally. The marketplace does not often reward those who trade based on wish fulfillment or the desire to make a statement Hanson (1990, 1992).

FX offers two types of securities. Of the first type, the standard security, the liquidation value is determined by a binary outcome, whether the underlying claim comes true or not. Traders may buy either "yes" or "no" coupons, effectively investing "for" or "against" it. Trading prices are percentages of the asset that backs the share, which is FX\$ 1.00. Thus, prices range from 0 to 100 cents, the numbers roughly corresponding to the market's consensus of how likely the claim is to be judged true. At the claim's due date, a judge, normally assigned when the claim was created, judges the claim either true or false. Traders holding shares of the winning security may redeem them for FX\$ 1.00 each; those owning losing shares receive nothing.

For the second type of FX security, so called "scaled claims", the liquidation value is determined by an arbitrary function that is made public as the claim is created and before respective securities are sold for the first time. Such FX securities are used to find a consensus on the value of a variable with arbitrary units over a range of possible values, e.g., on the date for a future event, neutrino mass in eV, or a performance measure at a point in time, such as the number of people in space or computer performance.

¹⁸⁷ with a typical time horizon of 2-20 years

¹⁸⁸ <www.ideosphere.com> as of October 2004

For example, a simple scaled claim may pay for a YES coupon for an uncertain future event FX\$ 1,00 if the event occurs before the date X. At the first of each successive month the YES coupon is worth \$0.10 less. Thus, 10 months after date X, the YES coupon is worth \$0.00. The liquidation value of NO coupons follows the reverse logic. Consequently, the coupon market prices should indicate the mean consensus as to when the event occurs in the given time frame.

Market performance. FX performance has been examined by Pennock, Lawrence et al. (2001), who find that FX market prices are good indicators of outcomes for events of broad scientific and societal interest.

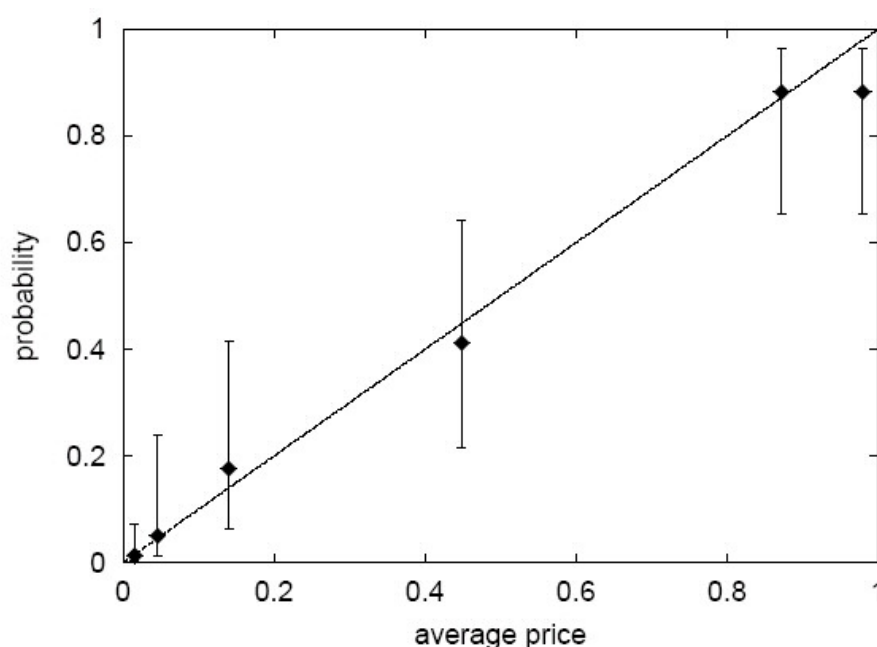


Figure 29: FX accuracy: Reliability diagram – correlation of option price group averages and corresponding observed outcome frequency for 161 claims that retired as of September 8, 2000 (Pennock, Lawrence et al. 2001)

Figure 26 shows how price group averages of claim prices collected 30 days prior to market closure correlate with their corresponding observed outcome frequencies for 161 FX claims that were retired as of September 8, 2000. If market prices are accurate, then among all claims with a price of FX\$0,1 about one in ten should end up "winning".

¹⁸⁹ see (Hanson 1990)

As the figure shows, prices collected correlate very well with the observed frequencies of their outcome, as all data points are very close to the diagonal of perfect accuracy.¹⁹⁰

Conclusion. FX performance adds further evidence that markets can be good predictors of uncertain events. Furthermore, it supports that such performance can be delivered even if market participants are motivated by other than tangible incentives. In addition and most notably, whereas IEM and HSX performance rests on a rather narrow focus on some information theme (U.S. political elections and Hollywood movies, respectively), FX markets achieve the task of collecting and aggregating information for very diverse interests, such as physics or politics, at the same, central and common exchange.

¹⁹⁰ Notably, the price group with the highest average price has a lower outcome frequency than its price suggests; this inaccuracy appears to reflect a systematic bias, see section 3.7.2 for a detailed discussion

3.7 Selected focus issues of market performance

3.7.1 Speed of information incorporation

According to the EMH and rational expectations theory, security prices in efficient markets should at all times reflect all available information.¹⁹¹ Consequently, the incorporation of new information into security prices must occur instantly, or near-instantly in a less-than-perfectly efficient market.

Of non-financial markets, analyses of horse racing markets¹⁹², Basketball betting markets¹⁹³, and a market game in the Euro 2000 soccer tournament¹⁹⁴, to name a few, are largely consistent with these efficiency assumptions. However, we present further research in which the speed of information incorporation is specifically examined for artificial asset markets.

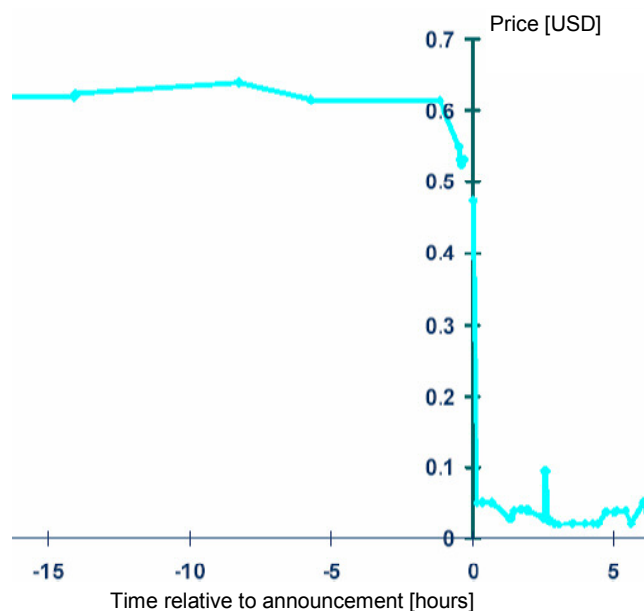


Figure 30: Speed of information incorporation: Price development of the security "YES" in the IEM "Powell nomination" market preceding the U.S. Presidential 1996 election ; Axis origin equals time of Powell's withdrawal announcement; (Berg, Nelson et al. 2002)

Figure 30 shows the price development of the contract "YES" in the IEM "Powell nomination" winner-takes-all market preceding the U.S. Presidential 1996 election.¹⁹⁵

¹⁹¹ see section 0

¹⁹² see (Thaler and Ziemba 1988)

¹⁹³ see (Gandar, Dare et al. 1998)

¹⁹⁴ see (Schmidt and Werwatz 2002)

¹⁹⁵ see section 3.6.1 for a detailed description of the IEM and its markets.

At liquidation, the contract would have paid \$1 if Powell's name would have been placed in nomination at the Republican convention, and 0\$ otherwise.

On November 8, 1995, Powell announced he would not run for the nomination¹⁹⁶; the axis origin in Figure 30 is calibrated to the exact point in time when the announcement was made.

As the figures displays, at the time of the announcement the price dropped from \$0,6 to approx. \$0,05 indicating that the information regarding Powell's withdrawal was incorporated virtually instantaneously. In fact, a price drop from \$0,6 to \$0,5 in the hour before the announcement reflects the market's anticipation of the withdrawal.¹⁹⁷

Another piece of research¹⁹⁸ of the speed of information incorporation analyzed in-game sports betting markets on the World Sports Exchange (WSE)¹⁹⁹ where traders can bet on sporting events continuously throughout a game.

The markets are double auctions in contracts that pay off \$100 if and only if the favored team wins the game by more than x points, where x is a nonnegative opening line or spread. Specifically, 34 markets corresponding to 34 soccer games played during the 2002 World Cup were examined. Prices were collected every 10 seconds during every game from the WSE as well as score changes and game clock information from CBS Sportsline.²⁰⁰

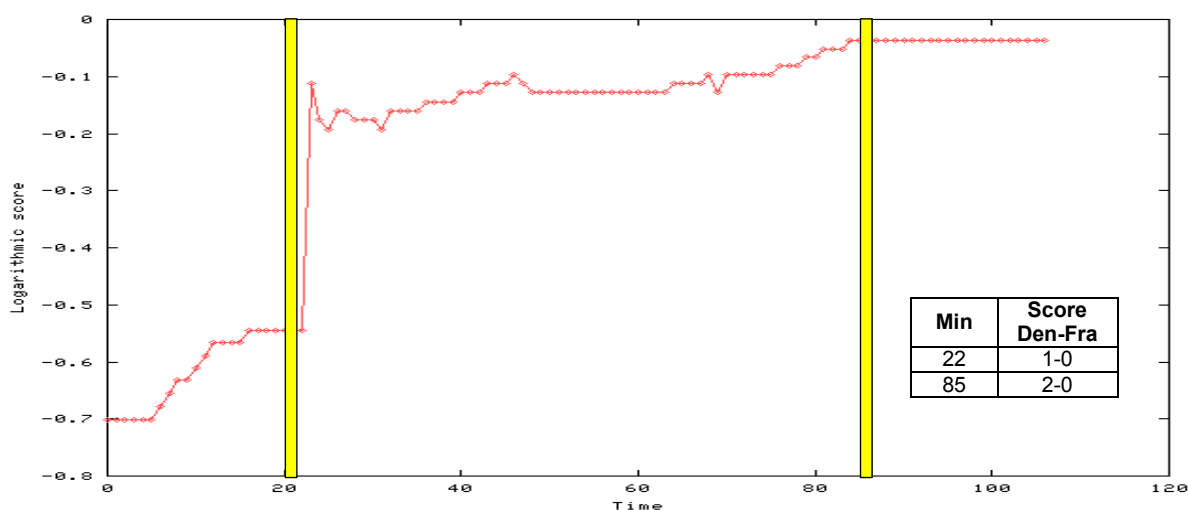


Figure 31: Speed of information incorporation: Logarithmic score over match time (~market price development) for Team Denmark in the Soccer World Cup match

¹⁹⁶ see, e.g. (Berg and Rietz 2003), p.83

¹⁹⁷ based on the unscheduled, short-term announcement of a press conference

¹⁹⁸ see (Debnath, Pennock et al. 2003b)

¹⁹⁹ <wse.com> as of October 2004

²⁰⁰ see (Debnath, Pennock et al. 2003b), p.1

**Denmark vs. France; time measurement includes half-break of approx. 15 mins;
(Debnath, Pennock et al. 2003a)**

To measure the accuracy of implied market forecasts over time, the logarithmic score, a standard measure of the accuracy of probabilistic forecasts, was used.²⁰¹ The speed of information incorporation was measured by how promptly the markets react to score changes in the games.

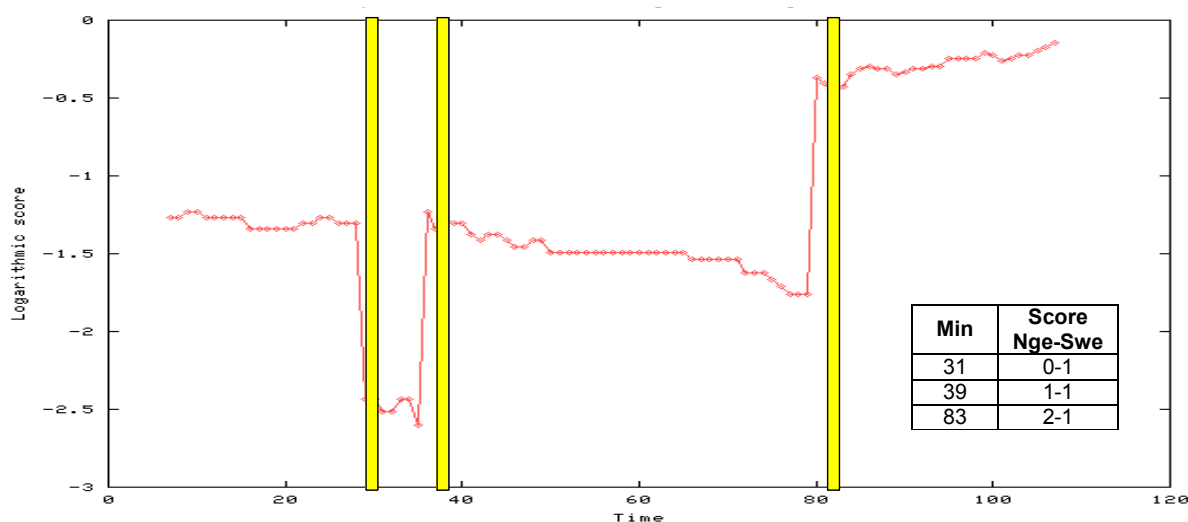


Figure 32: Speed of information incorporation: Logarithmic score over match time (~market price development) for Team Nigeria in the Soccer World Cup match Sweden vs. Nigeria; time measurement includes half-break of approx. 15 mins; (Debnath, Pennock et al. 2003a)

Figure 31 and Figure 32 show for two different soccer matches the development of the logarithmic score over match time. Diagram time includes the half-break of approx. 15 minutes, and yellow bars indicate score changes.

In Figure 31, whereas the first goal leads to an immediate and significant change in market price, the second goal does not lead to any significant market reaction, probably, as it confirms the winning team near the end of the game.

In Figure 32, it appears that all three goals were anticipated by the market, maybe fueled by specific game events such as heavy near-goal activity. Rather than making this assumption and in order to produce a conservative estimate, Debnath, Pennock et al. (2003b) assume no market foresight but attribute the time difference to communication delays during score and price reporting.

²⁰¹ see section 4.3.3 for details of this forecast verification method

In average, Debnath, Pennock et al. (2003b) calculated a delay of 31:63 seconds for the 74 goals scored in the 34 games. This difference reflects their conservative estimate, as any delay may be the result of website update delays or network delays in the course of data recording.

Furthermore, Debnath, Pennock et al. (2003b) analyzed on the same exchange markets from 18 games during the 2002 NBA (Basketball) Championship. They found that price changes in the markets were highly correlated with score changes; on average, the correlations for all games was 0,61

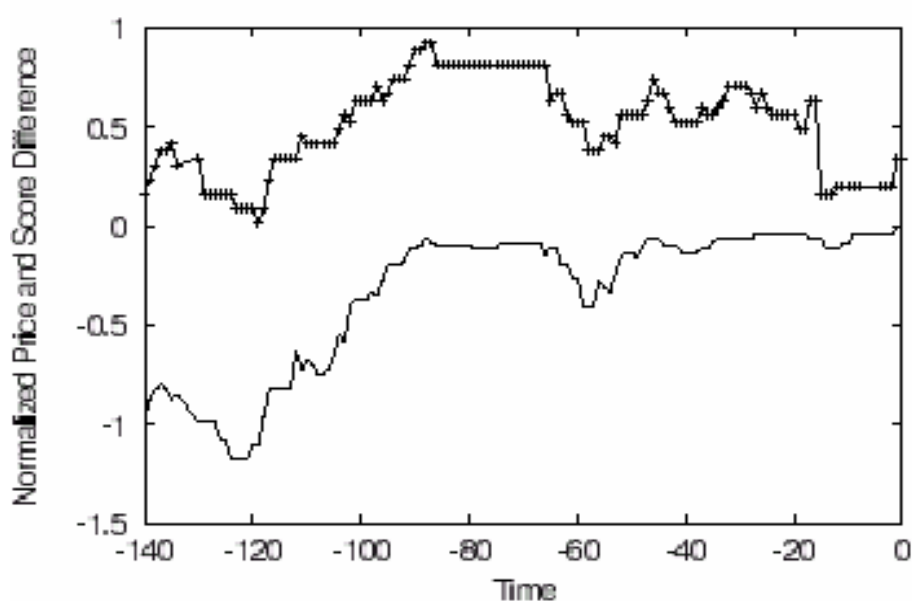


Figure 33: Speed of information incorporation: Correlation between logarithmic normalized price of the winner and the score difference in the basketball game between San Antonio and LA Lakers held on May 7, 2002; (Debnath, Pennock et al. 2003a)

For example, in Figure 33, the top curve is the normalized score difference between the two teams and the bottom curve is the logarithm of the price of the winner. The correlation between these two curves is 0,93.²⁰²

Conclusion. The examples of evidence presented demonstrate that markets are able to incorporate relevant information virtually instantaneously or with very little delay. The data supports the EMH and rational expectations theory that securities in efficient markets reflect at all times all available information.

²⁰² see (Debnath, Pennock et al. 2003b), p.2

3.7.2 Imperfect prices, bias and arbitrage

According to the EMH, competition between investors seeking abnormal profits drive asset prices to their fundamental value.²⁰³ The EMH does not assume that all investors are rational, but it does assume that markets as a result are rational.²⁰⁴ The EMH does not assume that markets can foresee the future, but it does assume that markets as a result make unbiased forecasts of the future.²⁰⁵

Meanwhile, a substantial body of evidence has accumulated which suggests that many (temporal) misvaluations by markets exist.²⁰⁶ Among other reasons, such as the textbook-type of temporal imbalances of supply and demand, such market misvaluations may be caused by the lack of full rationality of market participants.²⁰⁷

Psychologists and economists alike have demonstrated a variety of systematic departures from 'rational' decision making on the part of individuals.²⁰⁸ They have found, among other things, that individuals exhibit substantial information processing or judgment biases.

For instance, people tend to overvalue small probabilities and undervalue near certainties.²⁰⁹ For example, there is a well-known "longshot bias" in horse race betting markets, in which bettors tend to overvalue longshot bets (those that are unlikely to pay off) which results in relatively large negative average returns.²¹⁰ At the same time, bettors tend to undervalue "favorite" bets (those that are most likely to pay off), which results in relatively small negative or, sometimes, positive average returns.²¹¹

Evidence supports that the "longshot bias" appears to translate to field-deployed AAM such as HSX²¹² or FX²¹³. However, another study of FX markets actually shows the reverse effect of the "longshot bias".²¹⁴

²⁰³ see section 3.1 for a discussion of the theoretical background

²⁰⁴ see sections 3.1 and 3.2, and (Fama 1970; Fama 1991)

²⁰⁵ see (Ritter 2003), p.429

²⁰⁶ see, e.g. (Lo 1997) and (Russel and Torbey 2002)

²⁰⁷ see also section 3.2

²⁰⁸ see, e.g. (Kahneman 1982; Kahneman and Tversky 1986; Gilovich, Griffin et al. 2002)

²⁰⁹ Ibid.

²¹⁰ see (Thaler and Ziemba 1988)

²¹¹ Ibid.

²¹² see also Figure 26, where the price group with the highest average price has a higher outcome frequency than it's price suggests. Thus, the market consistently undervalues assets of this price group.

²¹³ see (Kittlitz 1999), where the "longshot bias" appears to be known as the "50 cent bias"

Furthermore, a study of IEM markets supports that the "longshot bias" appears to reverse in the context of field-deployed artificial asset markets.²¹⁵

In either case, these experiences suggest that AAM markets suffer in accuracy when predicting very small or very high probability events.

Misvaluations can be classified by two types: those that are recurrent and short-lived and those that infrequent and long-term, such as "bubbles".^{216,217}

The first type, recurrent misvaluations are arbitrageable, that is, they present a sizeable opportunity for a risk-free profit for the more rational market participants who apply appropriate trading strategies.²¹⁸ Consequently, such misvaluations eventually become corrected before they become large, and, as a result, they are usually short-lived. Hence, market efficiency is at place, as the EMH suggests.

For example, in the IEM political stock markets traders' preferences over parties or candidates tend to color their perceptions, creating a 'wishful thinking' effect.²¹⁹ This arises because traders who prefer a particular political party are overly optimistic about their preferred party's likely success in the election and they interpret news more favorably with respect to that party. Thus, they make larger investments (number of shares or proportion of funds) in their preferred party's contracts than traders who prefer other parties.²²⁰

Nonetheless, in spite of this evidence, these markets predicted the election outcomes extremely well.²²¹ Despite the imperfect rationality of the average trader, relatively few 'marginal' traders who are influential in setting market prices are all that is needed for market efficiency.²²² Marginal traders show no indication of a judgment bias in their transactions. They invested more than twice the level of non-marginal traders on

²¹⁴ see also Figure 29; the price group with the highest average price has a lower outcome frequency than its price suggests. Thus, the assets of this price group are overvalued

²¹⁵ see (Berg and Rietz 2002)

²¹⁶ see section 3.7.3 for a discussion of price bubbles

²¹⁷ see (Ritter 2003), pp.434-435

²¹⁸ see (Barberis and Thaler 2003), p.1054

²¹⁹ see (Forsythe, Nelson et al. 1992) pp.1153-1156 and (Forsythe, Rietz et al. 1999), p.89-90

²²⁰ Ibid.

²²¹ see (Forsythe, Nelson et al. 1992; Berg, Forsythe et al. 1997; Forsythe, Rietz et al. 1999; Berg, Forsythe et al. 2000)

²²² see (Forsythe, Nelson et al. 1992), pp.1156-1160

average, they traded more shares and were active in the market on more days, and marginal traders also earned significantly higher returns.²²³

Oliven and Rietz (1995) further refined the notion of marginal traders and report that market makers (traders who set bid and ask prices at the top of their respective queues) are far less prone to errors than price takers (traders who accept others' prices). The error rate for price takers was nearly six times the error rate for market makers. Thus, traders who set prices appeared to be far more rational than those who accepted prices. Further, it was shown that more active, experienced and educated traders and those who reported to be knowledgeable about financial markets were less subject to errors and that fewer errors were associated with larger orders on average. These traders, who tended to be market makers, were able to drive prices to efficient levels while profiting from the mistakes of more error-prone traders, who tended to be price takers.

The second type of misvaluation, infrequent and long-term, such as price bubbles, haven proven extremely difficult if not impossible for arbitrage.²²⁴ That is, even the most rational market participants are not able to exploit such opportunities for a risk-free profit.

Among the reasons is that it is impossible in real time to identify the price peaks and price troughs until they have passed.²²⁵ Furthermore, the forces of arbitrage fail against the massive capital volume that typically accumulates behind misvaluations of this kind due to capital constraints, short sales constraints, for instance, or if there is no guarantee that the mispricing will be corrected within a reasonable timeframe.²²⁶ Indeed, arbitrageurs may even choose to avoid the markets where the mispricing is most severe, because the risks are too great.²²⁷ This latter appears to be especially true for large markets, such as the Japanese stock market in the late 1980s or the U.S. market for technology stocks in the late 1990s.²²⁸

²²³ see (Forsythe, Nelson et al. 1992), pp.1156-1160

²²⁴ see (Ritter 2003), pp.434-435

²²⁵ Ibid.

²²⁶ see (Barberis and Thaler 2003). pp.1054-1063

²²⁷ Ibid.

²²⁸ see (Ritter 2003), pp.434-435

Eventually, the market corrects itself also for this second type of misvaluation.²²⁹ But until then, such misvaluations persist for a relatively long time and become larger and larger before they eventually become corrected. Thus, market efficiency appears to temporarily fail when confronted with such misvaluations. See the next section (3.7.3) for a detailed discussion of price bubbles as a prime example of misvaluations of this type.

Conclusion. Markets and assets traded therein are sometimes subject to misvaluation, as not all traders are fully rational at all times. Some misvaluations are short-lived as market forces exemplified by few, but highly rational "marginal traders" drive prices towards informational efficiency.

Other, infrequent misvaluations persist for relatively long time due to limits to arbitrage before the deviations are eventually corrected; market efficiency appears to be in disorder, at least temporarily. The next section (3.7.3) provides a more thorough discussion of the latter type of misvaluation and how it can be faced.

3.7.3 Price bubbles and crashes

Financial markets often exhibit sharply rising prices and subsequent declines that cannot be justified by fundamental or realistic economic assessments.²³⁰ Such phenomena are commonly known as "bubbles" (period of inflated prices) and "crashes" (sharp decline of prices following a period of inflated prices). The well documented recent dramatic rise and fall of Internet-related technology shares in global financial markets around 1999 is a case in point.

As such bubbles distort prices and thereby could undermine the use of artificial asset markets as an all-time reliable forecasting tool, we want to explore how such phenomena can be forestalled or considerably limited.

The most fruitful research appears to have come from laboratory experiments, as these hold out the possibility for the experimenter to know the "true price", and hence to observe deviations. Thus, the propensity for long-lived financial asset markets to

²²⁹ see (Ritter 2003), pp.434-435

²³⁰ see, e.g. (Dreman and Lufkin 2000)

exhibit price bubbles relative to the per-share expected dividend stream was first documented in experimental double auctions reported by.²³¹

Such price bubbles have been attributed to the lack of common knowledge of rationality of market participants and the resulting incentive to speculate.²³² Alternatively, another explanation claims that errors in decision making are the prime cause for bubble formation.²³³ The claim is that even after traditional amounts of training and testing residual confusion can remain in some market participants and leads to mistaken believe that aggressive buying of the asset for profitable resale is a good strategy.²³⁴

Wolfers and Zitzewitz (2004) argue, that unlike relatively small-scale AAM, traditional large financial markets may be subject to bubbles because of constraints on short selling and because investors will be reluctant to commit a large share of their wealth to an arbitrage opportunity. As currently operating AAM typically impose no restrictions on short selling, the markets are sufficiently small-scale, and the improbability of informed investors to be capital-constrained, the scope for bubbles in relatively small-scale AAM might be more limited.²³⁵

But research by laboratory experiments using the double auction asset trading environment has shown the phenomenon of bubbles to persist after changes in trading rules thought to discourage bubble formation, such as the introduction of short selling opportunities, margin buying opportunities, limit price-change rules, informed insider trading²³⁶, and a capital gains tax²³⁷.

Initially, the only reliable way found to generate prices that approximately reflected the intrinsic dividend value of an asset share was to increase the experience of traders as a group.²³⁸

²³¹ see (Smith, Suchanek et al. 1988)

²³² see (Plott 1991) and (Smith 1994)

²³³ see (Lei, Noussair et al. 2001; Lei, Noussair et al. 2002)

²³⁴ This view appears to be supported by (Williams 2002), as traders in laboratory experiments who maintain buying at excessive prices rarely choose to comment publicly on their market strategy, suggesting that they feel uncomfortable with their decision making

²³⁵ see sections 3.5 and 3.6

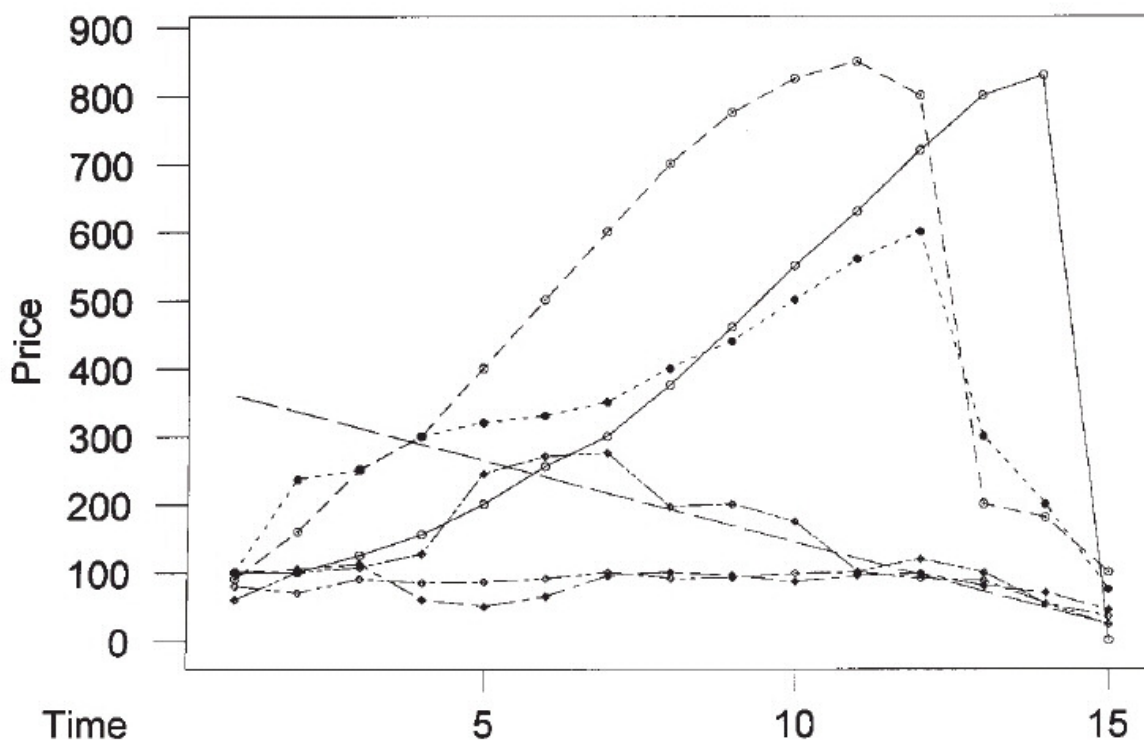
²³⁶ see (King, Smith et al. 1993)

²³⁷ see (Lei, Noussair et al. 2002)

²³⁸ see (King, Smith et al. 1993) and (Porter and Smith 1994)

Figure 34: Price evolution for 6 experiments under conditions maximizing and minimizing bubbles; (Caginalp, Porter et al. 2001)

In the three experiments, marked by circles, in which prices soar far above the fundamental value, there is an excess of cash, the dividends are distributed at the end of each period (adding more cash) and there is a closed book so that traders do not know the entire bid–ask book. In the experiments marked by diamonds, the opposite conditions prevail, and prices remain low and there is no bubble.



More recently, Caginalp, Porter et al. (2001) reported after a multiple series of experiments that three factors, applied in concert, could eliminate a laboratory bubble entirely: (i) a low initial liquidity level, i.e., less total cash than value of total shares, (ii) deferred dividends, and (iii) a bid–ask book that is open to traders. Conversely, large bubbles aroused when the opposite conditions existed.

Conclusion. The possible occurrence of price bubbles are not limited to large financial markets, they have been reproduced in laboratory experiments as well. Thus, it is not improbable that a field-deployed TFM is susceptible to price bubbles, too. To prevent a reduced reliability as forecasting tool, a TFM exchange should therefore consider for its design some proven measures that significantly reduce the probability of price bubbles. Among those measures are a low initial liquidity level, deferred dividends, and a bid–ask book that is open to traders. Another measure, the increase in experience of

traders is obviously practically limited, as in most non-laboratory markets, there are and will always be newcomers.

3.7.4 Price manipulation

For markets to be efficient and market-derived forecasts to be accurate, the EMH and rational expectations theory assume, among other things, that traders act to maximize their profit as they limit their losses.²³⁹ As a consequence, one or multiple traders who do not trade for profit, but primarily trade to manipulate prices, may decrease market efficiency and, thus, forecast accuracy. As we examine research on market price manipulation, we explicitly limit our review to manipulation by trading action and exclude indirect price manipulation, such as the spreading of disinformation or the staging of influential events.

Theoretical research on price manipulation has so far focused primarily on attempts of traders to manipulate in order to gain in the market, but not on exogenous preferences over prices.²⁴⁰ The little empirical research available on price manipulation of futures markets reports mixed results, see Table 13.

Table 13: Price manipulation attempts in field-deployed artificial asset markets

Market	Avg. market activity	Manipulation power	M-ratio	Manipulation effect
PSM Austria: Wahlbörse "Nationalratswahlen 1995" (Ortner 1996)	110 active traders with avg. deposit of 1000 cu	~4 traders with deposit of 5000 cu	~1/4	<u>Successful</u> : vote-share price of a ~15% party was inflated by 2%pts for the last 5 trading days
PSM Germany: "Wahl\$street" Berlin-state elections 1999 (Hansen, Schmidt et al. 2002)	n/a	n/a	n/a	<u>Successful</u> : vote-share price of a 5% party was inflated by 1,5%pts for the last 11 trading days
PSM Austria: "Presse"-Wahlbörse "Nationalratswahlen 2002" (Filzmaier, Beyrl et al. 2003)	~1000 regist. traders @50.000 virtual cu	166 traders @50.000 virtual cu	>1/6	<u>Failed</u> : vote-share price of a ~36% party was deflated by -15%pts for ~12 mins before it returned to previous price level
IEM 2004 Presidential vote-share market (Strumpf 2004)	10.000 USD trading volume	500 USD trades	~1/20	<u>Failed</u> : dissipated within 24 hours

cu ... currency units

²³⁹ see section 3.1

²⁴⁰ see (Hanson, Oprea et al. 2004), p.3-4

So far, it appears that in thick markets, where the quantity traded is large and where there are many liquidity traders who attract rational speculators, attempts of price manipulation have had hardly noticeable and short-lived effects. For example, an attempt by 166 traders to deflate a vote-share by 16 percentage points in the Austrian PSM "Nationalratswahlen 2002" failed, as other traders quickly responded to the arbitrage opportunity and drove the vote-share price to the previous level within 12 minutes.²⁴¹

In another example, the price impact from random \$500 trades in the IEM 2004 Presidential election vote-share market dissipated within 24 hours, suggesting that even fairly substantial noise trading is unlikely to move prices much from their equilibrium level.²⁴²

In other pieces of research, a review of price manipulation attempts in historical presidential betting markets appear to have failed as well²⁴³ as attempts to manipulate prices in horse racetrack betting by canceling large wagers at the last moment²⁴⁴.

However, in the case of thin markets, where the quantity traded is small and where there may be no liquidity traders to attract rational speculators, attempts of price manipulation have had mixed results. For example, some few traders in the Austrian PSM "Nationalratswahlen 1995" managed to accumulate sufficient relative market power to inflate a vote-share security by two percentage points for the last five days of trading.²⁴⁵ In another successful attempt to manipulate political information markets, manipulative traders in the German PSM "Berlin-state elections 1999" inflated a vote-share security by 1,5 percentage points for the last 11 days of trading.²⁴⁶

However, in a laboratory experiment attempts to manipulate prices by trading failed.²⁴⁷ Experiments on information aggregation in which partially informed subjects trade an asset with an unknown value were replicated from an earlier experiment.²⁴⁸ Furthermore, a subset of traders was given an incentive to manipulate prices through trade. The design of the experiment is such, that all participants know that manipulators

²⁴¹ see (Filzmaier, Beyrl et al. 2003), pp.12

²⁴² see (Strumpf 2004)

²⁴³ see (Strumpf and Rhode 2004)

²⁴⁴ see (Camerer 1998)

²⁴⁵ see (Ortner 1996), pp.35-36

²⁴⁶ see (Hansen, Schmidt et al. 2002)

²⁴⁷ see (Hanson, Oprea et al. 2004)

²⁴⁸ based on the experiment by (Plott and Sunder 1988)

are present, how strong the incentive to manipulate is and in what direction manipulators have incentives to push the price.²⁴⁹

As a result, price manipulators were unable to actually affect the relationship between price and asset value, as other traders compensated for the bias in offers from manipulators by setting a different threshold at which they were willing to accept trades. Thus, this evidence suggests that, when agents suspect the presence of manipulators and know in what directions manipulators would like to push the price, manipulation is ineffective.²⁵⁰

Accordingly, in a complementary research effort Hanson and Oprea (2004) develop a microstructure model motivated by thin information markets in which manipulation ends up causing market prices to be more accurate due to the liquidity they provide. More specifically, they argue, that the prospect of trading against someone who trades on non-asset-value considerations can entice other traders to become better informed, increasing average price accuracy.

Conclusion. The success of price manipulation attempts in artificial asset markets appears to largely depend on the "thickness" or "thinness" of the market. In thick markets, where the quantity traded is large and where there are many liquidity traders who attract rational speculators, attempts of price manipulation have only short-lived and hardly noticeable effects.

In thin markets, which is typically the case for artificial asset markets in their early maturity stages, the success of price manipulation attempts depends very much on whether traders recognize the manipulation attempt, and whether they are able²⁵¹ and willing²⁵² to profit by the given arbitrage opportunity. Only if all three conditions are given, attempts of price manipulation through trade is likely to fail, in all other cases manipulation is likely to succeed.

²⁴⁹ see (Hanson, Oprea et al. 2004)

²⁵⁰ see (Hanson, Oprea et al. 2004)

²⁵¹ e.g. enough funds to invest (real-money vs. play-money!), short-selling allowed

²⁵² e.g. risk attitude towards investing considerable funds (real-money vs. play-money!)

3.7.5 Play-money vs. real-money

For markets to be efficient, among other things, traders must be truly willing to maximize their profit as they want to limit their losses.²⁵³ Consequently, a clear implication is that markets where traders risk their own money (as in a real-money market) should produce better forecasts than markets where traders run no financial risk (as in a play-money market).

Clearly, in a real-money market, participants are likely trying to maximize their wealth levels. Although participants in play-money markets run no financial risk, this does not preclude, however, some material or psychological upside for the traders in the form of bragging rights, prizes, or cash. Typically, the participants in such markets are given an initial amount of play-money to invest, and a few of those with the largest net worth when markets close win some sort of prize.

However, there is little empirical evidence to the relative efficiency of real-money versus play-money markets, as we have found only one study that has directly compared the accuracy of actual- and virtual-currency markets in a real-world setting.²⁵⁴ The study compares the predictions of two popular online sports trading exchanges, TradeSports²⁵⁵ and NewsFutures²⁵⁶. Both exchanges offer similar contracts on sporting events that feature liquidation values of 100 currency units for the contract associated with the winning team, and 0 currency units for contracts of non-winning teams. Accordingly, trading prices translate directly into the traders' collective assessment of the probability for each team to win.

Essentially, both exchanges are comparable with the primary distinction being that TradeSports operates with real money and NewsFutures with play-money.²⁵⁷ The markets and contracts that were specifically compared by the study spanned 208 NFL games²⁵⁸ from September to December 2003. Traders were neither informed nor aware that their trading prices were being sampled for research.²⁵⁹

²⁵³ see section 3.1

²⁵⁴ see (Servan-Schreiber, Pennock et al. 2004)

²⁵⁵ <www.tradesports.com> as of October 2004

²⁵⁶ <us.newsutures.com> as of October 2004

²⁵⁷ Although NewsFutures traders cannot lose real money, a few of the top-scorers are able to convert their play-money winnings into real prizes.

²⁵⁸ National Football League (NFL): League of American Football in the U.S.

²⁵⁹ see (Servan-Schreiber, Pennock et al. 2004), pp.3-4

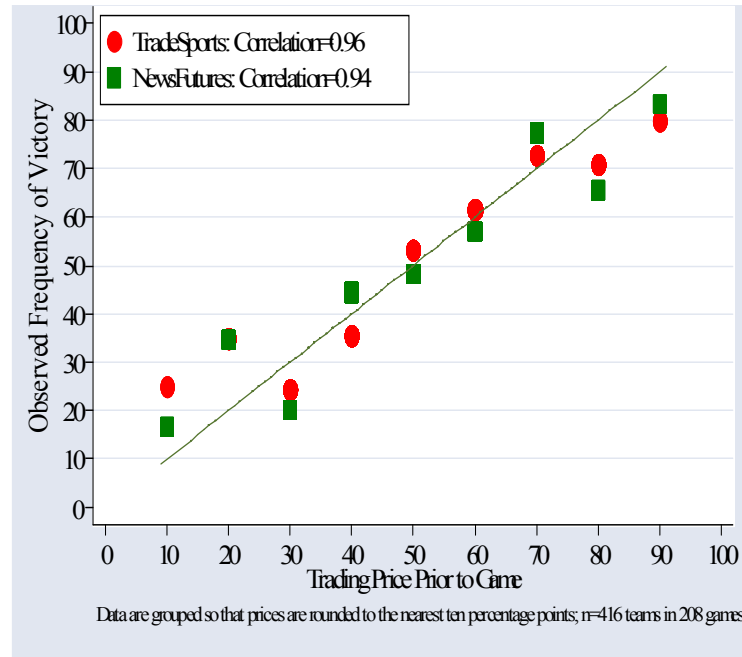


Figure 35: Forecast accuracy: Correlation of final price group averages collected from TradeSports and NewsFutures with corresponding observed outcome frequency for 208 NFL games in 2004; diagonal represents perfect accuracy; (Servan-Schreiber, Pennock et al. 2004)

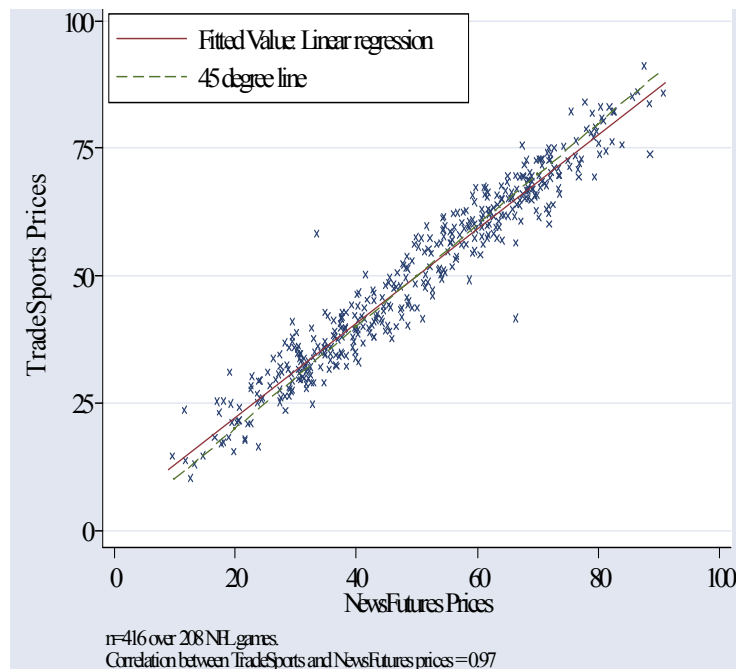


Figure 36: Comparison of final market prices of TradeSports and NewsFutures for 208 NFL games in 2004; diagonal represents correlation of 1 (=equal prices); (Servan-Schreiber, Pennock et al. 2004)

Figure 35 shows how final price group averages collected at TradeSports and NewsFutures correlate with observed outcome frequencies for the 208 NFL games. If market prices are accurate, then among all securities with a final price of 10, about one in ten should end up "winning".

As the figure shows, prices of both markets correlate very well with the observed frequencies of their outcome, as all data points are very close to the diagonal of perfect accuracy. While the real-money market TradeSports shows a correlation of 0,96, the play-money market shows a correlation of 0,94; neither market appears to reliably outperform the other.²⁶⁰

Figure 36 compares the final prices of NewsFutures with the corresponding prices from TradeSports. If both markets prices would be the same, they would meet on the diagonal reflecting a correlation of 1,0.

On average, NewsFutures and Tradesports prices differed by 3.4 per cent, with a standard deviation of 2.8 per cent.²⁶¹ As real- and play-money markets do not provide a link of opportunity for arbitrage, such differences in forecasts are reasonable.

Table 14: Comparison of forecast accuracy of a real-money and a play-money market by four common measures based on forecasts of 208 NFL games in 2004; (Servan-Schreiber, Pennock et al. 2004)

	TradeSports (real-money)	NewsFutures (play-money)	Difference TS - NF
Mean Absolute Error = <i>lose_price</i> [lower is better]	0.439 (0.011)	0.436 (0.012)	0.003 (0.016)
Root Mean Squared Error = <i>Average(lose_price²)</i> [lower is better]	0.468 (0.023)	0.467 (0.024)	0.001 (0.033)
Average Quadratic Score = <i>100 - 400*(lose_price²)</i> [higher is better]	12.410 (4.37)	12.427 (4.57)	-0.017 (6.32)
Average Logarithmic Score = <i>Log(win_price)</i> [higher (less negative) is better]	-0.631 (0.024)	-0.631 (0.025)	0.000 (0.035)

²⁶⁰ see (Servan-Schreiber, Pennock et al. 2004), p.4

²⁶¹ Ibid.

Table 14 compares the forecast accuracy of both markets for the same data set by four different, but commonly used forecast accuracy measures.²⁶² As the differences in predictive power across all four measures are so small, Servan-Schreiber, Pennock et al. (2004) conclude that the predictive accuracies of the two markets are statistically indistinguishable.

In trying to explain the equally good performance of real-money and play-money markets, the authors of the study argue, that in a real-money market, the weights given to each person's opinion reflect the amount that they are willing to bet, which might be largely affected by their wealth levels. Thus, in real-money markets, trader opinion likely reflects the distribution of wealth which can often reflect returns to skills other than predictive ability. By contrast, the only way to amass wealth in a play-money exchange is by a history of accurate predictions. As such, it seems plausible that play-money exchanges offset their missing or negligible financial incentive by producing more efficient opinion weights.²⁶³

Conclusion. Whereas the theories of EMH and rational expectations suggest that real-money markets perform better than play-money markets, as traders who risk their own money should produce better forecasts than markets where traders run no financial risk, we find empirical evidence that is contrary to such belief.

In fact, the, admittedly little, evidence so far suggests that play-money markets can perform as well as real-money markets. The decisive criteria for good market performance appears to be that a market features a knowledgeable and motivated community of traders, regardless if they are attracted by real money or by some other means.

3.8 Summary and conclusions

In this chapter we reviewed the pieces of literature that have accumulated so far on artificial assets markets and we investigated the evidence on AAM's ability to provide forecasts of any kind.

²⁶² see sections 4.3.1 and 4.3.2 for a discussion forecast validation methods

²⁶³ see (Servan-Schreiber, Pennock et al. 2004), pp.2,9

We established that theory, empirical, and experimental evidence suggest that asset markets are able to collect information that is dispersed, aggregate it like a statistician, and publish the findings in forms of prices.

In a perfectly efficient market, security prices reflect all information; prices reveal to the ignorant participants any initially private information, that is, participants learn by observing prices.

Empirical evidence suggests that, in reality, markets are neither perfectly efficient nor completely inefficient; all markets are efficient to a certain extent, some more so than others. Rather than being an issue of black or white, market efficiency is more a matter of shades of gray.

The results of laboratory experiments suggest that the successful aggregation of information in asset markets depends on the features of these markets—rules, information distribution, common knowledge, experience of traders, number, nature and relationship of assets traded, etc.

While speculative financial markets have long been used to identify and reallocate risk, only very recently have artificial asset markets been created primarily to make forecasts. For example, the Iowa Political Stock Market seems to predict election outcomes better than opinion polls. Several play-money markets have been found to aggregate information well, although they also seem to have problems with biases and limited participation. A few internal corporate real-money markets have also shown promising results.

Drawing on the presented evidence on artificial asset markets, we suggested some generalizations about the operating principles of AAM. Essentially, artificial asset markets perform three tasks:

1. Artificial asset markets provide incentives to seek information
2. Artificial asset markets provide incentives for truthful information revelation
3. Artificial asset markets provide an algorithm for aggregating diverse opinions

More specifically, artificial asset markets provide the following opportunities:

- Artificial asset markets are good information aggregators
 - absolutely
 - relative to the best alternative method
- Artificial asset markets react quickly/instantly to new information

- Artificial asset markets appear to be good forecasting tools
- Artificial asset markets can even convey what might have been (conditional forecasts)

Thus, we conclude that the evidence presented in the reviewed literature supports the hypotheses H1 and H2 in a general sense. However, it remains to be proven that the given evidence can be transferred to technological forecasting.

We continue to examine the reviewed literature in support of technological forecasting beyond our hypotheses.

The opportunities presented by artificial asset markets also require categorical attention of the following matters:

- Incentives and market structure have great influence on market success, e.g.
 - Play-money markets can perform as well as real-money markets
 - Price bubbles can be prevented by a low initial liquidity level, deferred dividends, and a bid–ask book that is open to traders
- The subject pool is important
 - Markets can only aggregate what is known
- Traders make mistakes and display biases
 - Large, "thick" markets show no bias as few very rational traders seize such opportunities for arbitrage
 - Small, "thin" markets may reflect bias
- Price manipulation by trade is difficult, but possible
 - Large, "thick" markets quickly compensate such manipulation attempts
 - Small, "thin" markets compensate such manipulation attempts only if sufficient traders recognize the manipulation attempt, and if they are able and willing to profit by the given arbitrage opportunity

Furthermore, the implementation of artificial asset markets raises some considerations:

- Implementable as fully automated, electronic market mechanism
- Off-the-shelf software is available
- Moderate costs for set-up and maintenance, advertising, searching, and transacting
- Worldwide audience potential by placement on internet

- Regulation depends on market currency
 - Play-money markets require no permission from government authorities or regulatory bodies and inherit negligible legal risk
 - Real-money markets are subject to extensive regulation which incurs very significant technical, regulatory, and fiduciary costs

Speculative, artificial asset markets appear to offer several apparent advantages over other prediction institutions, such as surveys, or reports by expert committees or by assigned specialists. Market estimates should be cheap to create, can be frequently updated, are numerically precise, and should offer contributors strong reasons to be careful and honest. Market estimates are also more immune to challenge, as dissenters can always be invited to trade and attempt to profit by correcting the errors they think they see.

Why is further exploration of the design of artificial asset markets necessary when other markets of this kind, such as the Iowa Political Stock Market have already shown the viability and improved accuracy of such markets? Because many potential pitfalls lie in the way of realizing good TF-relevant information aggregation through artificial asset markets.

NetExchange (2001) has identified that the three main potential problems in the development of a special purpose AAM are: participation, contract design, and market mechanism design. Thus, it is necessary to create and evaluate means to alleviate or avoid these problems.

Participation can be affected both by market incentives such as how much money is at stake and by non-market issues. For example, desirable participants might be prevented from participation by financial regulations, excessive conceptual or user-interface complexity, or simple disinterest. Thus, a market sponsor needs to find ways to surmount these obstacles and encourage active and accurate participation.

Contract and market mechanism design requires determining what information is relevant to TF-decision makers, and then creating a structure of contracts whose prices will provide that information. For example, if there are too many contracts and too few participants and if simple bulletin board markets are used, stable and informative market prices may fail to exist. Thus, the details of the market mechanism design need careful consideration.

4. Empirical investigation of artificial asset markets for technological forecasting

In this chapter we present the empirical evidence produced in the course of this thesis. First, we develop a research concept for the empirical investigation of the hypotheses developed in chapter 2; and, subsequently, we establish the data that is used for analysis.

Next, we operationalize each of both hypotheses by developing sub-hypotheses. We then perform the corresponding analysis on the empirical data, examine and discuss the support for the sub-hypotheses and the original hypotheses.

We conclude the chapter with a brief summary of the support provided by the empirical research of the hypotheses developed in this thesis.

4.1 Research concept

In chapter 2, section 2.6, we developed two broad hypotheses:

- H1: Artificial asset markets can forecast technological developments (in principle)**
- H2: Artificial asset markets can forecast technological developments better than alternative TF methods used in a comparable application context**

Subsequently, we develop a research concept to validate these hypotheses. For this purpose, we follow a four-step process as described below:

1. Operationalize hypotheses for quantifiable properties that can be measured
2. Acquire data for properties referred to by operationalized hypotheses
3. Analyze data
4. Interpret results

Hypotheses operationalization, data analysis and results interpretation are subsequently performed separately for each of both hypotheses. However, as a common data base is used to validate both hypotheses, we discuss the data acquisition first.

In principle, there are two choices in acquiring data: (1) generating the data in a designed experiment or (2) using existing data from past experiments. Figure 37 illustrates how these options apply to AAM for TF.

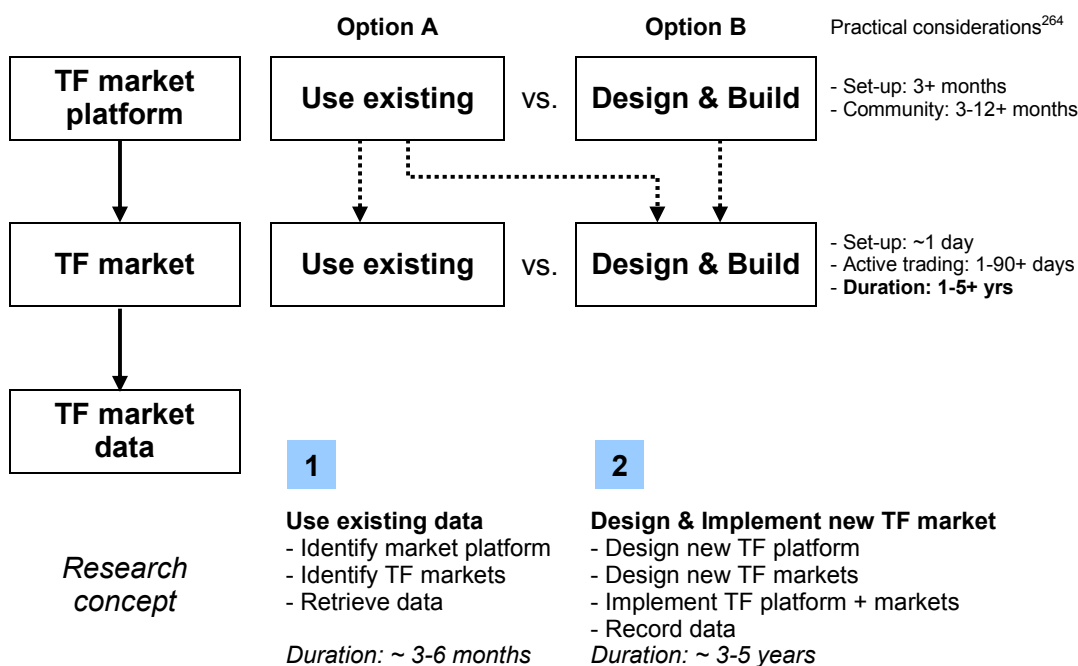


Figure 37: Empirical data source– options for data acquisition and research concept

Artificial asset markets need a market platform (a trading exchange) which provides the market's operating system.²⁶⁵ Thus, the first choice is to decide on the creation of a new market platform or the use of an existing platform.

The second choice concerns the market itself: a new market may be designed, built and run to generate the data for empirical research – which is necessary if a new market platform is created and optional if an existing market platform is used. Alternatively, the data from existing (matured) markets can be used.

Given the requirement of 3 to 5+ years for market duration and the time constraint of 1,5 years imposed on this (part of) research, the author has chosen a research concept based on two pillars:

²⁶⁴ based on literature survey used in sections 3.5 and 3.6, and (NetExchange 2003a)

²⁶⁵ see also section 5.1

- 1 Use of existing data** of an existing market platform with existing TF markets: this data forms the basis for the empirical research performed and presented in this thesis.
- 2 Design & set-up of a new** TF market platform with new markets that endure 3-5+ years: this data allows for subsequent research not covered by this thesis. However, the design and implementation of the experimental TF market platform is developed and described in chapter 6.

As the research concept has been established, we subsequently execute Pillar 1 of the concept, that is, we establish the data base next.

4.2 Data

In this section we establish the data used for analysis and subsequent validation of the hypotheses. According to the research concept developed in the previous section, existing data is to be acquired and used. Table 15 summarizes the necessary data acquisition steps, the qualification criteria and the search results.

Table 15: Acquisition of existing data: steps, qualification criteria and search results

#	Steps	Qualification criteria	Search results
1.	Identify AAM market platform	<ul style="list-style-type: none"> • publicly accessible (via Internet) • features markets with technology-related content • established trader community • Market price/transaction data retrievable 	<ul style="list-style-type: none"> ➤ Foresight Exchange (FX) ➤ MIT Innovation Futures (TRIF)
2.	Identify TF markets	<ul style="list-style-type: none"> • features a technological forecast • market has matured by 1.1.2004 • market duration > 1 year • more than 5 traders participated • more than 30 trades executed 	<ul style="list-style-type: none"> ➤ 10 FX markets ➤ 0 TRIF markets

Subsequently, both data acquisition steps and their results are discussed.

#1 – Identify AAM market platform. As a first step in acquiring existing TF market data, existing market platforms for AAM needed to be identified and screened for some qualification criteria. Among these criteria were public access to the market platform, namely via the internet, a feature of markets of technology-related content, an

established trader community, and an ability to retrieve market price and transaction data of the markets. In the course of establishing the literature review presented in chapter 3, and by using internet search engines, such as Google, two platforms were identified that met the criteria: the Foresight Exchange (FX)²⁶⁶ and the MIT Technology Review – Innovation Futures platform (TRIF)²⁶⁷.

#2 – Identify TF markets. As qualified AAM market platforms were identified, the markets on these platforms were screened against the next set of criteria to identify true TF markets. Among these criteria was the condition that the market features a technological forecast²⁶⁸, that the market has matured by 1.1.2004²⁶⁹, that market duration was greater than one year, that more than five traders completed more than a total of 30 trade transactions. A list of the reviewed claims is provided in the appendix. Of the markets held by the platforms FX and TRIF, only 10 FX markets met these criteria, and, thus, qualified for the data base used for the research presented in this work. Table 16 provides an overview of the AAM markets identified as TF markets.

Table 16: Overview of identified TF markets on existing AAM market platforms

ID	Descriptive title	Start-time	End-time	Duration		Traders	Trades
		[Date]	[Date]	[days]	[yrs]*	[Avg.No.]	[No.]
ADED	Amiga is dead by 1/1/97	11.07.1995	01.12.1996	509	1,4	25	113
OS2X	OS/2 is killed before 1997	07.04.1995	02.01.1997	636	1,7	55	284
MdCd	More MD's than CD's in 1997	28.06.1995	11.09.1997	806	2,2	12	104
X400	X.400 irrelevant by 2000	24.08.1995	04.12.1999	1563	4,3	15	204
OspX	OSPNEY 2 wave power gen fails	08.10.1995	14.12.1999	1529	4,2	6	41
DNAT	DNA-based Turing machine demo	17.04.1995	30.12.1999	1718	4,7	24	240
Tach	Time communication possible	28.03.1995	26.06.2000	1918	5,3	24	248
UNIX	UNIX is irrelevant by 2000	14.03.1995	08.01.2001	2127	5,8	65	1143
PlsCom	Radio "Pulse" Tech. popular	10.02.2000	11.04.2002	791	2,2	14	107
GrWv	Gravitational Waves by 2003	22.08.1995	22.11.2003	3014	8,3	44	541

*) 1 yr = 365 days

All but one of the claims was initiated in 1995 (the first year in which FX was operational). Their market durations range from 1,4 to 8,3 years; four markets endured around approx. 2 years; five markets endured around approx. 5 years; one market endured approx. 8 years.

²⁶⁶ the Foresight Exchange is one of multiple AAM platforms reviewed in this work, see section 3.6.3

²⁶⁷ <www.innovationfutures.com> as of October 2004

²⁶⁸ see section 2.2 for a definition of what constitutes a technological forecast

²⁶⁹ the deadline after which the data analysis for this research was performed

The TF content of a qualified markets is, e.g., that a universal turing machine is demonstrated on a DNA-based computer until the year 2000. Another qualified TF market trades on whether more MiniDisk's (recorded and recordable) than CD's would be sold in 1997. A detailed description of each market is provided in the appendix; a description of the market platform and security design is provided in section 3.6.3.

As the data base has now been established, we proceed with subsequent validation of the hypotheses based on data analysis.

4.3 Operationalization & Validation of Hypothesis H1: Absolute performance

In chapter 2, section 2.6, we have developed two broad hypotheses, the first of them being:

H1: Artificial asset markets can forecast technological developments (in principle)

As noted previously, the hypothesis refers to a minimum absolute performance in forecast capacity to acknowledge technological forecasts by artificial asset markets as reasonably accurate and reliable.²⁷⁰

For empirical validation, the hypothesis needs to be operationalized in a way that it contains quantifiable properties that can be measured. For this purpose, the hypothesis may be split into sub-hypotheses, which increase in order of fulfilling the original hypothesis, or which cover different possible aspects all of which fulfill the original hypothesis.

4.3.1 Basic performance

Thus, as we operationalize the above hypothesis, we develop a sub-hypothesis structure which fulfills the original hypothesis at the most basic level and can be measured in the market data:

H1.1: The final market price accurately and reliably indicates the event outcome

²⁷⁰ Forecast accuracy and reliability are two quality attributes that are commonly used for forecast verification. See the appendix for an overview and description of forecast verification.

H1.1.1: If the event outcome is 0, the final trading price is 0;

If the event outcome is 100, the final trading price is 100

As a first step, we visually inspect the relevant data. Table 1 summarizes for the established data base of ten FX markets the price data including final market prices and the corresponding actual outcome.

By comparing final market prices and the actual outcome, we can consistently observe a very strong correlation and close match, but not a single exact match. For example, the market with the ID code "MdCd" shows a final price of 1, whereas the outcome equals a price of 0. For another market with the ID code "X400" the final price is 99, whereas the outcome equals a price of 100. Moreover, we can observe the minimum and maximum price during trading is either 1 or 99, but never 0 or 100.

Table 17: Overview TF markets – comparison of final market price and actual outcome

ID	Descriptive title	Duration [yrs] ¹⁾	Price [0..100]			Outcome [0..100]	Reliability [%]
			Min	Max	Final		
ADED	Amiga is dead by 1/1/97	1,4	1	65	5	0	95,0%
OS2X	OS/2 is killed before 1997	1,7	1	50	1	0	99,0%
MdCd	More MD's than CD's in 1997	2,2	1	98	1	0	99,0%
X400	X.400 irrelevant by 2000	4,3	1	99	99	100	99,0%
OspX	OSPNEY 2 wave power gen fails	4,2	10	99	99	100	99,0%
DNAT	DNA-based Turing machine demo	4,7	1	55	1	0	99,0%
Tach	Time communication possible	5,3	1	60	1	0	99,0%
UNIX	UNIX is irrelevant by 2000	5,8	1	90	1	0	99,0%
PlsCom	Radio "Pulse" Tech. popular	2,2	1	90	1	0	99,0%
GrWv	Gravitational Waves by 2003	8,3	1	99	1	0	99,0%
						Average >>	98,6%

1) 1 yr = 365 days

We assume this observation corresponds to the way the trading system of FX issues and de-lists securities.²⁷¹ Contrary to a financial stock market IPO, where a limited number of shares is put on the market at an initial price, there is no limit on the number of contracts at FX. Sets of competing contracts are generated on demand by the trading system when traders invest in competing outcomes, that is, when they buy a complete set of contracts which always has the same aggregate value of 100.²⁷² Conversely, sets of competing contracts are taken out of the market when traders cash-in by selling competing outcomes to the trading system.

²⁷¹ see also section 3.6.3

²⁷² see also section 5.7.1

Therefore, at a price of 100, rational traders will always trade with the trading system, because they can trade complete contract sets, as well as instantly and at zero risk. At a price of 0, no rational trader will trade, as such a transaction is equivalent to giving securities away for free.

Thus, prices practically range from 1 to 99 when they are traded on an AAM platform such as FX.

After visual inspection of the data, we determine for each market the probability associated with the final market price in forecasting the outcome and calculate the average probability (= reliability) over all markets, which is 98,6%.

Thus, we conclude that the data supports the hypothesis H1 by support of the sub-hypotheses H1.1.1 and H1.1 in the way that AAM for TF eventually reflect the true outcome of an event.

4.3.2 Performance based on the probability-forecast horizon

Next, we continue to operationalize the original hypothesis H1 by developing a further sub-hypothesis structure which fulfills the original hypothesis beyond the most basic level and can be measured in the market data. As noted earlier, the intent is to identify a minimum absolute performance in forecast capacity to acknowledge technological forecasts by artificial asset markets as reasonably accurate and reliable.

To our knowledge there are no commonly agreed specified minimum values for forecast accuracy and reliability associated with specific forecast horizons.²⁷³ Thus, we arbitrarily choose a forecast reliability of 75% for a forecast horizon of 1 year as well as for a forecast horizon of the final 10% of market duration. Based on this choice, we develop the following sub-hypotheses:

H1.2: The market price indicates the eventual event outcome with a probability of 75% at least 1 year in advance

H1.2.1: If the event outcome is 0, the market price is <25 during the last year before market maturation

²⁷³ Based on a review of (Martino 1993), (Armstrong 2001b), (Makridakis, Wheelwright et al. 1998) and the Journal of Technological Forecasting and Social Change

H1.3: The market price indicates the eventual event outcome with a probability of 75% at least 10% of market duration in advance

H1.3.1: If the event outcome is 0, the market price is <25 during the last 10% of market duration

Again, as a first step, we visually inspect some sample data. Figure 38 shows the market price development for the FX market with the ID PlsCom. Prices are normalized ranging from 0 to 1 with 0 reflecting the true outcome of the underlying event and 1 reflecting the opposite outcome. The abscissa represents absolute time in days prior to market maturation (market closure). Plotted points represent actual transactions; the points are connected by smoothed lines to facilitate visualization.

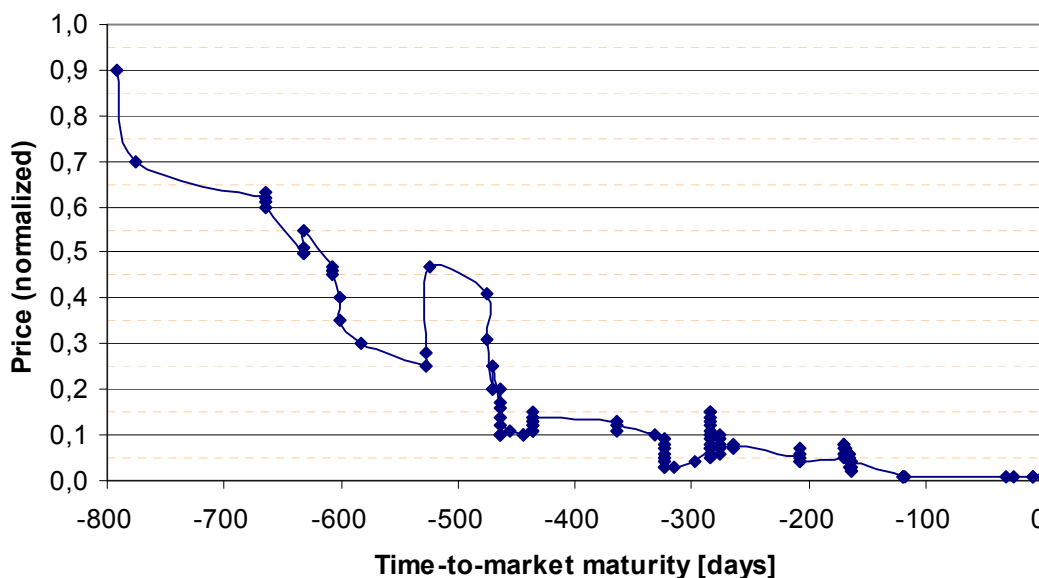


Figure 38: Price development in a sample market (ID PlsCom)

As noted earlier, prices can be directly translated into probabilities of the underlying event coming true. Thus, for the market displayed above we can make the following observations:

- From market initiation to approx. -480 days to market maturation the market followed a downwards trend, but remained undecided as prices fell from 0,9 to 0,25 but bounced back to 0,5
- After approx. -480 days to market maturation prices dropped and stayed below the level of 0,15

Based on these observations, we can say that the market initially believed that the event will result in a value of 1 – trading commenced at a price of 0,9 and stayed above 0,5. As time passed, the market reversed its opinion back and forth (presumably as event-relevant incidents unfolded in the "real world" and were priced in by traders). At a time of -480 days to market maturation the market finally decided that the eventual event will come true – reflected by a probability of approx. 85% ($0,85=1-0,15$).

Thus, at approx. -530 days to market maturation the market signaled a 75% probability that the event will eventually take a value of 0.²⁷⁴ However, the market was not able to maintain this level of probability; only after -480 days to market maturation did the market reach and surpass the probability level of 75%.

Thus, we can say that the FX market PlsCom was only able to maintain the correct forecast after approx. -480 days to market maturation (~1,3 yrs in advance) with a probability of more than 75%.

Consequently, we acknowledge as a performing forecast horizon for a market forecast of 75% probability only a forecast horizon after which the probability level is maintained.

By logic, the next step would be to determine within the data base the minimum forecast horizon after which all markets maintained a probability of >75%. However, to facilitate a broader comparison of forecast performance between all markets, we segment the forecast horizon of all markets by an absolute and a relative time interval, see Table 18 and Table 19, respectively. The intervals for segmentation have been chosen somewhat arbitrarily, yet, they are intended to offer sufficient resolution for providing results on forecast horizon performance.

Table 18: Forecast horizon segmentation for data analysis by absolute time intervals

Interval	1	2	3	4	5	6	7	8	9	10	11	12
Absolute [years- to-event]	0,25	-0,5	0,75	-1,0	-1,5	-2,0	-2,5	-3,0	-3,5	-4,0	-4,5	-5,0
	13	14	15	16								
	-6,0	-7,0	-8,0	-9,0								

²⁷⁴ Or, put differently, the market price reflected a remaining uncertainty of 25%

Table 19: Forecast horizon segmentation for data analysis by relative time intervals

Interval	1	2	3	4	5	6	7	8	9	10
Relative [% FC horizon-to-event]	-10%	-20%	-30%	-40%	-50%	-60%	-70%	-80%	-90%	-100%

After segmenting the forecast horizons of all markets by the above time intervals, we determine for each interval the market's worst forecast, that is, the least probability in determining the eventual outcome. This procedure is illustrated by Figure 39. Furthermore, all market price data is normalized as to 0 reflecting the eventual outcome and 1 reflecting a wrong forecast. Consequently, the worst forecast within an interval is equivalent to highest price within the interval.

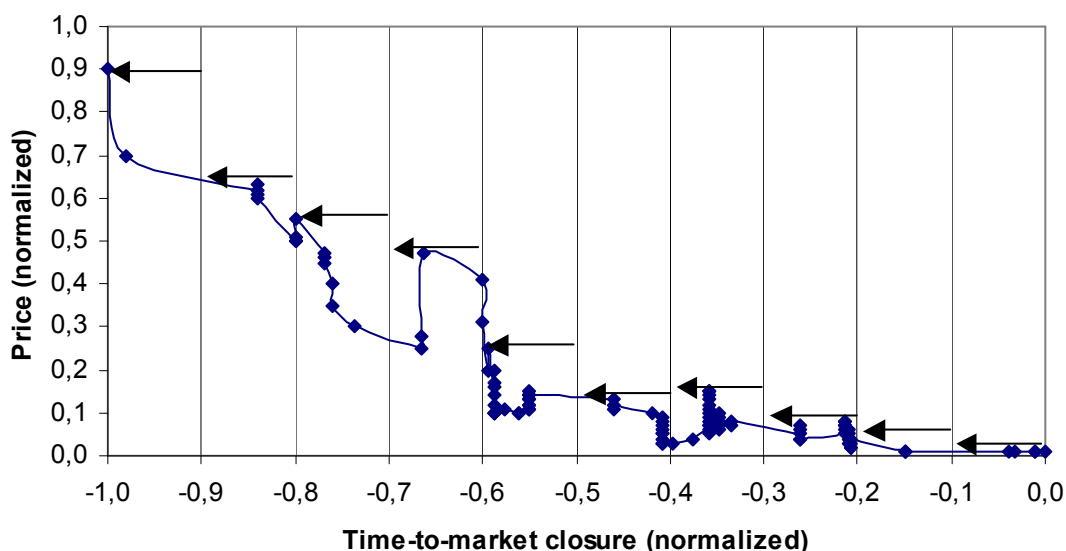


Figure 39: Illustration of determining the worst forecast per forecast horizon segment (sample market ID PlsCom)

Table 20 and

Table 21 show for the full dataset the worst forecast (= highest market price = least probability) for each forecast horizon – segmented by absolute and relative time, respectively. Columns correspond to the different markets, rows correspond to the forecast horizon segments as defined earlier.

Table 20: Comparison of worst forecast (=maximum price) per forecast horizon segment in absolute time (shaded fields indicate a max. price $\leq 0,25$)

.Price		Markets										Worst
Time [yrs]	.	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
-9											0,70	0,70
-8											0,88	0,88
-7											0,99	0,99
-6								0,60	0,90		0,82	0,90
-5					0,48	0,60	0,55	0,24	0,29		0,72	0,72
-4					0,30	0,68	0,37	0,35	0,50		0,68	0,68
-3,5					0,10		0,30	0,25	0,50		0,56	0,56
-3					0,08	0,70	0,21	0,25	0,85		0,54	0,85
-2,5				0,10	0,35		0,27	0,20	0,78	0,90	0,33	0,90
-2			0,40	0,05	0,51	0,90	0,24	0,18	0,47	0,63	0,67	0,90
-1,5		0,65	0,50	0,50	0,30	0,15	0,19	0,18	0,11	0,47	0,33	0,65
-1		0,10	0,15	0,06	0,12	0,04	0,13	0,02	0,07	0,15	0,11	0,15
-0,75		0,14	0,06	0,04	0,10		0,09		0,05	0,08	0,05	0,14
-0,5		0,10	0,02	0,05	0,99		0,06	0,03	0,06	0,08	0,02	0,99
-0,25		0,14	0,01	0,98	0,03	0,01	0,02	0,03	0,08	0,01	0,02	0,98
Time after price<0,25		-1	-1	-1	-0,25	-1,5	-3	-3,5	-1,5	-1	-1	-0,25

Table 21: Comparison of worst forecast (=maximum price) per forecast horizon segment in relative time (shaded fields indicate a max. price $\leq 0,25$)

.Price		Markets										Worst
Time [norm.]	.	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
-1,0		0,65	0,40	0,10	0,48	0,68	0,55	0,60	0,90	0,90	0,75	0,90
-0,9		0,44	0,35	0,03	0,20	0,61	0,37	0,10	0,40	0,63	0,99	0,99
-0,8		0,51	0,50	0,05	0,10		0,35	0,35	0,29	0,55	0,82	0,82
-0,7		0,04	0,23	0,02	0,08	0,70	0,30	0,15	0,50	0,47	0,71	0,71
-0,6		0,14	0,15	0,50	0,35		0,27	0,25	0,50	0,25	0,72	0,72
-0,5		0,08	0,12	0,03	0,22	0,90	0,25	0,25	0,85	0,13	0,68	0,90
-0,4		0,08	0,06	0,06	0,51	0,22	0,22	0,18	0,78	0,15	0,55	0,78
-0,3		0,10		0,04	0,12	0,15	0,19	0,18	0,27	0,08	0,67	0,67
-0,2		0,14	0,02	0,05	0,12	0,04	0,12	0,03	0,07	0,01	0,40	0,40
-0,1		0,05	0,01	0,98	0,99	0,01	0,05	0,03	0,08	0,01	0,05	0,99
Time after price<0,25		-0,7	-0,7	-0,5	-0,3	-0,4	-0,6	-0,7	-0,3	-0,6	-0,1	-0,1

In Table 20, as the markets in the data set are of different duration, the different markets' price data series start at different forecast horizons. The segmentation of the forecast horizon by absolute time allows us to compare forecast performance on an absolute basis in time before market maturation.

In

Table 21, as time is normalized from -1 to 0 , a time value of -1 corresponds to market initiation, whereas a time value of 0 corresponds market maturation (= time of event outcome). Using this segmentation allows us to compare market data on a relative basis in time before market maturation.

In both tables, forecast segments are highlighted in which the worst forecast reaches or exceeds a probability of 75% (that is, a price of $\leq 0,25$) on the eventual outcome. See Figure 40 for an illustration.

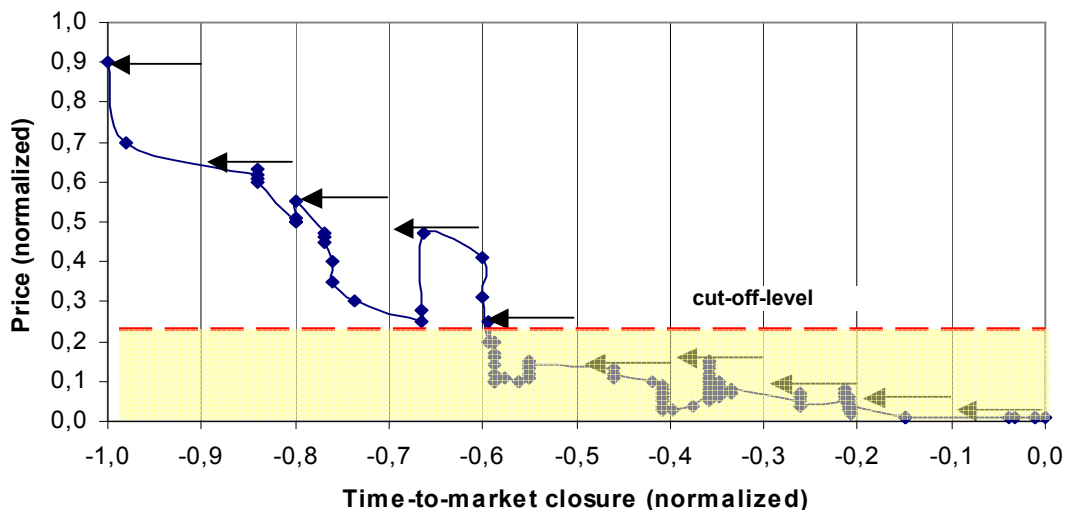


Figure 40: Illustration of the cut-off level for highlighting forecast horizon segments with a probability of $\geq 75\%$ (=max. price $\leq 0,25$) (sample market ID PlsCom)

A first observation of Table 20 suggests that AAM for TF are able to forecast the true outcome with a maintained probability of $>75\%$ for at least 1,0 yrs in advance of claim expiration – even up to 3,5 yrs in advance is possible.

Obviously, there are, however, some exceptions to the above assertion. The markets with the IDs MdCd and X400 both feature a major price fluctuation to the end of their market duration. Regardless of the underlying cause for the fluctuations, we would need to analyze how enduring these variations were. We could then judge if these fluctuations are just speculative blips that possibly can be ignored or if they reflect essential developments concerning the underlying event that is forecasted. We will return to this analysis later.

A second observation based on Table 20 shows that none of the markets in the data set instantly maintains a confidence of $>75\%$ on the eventual outcome. Furthermore, we find no evidence that the markets reach and maintain a confidence of $>75\%$ on the eventual outcome within a specific absolute time after market initiation. Whereas four markets (IDs: ADED, OS2X, MdCd, and PlsCom) meet the respective criteria within the first two years after market initiation; six markets (IDs: X400, OspX, DNAT, Tach, UNIX, and GrWv) need longer to reach and maintain a confidence level of $>75\%$.

As we turn to the data presented in

Table 21, we can observe that the TF markets are able to forecast the eventual outcome with a probability of >75% for at least 10% of market duration in advance of market maturation – even up to 70% of market duration in advance is possible.

As pointed out above, two markets are notable exceptions (IDs: X400 and MdCd); again, these exceptions will be treated later more thoroughly.

The above observation, that none of the markets in the data set instantly maintains a confidence of >75% on the eventual outcome, is confirmed by the data of

Table 21. Similarly, we see no clear evidence of markets reaching and maintaining a confidence of >75% on the eventual outcome within a specific relative time after market initiation.

As pointed out above, AAM for TF may experience major price fluctuations even when already very close to market maturation and event outcome. In the data base, for example, the markets MdCd and X400 show fluctuations so big that they inverse the forecast only <0,5 years before event outcome (or in the final 10% of the forecast horizon).

By theory, we recapitulate from section 3.2, price fluctuations can be seen as to reassemble a temporal (im-)balance of two driving forces: a rational incorporation of new fundamental information versus an incorporation of irrational expectations (speculation).

Whatever the reason for the price fluctuation, relevant for our analysis is the impact of the price fluctuation to the forecast. If the fluctuation is of relatively long duration or involves an unusually high activity of trade, we regard it as relevant for the forecast – the fluctuation should be maintained when determining the worst forecast performance per horizon segment. If the fluctuation is of very short duration and is caused by a single or very few trades, we neglect its relevance for the forecast.

Thus, we need a method that accounts for the logic outlined above to adjust market price development towards a steadier course that more accurately describes the trend and the momentum of the forecast. For this purpose, we perform regression analysis. First, we need to select among the many available regression types. As a data reflecting a market price development generally features a high number of fluctuations, we decide to apply the two most appropriate methods:

- **polynomial trend line:** A polynomial trend line is a curved line that is used when data fluctuates. It is useful, for example, for analyzing gains and losses over a large data set. The order of the polynomial can be determined by the number of fluctuations in the data or by how many bends (hills and valleys) appear in the curve. An Order 2 polynomial trend line generally has only one hill or valley. Order 3 generally has one or two hills or valleys. Order 4 generally has up to three.

For practical purposes we choose a polynomial to the order of 5.²⁷⁵ The amount of fit is indicated by the calculation of R2 and, additionally, by the display of the respective chart for each market data series.

- **moving average trend line:** A moving average trend line smoothes out fluctuations in data to show a pattern or trend more clearly. A moving average uses a specific number of data points, averages them, and uses the average value as a point in the line. If Period is set to 2, for example, then the average of the first two data points is used as the first point in the moving average trend line. The average of the second and third data points is used as the second point in the trend line, and so on. Each moving average provides a different interpretation on what the stock price will do. There really isn't just one "right" time frame. Moving averages with different time spans each tell a different story. The shorter the time span, the more sensitive the moving average will be to price changes. The longer the time span, the less sensitive or the more smoothed the moving average will be. Based on an analysis of the average number of trades over all 10% time segments over all markets, we set the period to 25 trades.

Thus, both regression methods differ in how they reflect price fluctuations, see Table 22. Marked or shaded fields indicate that the respective fluctuation characteristic drives a method's display of price fluctuations.

Table 22: Reflection of price fluctuation characteristics by regression method

Regression method	Fluct. Amplitude [chg. in price]		Fluct. endurance [chg. in time]		Fluct. intensity [chg. in # of trades]	
	small	big	short	long	few	many
Polynomial	-	X	X	X	-	-
Moving Average	-	X	-	-	X	X

²⁷⁵ Not the least due to a limitation imposed by our software, MS Excel XP

If the fluctuation endures for a relatively long time it will be reflected by the polynomial trend line, even if the fluctuation amplitude is low or if the fluctuation is driven by very few trades. In contrast, if fluctuation endurance is relatively brief it is neglected by the polynomial, even if the fluctuation amplitude is high and is backed by many trades. If the fluctuation is caused by a single or very few trades, the fluctuation is essentially neglected by the moving average of the last 25 trades, even if the fluctuation endures for longer time and the amplitude is high. In contrast, if the fluctuation is backed by many trades it is essentially reflected proportionally to the number of trades and their amplitudes.

We return to the markets MdCd and X400 which initiated this discussion by showing fluctuations so big that they appeared to inverse their forecast only <0,5 years before event outcome (or in the final 10% of the forecast horizon), apply both methods of regression analysis to these markets and visually inspect the results, see Figure 41 and

Both figures illustrate how the two selected regression methods account for the actual market price development as summarized by Table 22. A distinction between the two methods not pointed out yet concerns the fraction of the market duration supplied by the resulting price trend lines. Whereas the polynomial trend line (labeled Poly) provides a trend line over full market duration, the moving average trend line (labeled MAVG-25), in contrast, does not supply a trend line for the fraction of market duration with the first 25 trades.

Figure 42.

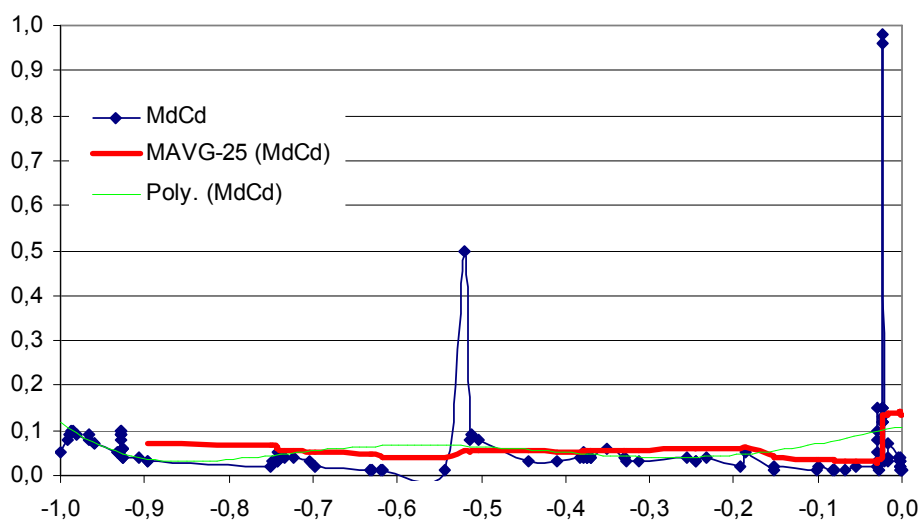


Figure 41: Price/trend chart for market MdCd

Both figures illustrate how the two selected regression methods account for the actual market price development as summarized by Table 22. A distinction between the two methods not pointed out yet concerns the fraction of the market duration supplied by the resulting price trend lines. Whereas the polynomial trend line (labeled Poly) provides a trend line over full market duration, the moving average trend line (labeled MAVG-25), in contrast, does not supply a trend line for the fraction of market duration with the first 25 trades.

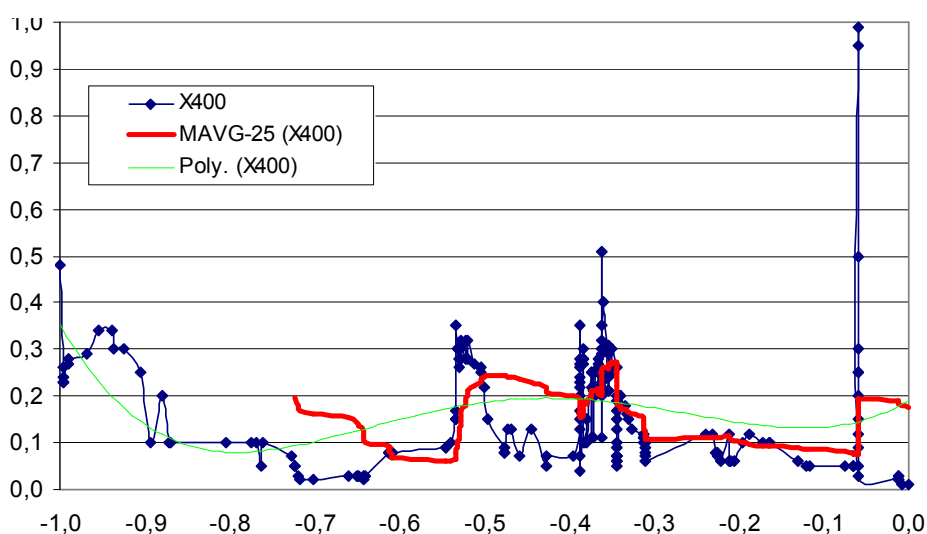


Figure 42: Price/trend chart for market X400

With respect to AAM forecast performance, substituting unprocessed prices with trend line prices yields improved performance. For example, after smoothing out major price fluctuations at a normalized forecast horizon of -0,5 and -0,1 in the market MdCd, both trend line prices indicate that the market forecasted the eventual outcome with a confidence of 75% right-on from market initiation over the full forecast horizon (!) of 2,2 years.

Essentially, the same is true for the market X400, where a confidence of 75% is maintained over the full forecast horizon of 4,3 years.

In contrast, when using unprocessed data to assess forecast performance, both markets have a forecast horizon of <0,1 or 0,5 years, as the confidence threshold of 75% is breached by price fluctuations in the final horizon segment.

Thus, as a next step, we apply to all markets in the data base both regression methods for price fluctuation smoothing to analyze how AAM for TF forecasting performance improves for all markets.

First, we start by smoothing prices based on polynomial regression. Table 23 and Table 24 show for the complete dataset the worst forecast (= highest market price = least probability) for each forecast horizon – segmented by absolute and relative time, respectively.

Table 23: Comparison of worst forecast (=maximum price) per forecast horizon segment in absolute time based on polynomial price regression (shaded fields indicate a max. price <= 0,25)

.Price-trend_Poly5		Markets										Worst
Time [yrs]	.	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
-9											0,66	0,66
-8											0,76	0,76
-7											0,76	0,76
-6								0,23	0,38		0,72	0,72
-5					0,35	0,61	0,40	0,16	0,29		0,62	0,62
-4					0,17	0,63	0,33	0,09	0,34		0,55	0,63
-3,5					0,10		0,28	0,14	0,49		0,53	0,53
-3					0,15	0,92	0,24	0,17	0,55		0,49	0,92
-2,5				0,12	0,19		0,22	0,18	0,55	0,81	0,45	0,81
-2			0,25	0,05	0,20	0,50	0,20	0,17	0,45	0,60	0,38	0,60
-1,5		0,54	0,29	0,07	0,19	0,06	0,17	0,13	0,20	0,27	0,31	0,54
-1		0,09	0,17	0,06	0,15	0,02	0,13	0,06	-0,14	0,09	0,18	0,18
-0,75		0,09	0,03	0,04	0,14		0,09		-0,28	0,07	0,09	0,14
-0,5		0,10	0,12	0,05	0,15		0,06	0,00	-0,20	0,05	-0,11	0,15
-0,25		0,08	0,15	0,11	0,19	0,01	0,01	0,04	0,23	0,01	-0,25	0,23
Time after price<0,25		-1	-1	-2,5	-4	-1,5	-3	-6	-1,5	-1,5	-1	-1,00

Table 24: Comparison of worst forecast (=maximum price) per forecast horizon segment in relative time based on polynomial price regression (shaded fields indicate a max. price <= 0,25)

.Price-trend_Poly5		Markets										Worst
Time [norm.]	.	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
-1,0		0,54	0,22	0,12	0,35	0,62	0,40	0,23	0,38	0,81	0,74	0,81
-0,9		0,39	0,28	0,04	0,13	0,63	0,36	0,11	0,34	0,60	0,76	0,76
-0,8		0,24	0,29	0,05	0,10		0,31	0,08	0,22	0,51	0,75	0,75
-0,7		0,09	0,28	0,07	0,15	0,92	0,27	0,12	0,34	0,27	0,67	0,92
-0,6		0,07	0,18	0,07	0,19		0,24	0,16	0,50	0,18	0,62	0,62
-0,5		0,08	0,09	0,06	0,20	0,50	0,22	0,18	0,55	0,09	0,56	0,56
-0,4		0,10	0,02	0,05	0,19	0,27	0,20	0,17	0,54	0,08	0,51	0,54
-0,3		0,10		0,04	0,16	0,06	0,17	0,14	0,35	0,06	0,45	0,45
-0,2		0,07	0,12	0,07	0,14	0,02	0,12	0,06	-0,04	0,03	0,34	0,34
-0,1		0,08	0,15	0,11	0,18	0,01	0,06	0,02	0,21	0,01	0,12	0,21
Time after price<0,25		-0,8	-0,6	-1,0	-0,9	-0,4	-0,7	-1,0	-0,1	-0,7	-0,1	-0,1

Based on the new results, we can confirm that AAM for TF appear to be able to forecast the eventual outcome with a maintained probability of >75% for at least 1,0

year or 10% of market duration in advance of market maturation. Furthermore, we can observe considerable performance gains up to 3,75 years or 0,6 of market duration (market X400). See Table 25 and Table 26 for a summary of TF market performance improvements based on polynomial trend prices.

Table 25: Forecast horizon (absolute, in years) after which a probability of 75% was maintained: comparison of unprocessed and polynomial trend prices

Time after price<0,25 [yrs before end]	Markets										TTL
	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
.Max price	-1	-1	-1	-0,25	-1,5	-3	-3,5	-1,5	-1	-1	-0,25
.Max price_poly5	-1	-1	-2,5	-4	-1,5	-3	-6	-1,5	-1,5	-1	-1
Difference	0	0	1,5	3,75	0	0	2,5	0	0,5	0	0,75

Table 26: Forecast horizon (relative) after which a probability of 75% was maintained: comparison of unprocessed and polynomial trend prices

Time after price<0,25 [norm. market time]	Q2										TTL
	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
.Max price	-0,7	-0,7	-0,5	-0,3	-0,4	-0,6	-0,7	-0,3	-0,6	-0,1	-0,1
.Max price_poly5	-0,8	-0,6	-1	-0,9	-0,4	-0,7	-1	-0,1	-0,7	-0,1	-0,1
Difference	0,1	-0,1	0,5	0,6	0	0,1	0,3	-0,2	0,1	0	0

Next, we investigate price smoothing based on regression by moving average. Table 27 and Table 28 show for the complete dataset the worst forecast (= highest market price = least probability) for each forecast horizon – segmented by absolute and relative time, respectively.

Table 27: Comparison of worst forecast (=maximum price) per forecast horizon segment in absolute time based on moving average price regression (shaded fields indicate a max. price <= 0,25)

.Price-trend_MAVG		Markets										Worst
Time [yrs]	.	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
-9											#N/A	#N/A
-8											0,65	0,65
-7											0,75	0,75
-6								#N/A	#N/A		0,72	#N/A
-5					#N/A	#N/A	#N/A	0,19	0,29		0,72	#N/A
-4					#N/A	#N/A	0,34	0,10	0,30		0,66	#N/A
-3,5					#N/A		0,34	0,09	0,43		0,62	#N/A
-3					0,15	#N/A	0,28	0,18	0,68		0,52	#N/A
-2,5					#N/A	0,24	0,23	0,19	0,73	#N/A	0,34	#N/A
-2					#N/A	#N/A	0,22	0,17	0,46	#N/A	0,60	#N/A
-1,5		#N/A	0,36	0,05	0,27	0,35	0,19	0,16	0,11	#N/A	0,35	#N/A
-1		0,23	0,18	0,06	0,11	0,31	0,17	0,12	0,09	0,14	0,12	0,31
-0,75		0,18	0,12	0,06	0,09		0,12		0,08	0,09	0,03	0,18
-0,5		0,08	0,05	0,06	0,19		0,09	0,10	0,07	0,09	0,02	0,19
-0,25		0,09	0,05	0,14	0,19	0,26	0,07	0,05	0,06	0,05	0,02	0,26
Time after price<0,25		-1	-1	-1,5	-3	-0,25	-2,5	-5	-1,5	-1	-1	-0,25

Table 28: Comparison of worst forecast (=maximum price) per forecast horizon segment in relative time based on moving average price regression (shaded fields indicate a max. price $\leq 0,25$)

.Price-trend_MAVG		Markets										Worst
Time [norm.]	.	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
-1,0		#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
-0,9		0,50	0,31	#N/A	#N/A	#N/A	0,40	0,12	0,39	#N/A	0,68	#N/A
-0,8		0,26	0,36	0,07	#N/A	#N/A	0,34	0,10	0,24	#N/A	0,75	#N/A
-0,7		0,23	0,35	0,05	0,15	#N/A	0,31	0,10	0,30	#N/A	0,72	#N/A
-0,6		0,20	0,18	0,05	0,23	#N/A	0,27	0,15	0,43	#N/A	0,72	#N/A
-0,5		0,09	0,16	0,05	0,24	#N/A	0,22	0,19	0,69	0,14	0,67	#N/A
-0,4		0,08	0,11	0,06	0,27	0,51	0,22	0,17	0,73	0,09	0,55	0,73
-0,3		0,08		0,06	0,11	0,35	0,19	0,17	0,26	0,09	0,60	0,60
-0,2		0,09	0,05	0,06	0,10	0,28	0,16	0,14	0,09	0,06	0,48	0,48
-0,1		0,09	0,05	0,14	0,19	0,26	0,09	0,10	0,08	0,05	0,05	0,26
Time after price<0,25		-0,8	-0,6	-0,8	-0,7	-0,1	-0,6	-0,9	-0,3	-0,5	-0,1	-0,1

Based on price smoothing by moving average price regression, we again can confirm that AAM for TF appear to be able to forecast the eventual outcome with a maintained probability of >75% for at least 1,0 year or 10% of market duration in advance of market maturation. Furthermore, we can observe considerable performance gains of up to 2,75 years or 0,4 of market duration (market X400). See Table 28 and Table 29 for a summary of TF market performance improvements based on moving average trend prices.

Table 29: Forecast horizon (absolute, in years) after which a probability of 75% was maintained: comparison of unprocessed and polynomial trend prices

Time after price<0,25 [yrs before end]											TTL
	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
.Max price	-1	-1	-1	-0,25	-1,5	-3	-3,5	-1,5	-1	-1	-0,25
.Max price_MAVG	-1	-1	-1,5	-3	-0,25	-2,5	-5	-1,5	-1	-1	-0,25
Difference	0	0	0,5	2,75	-1,25	-0,5	1,5	0	0	0	0

Table 30: Forecast horizon (relative) after which a probability of 75% was maintained: comparison of unprocessed and polynomial trend prices

Time after price<0,25 [norm. market time]	Q2										TTL
	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	
.Max price	-0,7	-0,7	-0,5	-0,3	-0,4	-0,6	-0,7	-0,3	-0,6	-0,1	-0,1
.Max price_MAVG	-0,8	-0,6	-0,8	-0,7	-0,1	-0,6	-0,9	-0,3	-0,5	-0,1	-0,1
Difference	0,1	-0,1	0,3	0,4	-0,3	0	0,2	0	-0,1	0	0

We have investigated two techniques for price smoothing, essentially, to filter out temporal and highly speculative price fluctuations. In large, both techniques perform well and give a good approximation of fundamental forecast performance of AAM for TF. However, both techniques also show some shortcomings. Most notably, they tend

to give a rather conservative trend approximation and occasionally undershoot fundamental forecast performance by a considerable margin.

Thus, we develop a composite performance measure by combining the results of both price smoothing techniques. Based on the data processing applied up to this section, we first compare forecast performance (that is, the worst price per forecast horizon segment) on basis of the unprocessed original data, the moving average price data, and the polynomial price data. See Table 31 and Table 32 for a summary of this data.

Next, we identify the weaker forecast performance (that is, the less negative forecast horizon after which a probability of 75% was maintained) among the two price smoothing techniques, the moving average-based price data and the polynomial-based price data.

In a final step, we take the identified weaker forecast performance as given by the tow price smoothing techniques and compare it with the performance based on the original and unprocessed data. Of this comparison, the "better" performance (that is, the more negative forecast horizon) is established as composite performance.

Table 31: Forecast horizon (absolute, in years) after which a probability of 75% was maintained: comparison of unprocessed and polynomial trend prices

Time after price<0,25 [yrs before end]	Q2										TTL	TTL	TTL
	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	Worst	Best	Avg.
.Max price	-1	-1	-1	-0,25	-1,5	-3	-3,5	-1,5	-1	-1	-0,25	-3,5	-1,48
.Max price_MAVG	-1	-1	-1,5	-3	-0,25	-2,5	-5	-1,5	-1	-1	-0,25	-5	-1,78
.Max price_poly5	-1	-1	-2,5	-4	-1,5	-3	-6	-1,5	-1,5	-1	-1	-6	-2,30
.Max price_composite	-1	-1	-1,5	-3	-1,5	-3	-5	-1,5	-1	-1	-1	-5	-1,95
Difference to A	0	0	0,5	2,75	0	0	1,5	0	0	0	0,75	1,5	0,48

Table 32: Forecast horizon (relative) after which a probability of 75% was maintained: comparison of unprocessed and polynomial trend prices

Time after price<0,25 [norm. market time]	Q2										TTL	TTL	TTL
	ADED	OS2X	MdCd	X400	OspX	DNAT	Tach	UNIX	PlsCom	GrWv	Worst	Best	Avg.
.Max price	-0,7	-0,7	-0,5	-0,3	-0,4	-0,6	-0,7	-0,3	-0,6	-0,1	-0,1	-0,7	-0,49
.Max price_MAVG	-0,8	-0,6	-0,8	-0,7	-0,1	-0,6	-0,9	-0,3	-0,5	-0,1	-0,1	-0,9	-0,54
.Max price_poly5	-0,8	-0,6	-1	-0,9	-0,4	-0,7	-1	-0,1	-0,7	-0,1	-0,1	-1	-0,63
.Max price_composite	-0,8	-0,7	-0,8	-0,7	-0,4	-0,6	-0,9	-0,3	-0,6	-0,1	-0,1	-0,9	-0,59
Difference to A	0,1	0	0,3	0,4	0	0	0,2	0	0	0	0	0,2	0,10

Based on this composite performance measure we can make the following final observations in respect to the associated probability forecast horizon:

- AAM for TF forecast the eventual outcome with a probability of >75% for at least 1,0 years or 10% of market duration in advance of market maturation, respectively, in advance of the event outcome

- AAM for TF are able to forecast the eventual outcome with a probability of >75% for up to 5 yrs or 90% of market duration in advance of market maturation, respectively, in advance of the event outcome
- On average, AAM for TF forecast the eventual outcome with a probability of >75% for approx. 2 years or 59% of market duration in advance of market maturation, respectively, in advance of the event outcome
- None of the markets instantly maintains over the full market duration a probability of >75% on the eventual outcome

Thus, we conclude that the data supports the hypothesis H1 by support of the sub-hypotheses H1.2.1 and H1.2 as well the sub-hypotheses H1.3.1 and H1.3 in the way that AAM for TF market prices indicate the eventual event outcome with a probability of 75% at least 1 year or 10% of market duration in advance.

We conclude this section by investigating the correlation between forecasting performance (based on the absolute and relative forecast horizon maintaining a probability of >75%) and TF market properties, such as market duration (Figure 43), the amount of completed trades (Figure 44) and the number of distinct traders (Figure 45).

A visual inspection shows that there is no considerable correlation between absolute or relative forecast performance of AAM for TF and the selected TF market properties. Thus, we do not continue to further analyze these correlations.

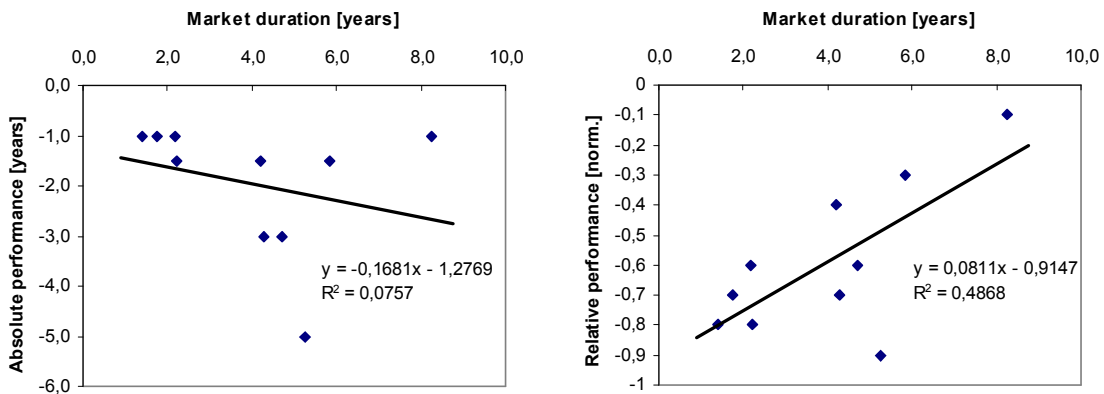


Figure 43: Correlation between market duration and absolute (left) and relative (right) forecast horizon performance for a maintained probability of 75%

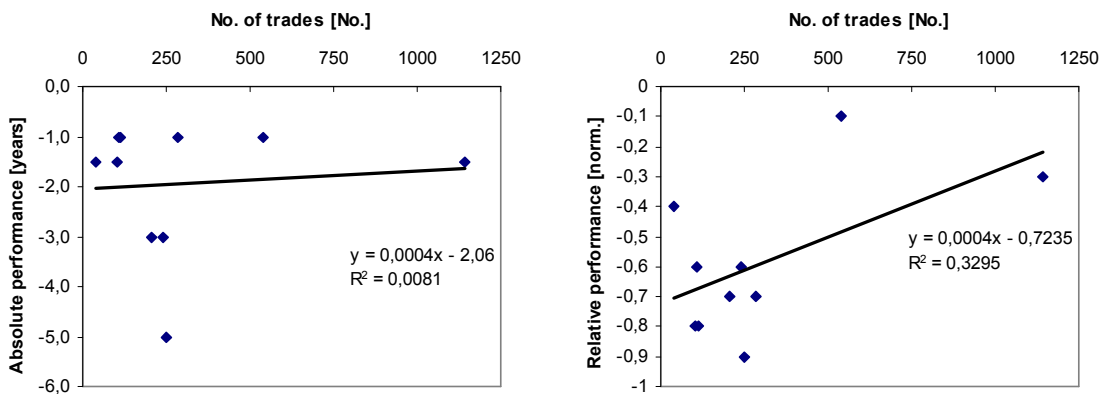


Figure 44: Correlation between amount of trades and absolute (left) and relative (right) forecast horizon performance for a maintained probability of 75%

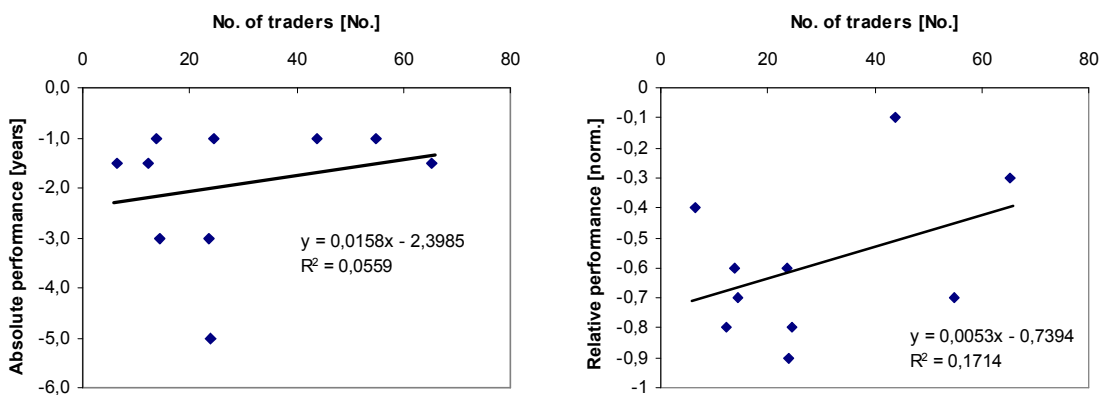


Figure 45: Correlation between no. of traders and absolute (left) and relative (right) forecast horizon performance for a maintained probability of 75%

4.3.3 Performance based on the Average Logarithmic Score (ALS)

In this section, we continue to operationalize the original hypothesis H1 by developing a further sub-hypothesis structure based on a common performance measure of probabilistic forecasts, the average logarithmic score (ALS).²⁷⁶

The logarithmic score is a powerful measure of forecast performance by evaluating forecast consistency and forecast accuracy. It has recently been used by researchers in the field of artificial asset markets to evaluate different field-deployed markets such as the IEM, HSX, and FX²⁷⁷. These researchers advocate the logarithmic score as to evaluate the market in the same way as to evaluate experts providing forecasts.²⁷⁸ A detailed introduction to scoring rules and the average logarithmic score is provided in the appendix.

In scoring rules, when experts are rewarded according to a proper score, they can maximize their expected return by reporting their probabilities truthfully.²⁷⁹ Additionally, more accurate experts can expect to earn a higher average score than less competent experts. Suppose an expert reports probabilities p_1, p_2, \dots, p_k for k mutually exclusive and exhaustive alternatives. Let $w_i = 1$ if and only if the i th event occurs, and $w_i = 0$ otherwise. Then the experts score for the current event is $\log\left(\sum_{i=1}^k w_i p_i\right)$. Higher scores indicate more accurate forecasts, with 0 the maximum and negative infinity the minimum. The "expert assessments" given by the market are taken to be the (normalized) prices of the technology events.

$$\text{Average Logarithmic Score (ALS)} = \frac{1}{N} \cdot \sum_{i=1}^N \log p_{win}(t)$$

Under the logarithmic scoring rule, an expert's expected score equals the entropy of his or her probability distribution. Stated another way, the negative of the logarithmic score gives the amount that the expert is "surprised" by the actual outcome.

²⁷⁶ see the appendix for an introduction to forecast verification and a description of the ALS

²⁷⁷ see, e.g. (Pennock, Lawrence et al. 2000; Pennock, Lawrence et al. 2001; Pennock, Debnath et al. 2002; Debnath, Pennock et al. 2003b)

²⁷⁸ see (Pennock and Wellman 2004), p.104

²⁷⁹ this section is based on (Pennock, Lawrence et al. 2000)

Thus, the logarithmic score applied to AAMs is both a measure of forecast accuracy and an information-theoretic measure of the amount that the market is surprised when the winning event is finally determined. Note that the logarithmic score can only be computed after the forecast event occurred, as it depends on the identity of the winning outcome.

In support of the original hypothesis H1, the intent is to identify a minimum absolute performance in forecast capacity to acknowledge technological forecasts by artificial asset markets as reasonably accurate and reliable.

Based on the literature cited in the introduction to this section, we have identified no commonly agreed specified minimum values for forecast accuracy and reliability associated with specific forecast horizons. Thus, we arbitrarily choose a forecast reliability of $ALS \geq -0,1$ for a forecast horizon of 1 year as well as for a forecast horizon of the final 10% of market duration. Based on this choice, we develop the following sub-hypotheses:

H1.4: AAM for TF achieve an average logarithmic score of better than -0,1 at least 1 year in advance of market maturation

H1.5: AAM for TF achieve an average logarithmic score of better than -0,1 at least 10% of market duration in advance of market maturation

As a first step, we visually inspect some sample data. Figure 38 shows the development of the ALS for the FX market with the ID PlsCom. The ALS is calculated from market prices according to formula presented above. A higher ALS indicates a more accurate forecast, with 0 the maximum and negative infinity the minimum. The abscissa represents absolute time in days prior to market maturation (market closure). Plotted points represent actual transactions, a linear trend line approximates the ALS development.

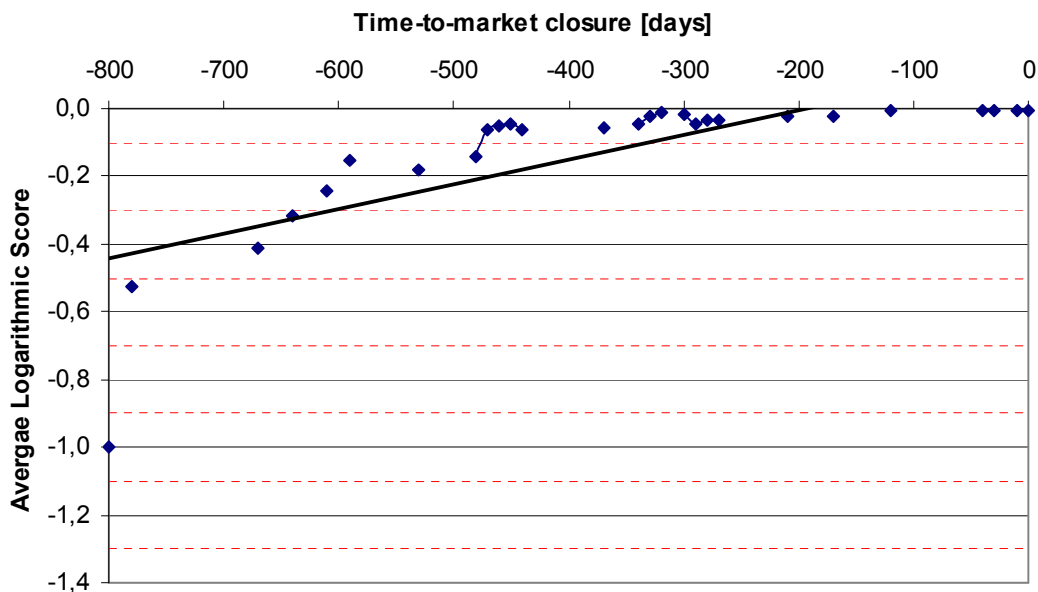


Figure 46: Illustration of the Average Logarithmic Score (ALS) chart for FX claim PlsCom

Thus, for the figure displayed above we can make the following observations:

- the IM opens with an ALS of -1,0 and quickly halves to approx. -0,5
- From approx. 700 to 600 days before market closure the ALS improves to -0,2
- After approx. 480 days before market closure the ALS improves and sustains to -0,1

We now have an ALS development that can be directly compared to the ALS achieved by other forecasts or other forecasting methods. But first, we examine the internal coherence of our data set by comparing the individual logarithmic scores of all qualified FX claims, see Figure 49.

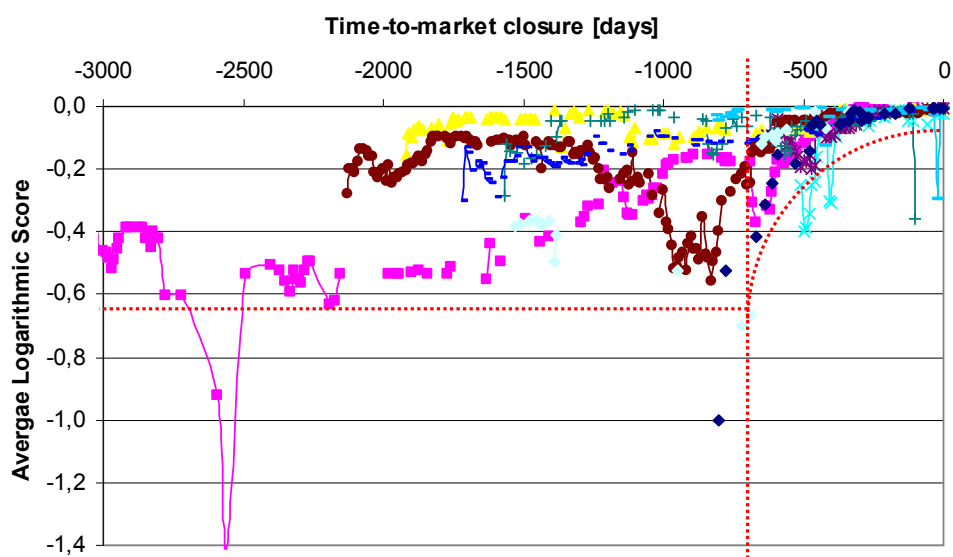


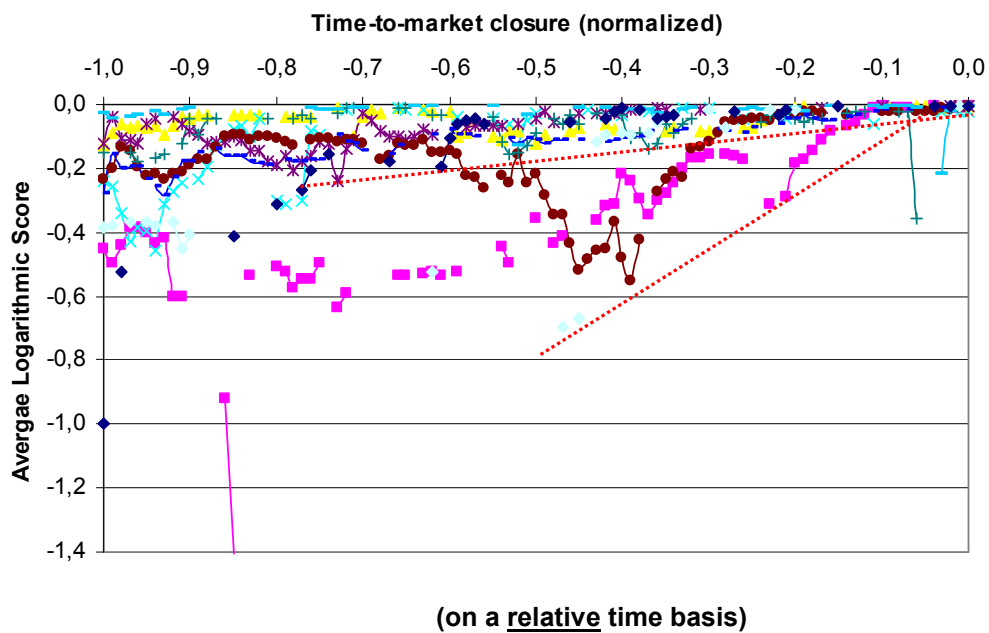
Figure 47: Individual logarithmic score development for all of the 10 qualified FX claims (on an absolute time basis)

In Figure 49, we compare the ALS development of all qualified markets in absolute time, that is, in days before market closure. By definition of the time scale in this figure, all markets are arranged in a way that they end at the same point in time. As we are comparing markets of different duration, the markets start at different points in time. We can make the following observations:

- All observed markets score a better ALS than -0,6 until approx. 700 days to market closure – leaving fluctuations unconsidered
- After approx. 700 days to market closure all observed markets improve exponentially, underscoring an ALS of -0,2 at approx. 500 days to closure – again, leaving fluctuations unconsidered

In Figure 50, we make the same ALS development comparison in relative time, that is, in normalized time to market closure. By definition of the time scale in this figure, all markets are arranged in a way that they start at a common time and they end at a different common time

Figure 48: Individual logarithmic score development for all of the 10 qualified FX claims



We can make the following observations for the data displayed above:

- All observed markets score a better ALS than -0,6 until approx. -0,4 to market closure – leaving fluctuations unconsidered
- A majority of markets appear to perform even better, improving linear from an ALS of -0,3 at -80% time, reaching an ALS of -0,2 at approx. -60% time, and reaching an ALS of -0,1 at approx- -25% time – again, this observation is made leaving fluctuations unconsidered
- Two markets (GrWv, UNIX) noticeably perform worse than the rest. Only at approx. -40% time and an ALS of -0,6 do they start improving linearly, reaching an ALS of -0,2 at approx. -20% time

Next, as we have analyzed the individual logarithmic scores of our data set, we move on to analyze the average logarithmic score.

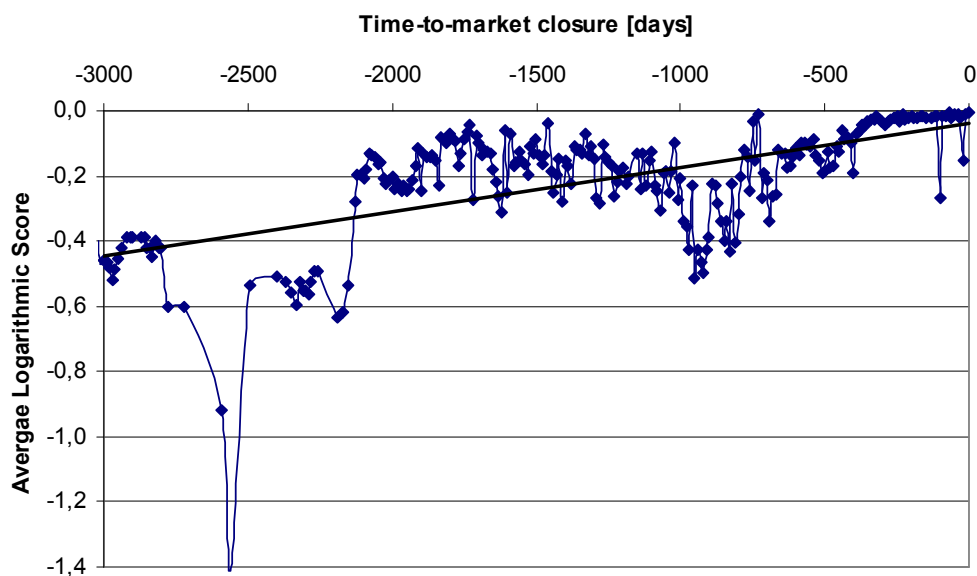


Figure 49: Average logarithmic score for all of the 10 qualified FX claims (on an absolute time basis)

We can make the following observations for the ALS plotted over absolute time in days before market closure (see Figure 49):

- Until approx. -2100 days to closure the ALS is determined by the ALS of the FX claim GrWv; only later do other markets start trade and, thus, influence the overall ALS
- At approx. -2100 days to closure the ALS improves to at least -0,3; this performance is sustained until approx. -1000 days to closure, as a bulk of new markets start trade and, thus, only now are considered in the ALS.
- At approx. -900 days to closure, as a bulk of new markets start trade and are added to the ALS, the performance worsens to -0,5; but thereafter ALS linearly improves to -0,2 by -500 days to closure
- At approx. -400 days to closure ALS improves even further and sustains at an ALS of -0,05 – fluctuations not being considered.

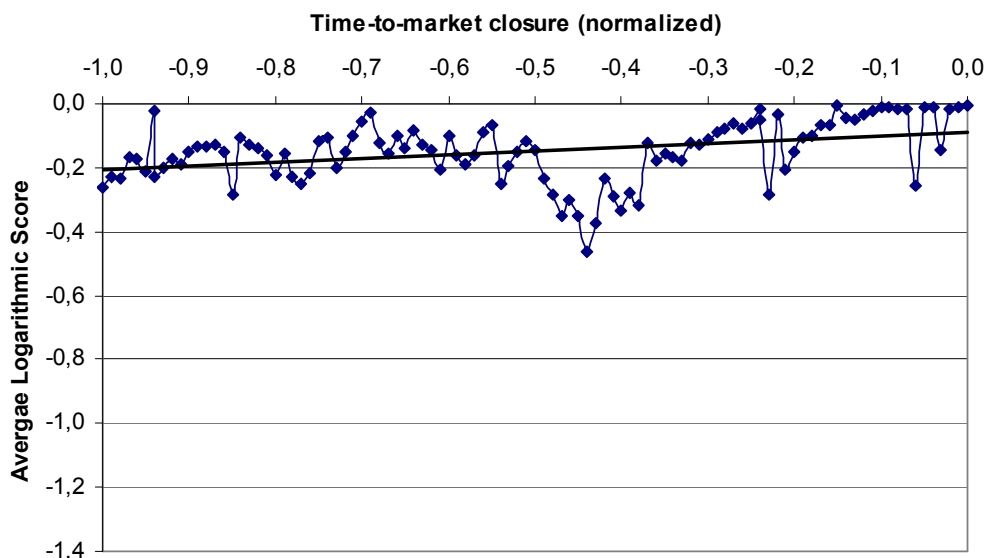


Figure 50: Average logarithmic score for all of the 10 qualified FX claims (on a relative time basis)

For the ALS plotted over normalized time (see Figure 50), we can make the following observations:

- From market initiation an ALS of approx. -0,2 is sustained over most of the market duration
- From -50% to -40% of market duration the ALS temporarily worsens to approx. -0,5
- After -20% of market duration the ALS exponentially improves to approx. -0,05 – fluctuations not being considered

Next, we consider how price fluctuations influence ALS performance. For this purpose, we calculate for all markets in the data set the moving average of the last 25 trades. We then calculate the ALS based the moving averages (MVAG-25) and compare with the original ALS, see Figure 51 and Figure 52.

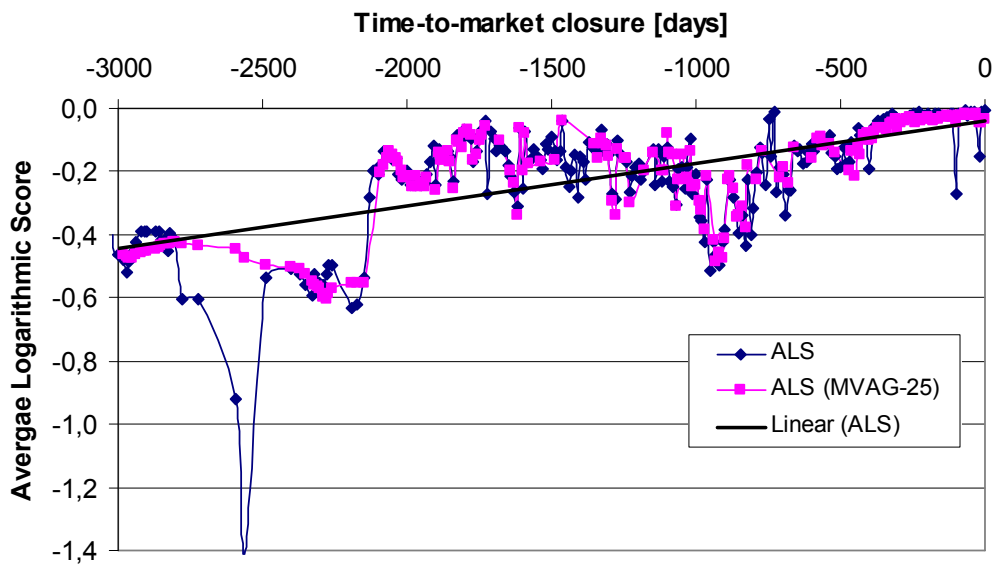


Figure 51: Average logarithmic score for all 10 qualified FX claims for unprocessed and processed (moving average of last 25 trades) prices (on an absolute time basis)

For the ALS plotted over absolute time, we can observe the neglect of major fluctuations at approx. -2500 and at approx. -200 days to closure. Apart from those differences, there is a high degree of conformance between both curves.

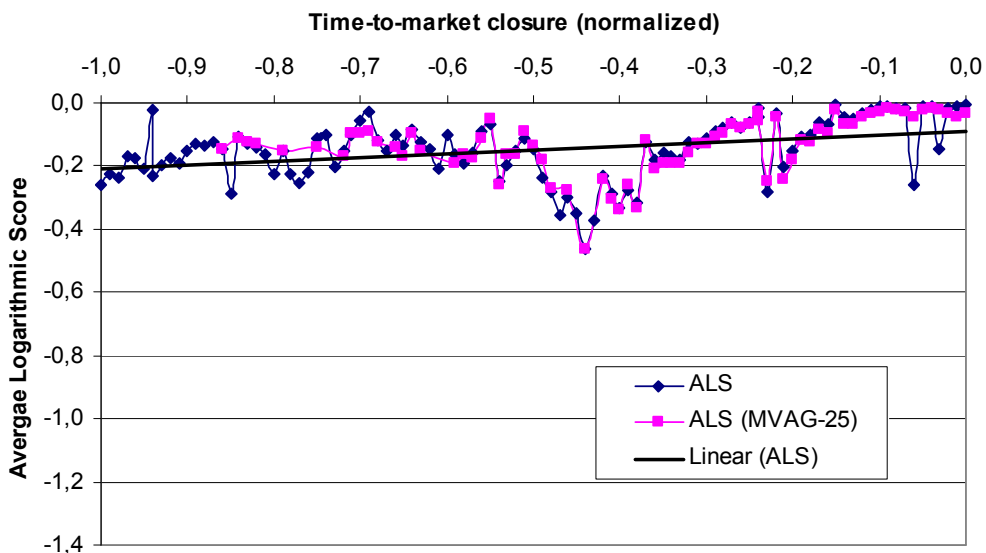


Figure 52: Average logarithmic score for all 10 qualified FX claims for unprocessed and processed (moving average of last 25 trades) prices (on a relative time basis)

For the ALS plotted over normalized time, we can observe the neglect of major fluctuations at approx. -5% of market duration to closure. Again, apart from those differences, there is a high degree of conformance between both curves.

Thus, we maintain our observations made earlier which describe ALS performance without taking into account the neglected fluctuations.

Table 33 and Table 34 complement the above figures on ALS performance by summarizing the worst (the most negative) ALS per absolute and per normalized time segment of market duration.

Table 33: "Worst" Average Logarithmic Score per absolute time segment for unprocessed and moving average prices

ALS			
		ALS	ALS_MA25
Time [yrs]			
-9		-0,456	
-8		-0,467	-0,436
-7		-0,643	-0,546
-6		-0,198	-0,554
-5		-0,146	-0,233
-4		-0,171	-0,201
-3,5		-0,187	-0,169
-3		-0,289	-0,169
-2,5		-0,318	-0,176
-2		-0,162	-0,137
-1,5		-0,129	-0,095
-1		-0,034	-0,064
-0,75		-0,023	-0,036
-0,5		-0,073	-0,030
-0,25		-0,045	-0,040

Table 34: "Worst" Average Logarithmic Score per normalized time segment for unprocessed and moving average prices

ALS			
		ALS	ALS_MA25
Time [normalized]			
-1		-0,211	
-0,9		-0,150	-0,193
-0,8		-0,180	-0,172
-0,7		-0,121	-0,148
-0,6		-0,163	-0,139
-0,5		-0,313	-0,143
-0,4		-0,214	-0,126
-0,3		-0,148	-0,093
-0,2		-0,085	-0,058
-0,1		-0,059	-0,040

Based on these results we can make the following final observations in respect to the forecasting performance of AAM for TF:

- AAM for TF achieve an ALS of -0,1 or better (higher) at least 1,0 years in advance – and even 2,0 years in advance if based on a moving average.
- AAM for TF achieve an ALS of -0,1 or better (higher) at least 20% of market maturation in advance of the event – and even 40% of market maturation in advance if based on a moving average.

Thus, we conclude that the data supports the hypothesis H1 by support of the sub-hypotheses H1.4 and H1.5 in the way that AAM for TF achieve an ALS of higher than -0,1 for at least 1 year or 10% of market duration in advance.

As we have established empirical evidence in support of the hypothesis H1 on absolute performance, we proceed with the validation of the hypothesis H2 on comparative performance of AAM for TF.

4.4 Operationalization & Validation of Hypothesis H2: Comparative performance

In chapter 2 we have developed two broad hypotheses, the first of them being:

H2: Artificial asset markets can forecast technological developments better than alternative TF methods used in a comparable application context

As noted previously, this hypothesis asserts that technological forecasts provided by artificial asset markets are more accurate and more reliable than those of alternative TF methods used in a comparable application context.²⁸⁰

For empirical validation, the hypothesis needs to be operationalized in a way that it contains quantifiable properties that can be measured. For this purpose, the hypothesis may be split into sub-hypotheses, which increase in order of fulfilling the original hypothesis, or which cover different possible aspects all of which fulfill the original hypothesis.

4.4.1 Direct performance comparison

Thus, as we operationalize the above hypothesis, we develop a sub-hypothesis structure which fulfills the original hypothesis and can be measured in the market data:

H2.1: The market price indicates the event outcome more accurately and reliably than forecasts based on alternative TF methods used in the same application context

²⁸⁰ Forecast accuracy and reliability are two quality attributes that are commonly used for forecast verification. See appendix for an overview and description of forecast verification.

- H2.1.1: The market price indicates the event outcome with a higher probability than forecasts based on alternative TF methods used in the same application context at the same time in advance
(EQUAL TO: the market price indicates the event outcome equally probable at an earlier time in advance than forecasts based on alternative TF methods used in the same application context)*
- H2.1.2: The market forecast achieves a less negative ALS than forecasts based on alternative TF methods used in the same application context*

In order to be able to test these hypotheses on the established data base, comparable forecasts based on alternative TF methods need to be identified for each of the ten FX markets in the data set.

The criteria for identifying forecasts as comparable are summarized by Table 35. Comparable forecasts need to be of the same forecast subject, refer to the same deadline year (in which the outcome of the event is determined), and to be given within the same time frame as of the duration of the compared TF market.

Table 35: Summary of criteria for identifying comparable forecasts

Criteria for comparable forecasts
<ul style="list-style-type: none"> • Same forecast subject • Same deadline year (in which the event outcome is determined) • given within same time frame as for market duration

The range of sources searched for comparable forecasts was determined by the access of TU Vienna to online databases and publications as of January 2004. Table 36 gives an overview of these sources. Furthermore, several forecasting institutions were contacted for supply of comparable forecasts, all of which declined to do so.²⁸¹

Table 36: Overview of sources searched for comparable forecasts

Reviewed sources
<ul style="list-style-type: none"> • ACM Digital Library (Association for Computing Machinery) • Academic Press (Elsevier) • American Chemical Society (ACS) • American Mathematical Society (AMS): MathSciNet (Journals + Online-Books) • American Society of Civil Engineers ASCE • Elsevier ScienceDirect

²⁸¹ The forecasting institutions contacted include Forrester Research, IDC, Gartner Group, and the Yankee Group

-
- Harcourt (Elsevier)
 - IEEE Xplore (Journals, Conference Proceedings, Standards)
 - Kluwer Online
 - SpringerLink
 - Wiley InterScience
 - Google (WWW, Newsgroups)
-

Table 37 summarizes the results of the search for comparable forecasts of the TF markets in the data set. More than one comparable forecast was found for the markets OS2X and UNIX. At least one comparable forecast was found for another five of the ten TF markets. For three TF markets (ADED, MdCd, and OspX) no forecast that matched the necessary criteria could be found.

Table 37: Overview of TF markets and comparable forecasts

ID	Descriptive title	Start-time [Date]	End-time [Date]	Duration [yrs]*	No. of comparable Forecasts identified
ADED	Amiga is dead by 1/1/97	11.07.1995	01.12.1996	1,4	0
OS2X	OS/2 is killed before 1997	07.04.1995	02.01.1997	1,7	4
MdCd	More MD's than CD's in 1997	28.06.1995	11.09.1997	2,2	0
X400	X.400 irrelevant by 2000	24.08.1995	04.12.1999	4,3	1
OspX	OSPNEY 2 wave power gen fails	08.10.1995	14.12.1999	4,2	0
DNAT	DNA-based Turing machine demo	17.04.1995	30.12.1999	4,7	1
Tach	Time communication possible	28.03.1995	26.06.2000	5,3	1
UNIX	UNIX is irrelevant by 2000	14.03.1995	08.01.2001	5,8	4
PlsCom	Radio "Pulse" Tech. popular	10.02.2000	11.04.2002	2,2	1
GrWv	Gravitational Waves by 2003	22.08.1995	22.11.2003	8,3	1

To determine whether TF markets perform better or worse on average than comparable forecasts based on alternative methods, we develop our assessment by discussing the matter for a single TF market first. For this discussion we select the TF market OS2X, as it is one of two claims that feature the highest number of identified comparable forecasts. Table 38 describes the details of the forecast tempted by the selected TF market and the comparable forecasts.

Table 38: Details of the TF market forecast OS2X

Criteria	Value
Subject	IBM's PC operating system OS/2 is discontinued, that is, it is no longer an IBM product or IBM releases a statement saying that OS/2 is not a competitor to Windows 95
Horizon	31.12.1996
Time frame	07.04.1995 – 31.12.1995
Outcome	The statement was FALSE as the horizon was reached

As indicated in Table 37, four comparable forecasts were identified for the TF market forecast OS2X. The details for these forecasts, such as their date of issuance, their source, the forecast statement and the corresponding TF market forecast for the same date, are summarized in Table 39.

Table 39: Overview of comparable forecasts for the TF market forecast OS2X
 (">>" indicates interpretation by the author)

ID	Date & Source	Forecast statement	Corresponding TF market FC
1	07.08.1995 Expert (in Computerworld, Aug 1995)	"Even if Windows 95 and Windows NT combine to stomp the competition in the desktop and server markets, IBM has good reason not to pull the plug on OS/2. Its most loyal customers are demanding the oft-dismissed operating system be kept from death's door. >> ~ 75% probability of no discontinuation	64-67% probability of no discontinuation
2	07.08.1995 Insider [IBM representative] (in Computerworld, Aug 1995)	Steve Mills, general manager of IBM's Software Solutions division, agreed that most of OS/2's success comes in "large accounts and classical top-down, decision-making environments." Those customers typically buy "a lot more than just a desktop operating system," he said. "OS/2 is not the kind of thing we're going to walk away from because it impacts our total business." >> ~ 100% probability of no discontinuation	64-67% probability of no discontinuation
3	30.09.1996 Expert (in Computerworld, Sept 1996)	Shaku Atre, president of The Atre Group, Inc. in Port Chester, N.Y., said IBM is unlikely to drop OS/2 altogether because the product is used by IBM's most valuable customers Fortune 100 corporations. "They can't leave those companies in the dark," Atre said. "I think IBM will keep coming up with new features." >> ~ 85% probability of no discontinuation	98% probability of no discontinuation
4	30.09.1996 Insider [IBM representative] (in Computerworld, Sept 1996)	"We've got 14 million OS/2 Warp users, and it's unfathomable that we would abandon the [operating system] when so many people rely on it," Barnes said. >> ~ 100% probability of no discontinuation	98% probability of no discontinuation

As we review the forecast statements of the alternative forecasts, we notice that these declarations do not explicitly provide a statement of probability and neither provide one for the forecast horizon (that is, the time at which the event outcome is determined). However, we added our interpretation for all four forecast statements in terms of probability for the forecast horizon equivalent to the one of OS2X, namely 1.1.1997. Thus, to compare the alternative forecasts to the TF market forecast we compare the probabilities given at the same time. For example, the alternative forecast ID 1 gives a probability of approx. 75% on 07.08.1995 for the corresponding event outcome, whereas the TF market forecasts with a probability of 64-67%.

To further facilitate our discussion, we visualize the forecasts in a probability-time diagram; see Figure 53. For the first time frame, from TF market initiation to 513 days before the event outcome, the TF market provides the only forecast as alternative forecasts could not be identified.

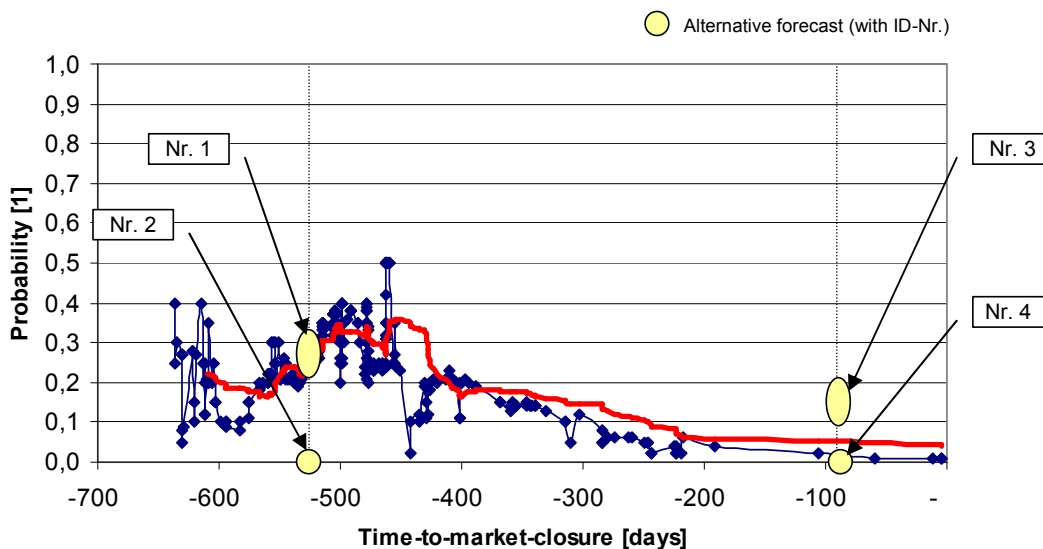


Figure 53: Illustration of comparing alternative forecasts with a TF market forecast (OS2X; data points with trend line) on a probability-time chart

On 7.8.1995 (-514 days to outcome) the forecast by an insider clearly outperforms the approximately ex aequo forecasts by the TF market and some expert. In the next time frame, again, no other forecast than the TF market forecast could be identified.

Table 40: Qualitative forecast performance comparison by time frame (for OS2X)

Time frame	Forecast performance comparison
7.4.1995 – 6.8.1995 (636 – 513 days before outcome)	1. TF market OS2X 2. <i>no alternative forecast identified</i>
7.8.1995 (514 days before outcome)	1. Forecast by IBM representative (ID 2) 2. Ex aequo: TF market OS2X Expert forecast (ID 1)
8.8.1995 – 29.9.1996 (515 – 95 days before outcome)	1. TF market OS2X 2. <i>no alternative forecast identified</i>
30.9.1996 (94 days before outcome)	1. Ex aequo: TF market OS2X Forecast by IBM representative (ID 4) 2. Expert forecast (ID 3)
1.10.1996 – 1.1.1997 (93-1 days before outcome)	1. TF market OS2X 2. <i>no alternative forecast identified</i>

On 30.9.1996 (-94 days to outcome) the TF market forecast matches another insider forecast and appears to outperform an expert forecast. Thereafter, no other forecast than the TF market forecast could be identified. This comparison is summarized by Table 40.

Thus, to conclude from the above comparison the TF market OS2X performed worse or same than insider forecasts and performed same or better than expert forecasts. However, several problems prohibit making an authoritative conclusion from the above comparison:

- We had to add our interpretation for all four forecast statements in terms of probability for the given forecast horizon. Although we acted in good faith, the data cannot be qualified as objective.
- Insider forecasts that are communicated openly to the public by company executives are questionable, as there is typically a strong conflict of interest. For example, executives will not openly speculate about the termination of a product until a final decision has been made (thus, they will tend to forecast an extreme probability).
- The identified expert forecasts do not state which forecasting method was used, e.g. unaided judgment or some structured method (furthermore, it is not disclosed whether the alternative forecasts somehow considered the TF market forecast).
- It is unlikely that all comparable forecasts have been identified. Thus, those forecasts which were identified may not be representative enough to allow general conclusions on comparative forecasting performance
- The lack of forecasts providing multiple forecasts for the given time horizon does not allow a comparison of methodically consistent forecasting methods
- The lack of comparable forecasts in general does not allow general conclusions on comparative forecasting performance

For these reasons, there is little value in computing and comparing the average logarithmic score for the various forecasting methods. Nevertheless, we are still able to make some valid observations:

- The TF market OSPX performs roughly similar to alternative forecasts by authoritative sources – thus, the TF market does not perform drastically better nor drastically worse
- Specific technological forecasts are scarce: we could not identify a single alternative forecast which perfectly met the comparison criteria by stating the probability of the forecast for the given time horizon, and the forecasting method that was used.

Essentially, these findings apply to all TF markets in the data set. Thus, we forgo a detailed discussion of the remaining TF markets in the data set in respect to their performance compared to alternative forecasts. However, an overview of comparable forecasts for each TF market, such as the overview given by Table 39, is provided in the appendix.

Thus, based on the findings summarized above we can make the following final conclusions in respect to the hypotheses guiding this part of research:

The empirical evidence presented here is NOT sufficient to support the hypothesis H2.1 by support of the sub-hypotheses H2.1.1 and H2.1.2 in the way that AAM for TF market prices indicate the eventual event outcome more accurately and reliably than forecasts based on alternative TF methods.

However, the evidence does not disprove the above hypothesis, as it remains to be validated by further research.

4.4.2 Indirect performance comparison

In the previous section, we attempted a direct performance comparison of TF market forecasts to forecasts based on alternative methods. Unfortunately, we did not find sufficient evidence to support our hypothesis H2, that is, artificial asset markets can forecast technological developments better than alternative TF methods used in a comparable application context.

There is, however, an alternative way of comparing forecast performance: If we are able to compare TF market performance to some other AAM performance which has in turn been compared to alternative forecasting methods, we can indirectly relate TF market performance to alternative forecasting methods.

The IEM, an AAM established in 1988, are the longest running set of prediction markets known to us and well known for their remarkable performance (Berg, Forsythe et al. 2001). See section 3.6.1 for a detailed review of the IEM and its performance record. Hence, we select the IEM for performance comparison with TF markets.

Based on the outlined reasoning, we operationalize the hypothesis H2 by developing a sub-hypothesis structure which fulfills the original hypothesis and can be measured in the market data:

H2.2: By performing as good as or better than IEM markets, AAM for TF perform better than alternative forecasting methods

H2.2.1: IEM markets perform better than alternative forecasting methods used in a comparable application context

H2.2.2: AAM for TF perform better than IEM markets: AAM for TF achieve a higher average logarithmic score (ALS) on a normalized time scale than IEM

First, we investigate the performance of IEM markets in comparison to alternative forecasting methods. As noted earlier, ample evidence has been published in this respect – some of this material is reviewed and presented in section 3.6. Subsequently, we review further research documenting comparative IEM performance.

For example, Table 11 presents evidence of whether the IEM markets or polls predict the election outcome more closely—with more focus on long-term performance.

Binomial tests compare IEM markets for the four presidential elections from 1988-2000 with the corresponding poll predictions for relative predictive accuracy.

Table 41: IEM accuracy: Binomial tests for relative accuracy of the market and contemporaneous poll predictions (Berg, Nelson et al. 2003)

Days included in sample	Item	1988	1992	1996	2000	all years
All (from the beginning of the market)	Number of polls	59	151	157	229	596
	poll "wins"	25	43	21	56	145
	market "wins"	34	108	136	173	451
	% market	58%	72%	87%	76%	76%
	p-value (1sided)	0.148	0.000	0.000	0.000	0.000
Last 100	Number of polls	45	82	124	180	431
	poll "wins"	24	23	18	54	119
	market "wins"	21	59	106	126	312
	% market	47%	72%	85%	70%	72%
	p-value (1sided)	0.724	0.000	0.000	0.000	0.000

As the results of this test show, market predictions are closer to the final outcomes than poll predictions for most of periods of each election. Thus, this evidence suggests that the markets are accurate months in advance and are better than polls at longer horizons. Figure 54 illustrates this superior IEM performance against polls.

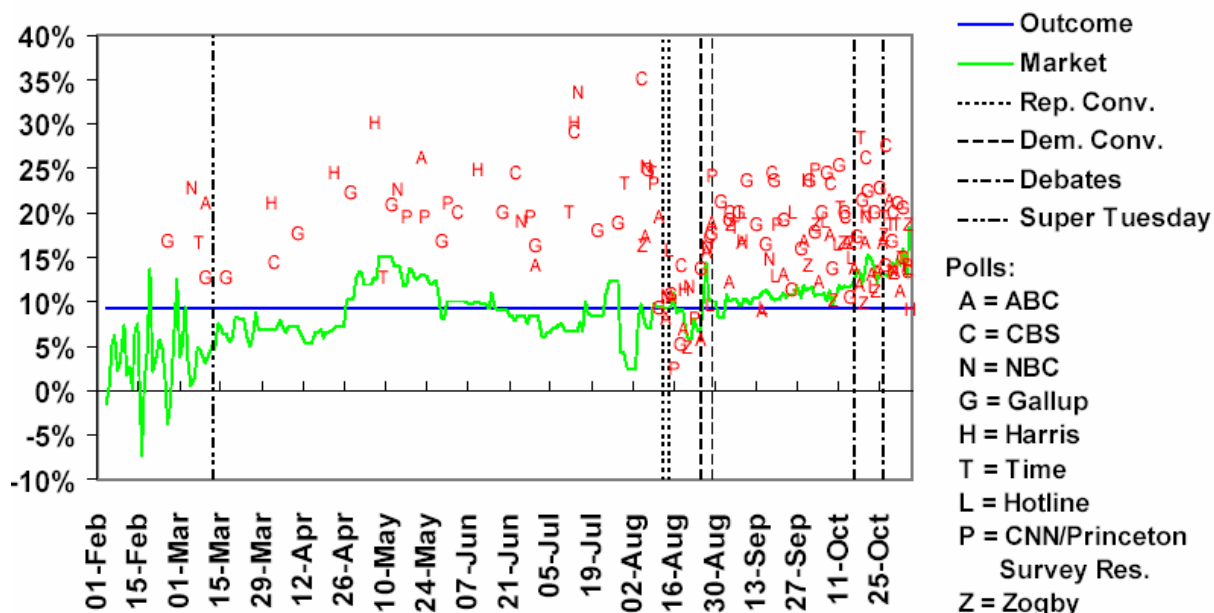


Figure 54: Comparison of IEM performance to polls in the US presidential election 1996 (Berg, Nelson et al. 2002)

The evidence presented so far supports an IEM performance that is superior to the alternative method of polling. There is, however, further evidence that IEM markets outperform other forecasting methods as well, such as quantitative models (the class of structured methods performed by individuals based on the classification presented in FIX) and the Delphi method. Such research by Cuzán, Jones et al. (2004) is presented in Figure 55.

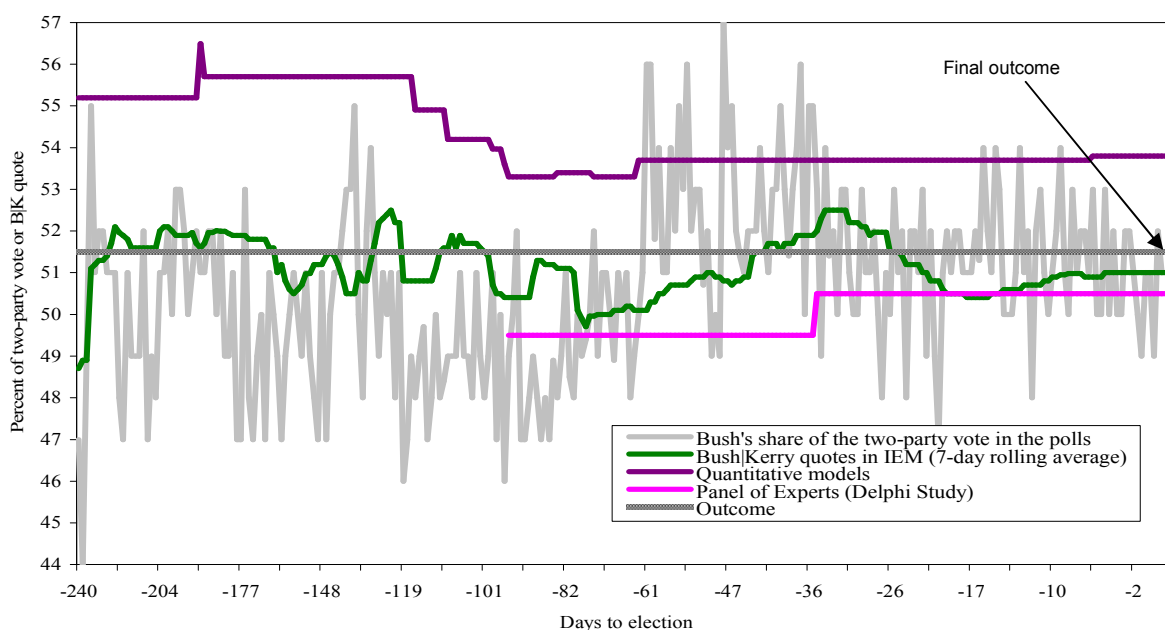


Figure 55: Comparison of IEM performance to alternative forecasting methods in the US presidential election 2004; adapted from (Cuzán, Jones et al. 2004)

The above figure compares the forecasts based on various forecasting methods for the popular vote in the US presidential election in 2004 from 240 days before the event to election eve. In reference to the final outcome, the IEM shows the best performance over time in comparison to the Delphi forecasts and the forecasts by the quantitative models. The details of this comparison are documented by Cuzán, Jones et al. (2004).

Thus, we conclude that the evidence published in the literature supports the hypothesis H2 by support of the sub-hypothesis structure H2.2 and H2.2.1 in the way that IEM markets perform better than alternative forecasting methods used in a comparable application context.

Next, we investigate the sub-hypothesis H2.2.2, whether AAM for TF perform better than IEM markets by achieving a higher average logarithmic score (ALS) on a normalized time scale than IEM markets.

The ALS for the TF markets in our data base has been calculated earlier in section 4.3.3; see specifically Figure 50 and Table 34.

To calculate the ALS for the IEM markets, we collected daily prices from 20 political US election markets on the IEM. For comparability our selection of IEM markets was limited to binomial markets (= "Winner-takes-all" markets, see also 3.6.1) in which winning contracts fully pay off while non-winning contracts receive no pay-off at all. Selected markets range from the 1992 US Presidential election to the 2002 US Congressional election.

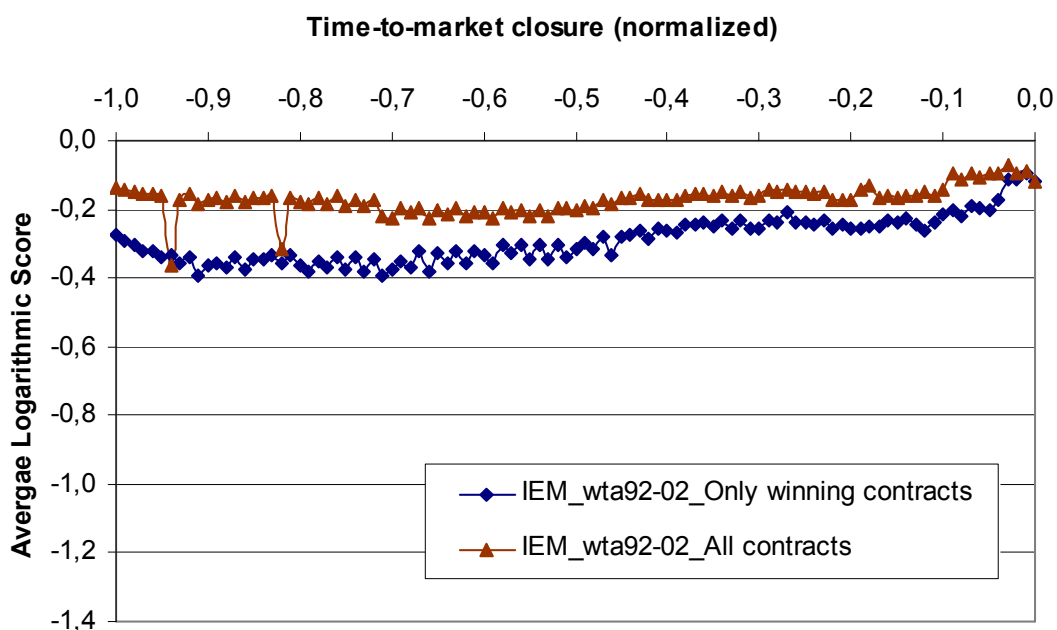


Figure 56: Average Logarithmic Score (ALS) for IEM markets over normalized time

Figure 56 shows the Average Logarithmic Score over normalized time for the selected 20 IEM markets. We distinguish between the ALS based on winning contracts only and the ALS based on all contracts.

A political election market such as the 2000 NY senate election usually offers multiple contracts to cover all the nominees (five: Giuliani, Clinton Hi., Other NY Republican, Other NY Democrat, Other NY Independent). As only one contract can emerge as the winner, all other contracts must inherently and ultimately lose. Under the assumption

that all non-winning contract prices correlate to the winning contract price, $p_{non-win} \approx (1 - p_{win})$, the different number of non-winning contracts for each markets leads to an uneven weighting of the markets when calculating the ALS for all markets. Furthermore, non-winning contract prices do not perfectly correlate to the winning contract price. Contracts on offer must also cover those nominees who predictably have no chance of winning – the respective market contracts reflect this correspondingly. Bundled together with the more improbable winning contract, ALS performance appears to be much better.

As displayed in Figure 56, the ALS for the IEM markets solely based on winning contracts performs less good than the ALS based on all contracts, but gradually the performance gap closes. Notably, just prior market closure both ALS meet at approx. -0,1

Thus, for a true ALS performance comparison, we argue, the appropriate reference ALS for the IEM has to be based on winning contracts only.

Next, as we have calculated the ALS for both, the TF markets in our data base and the IEM, we compare their performance. For this purpose, we visually inspect the data, as displayed by Figure 57.

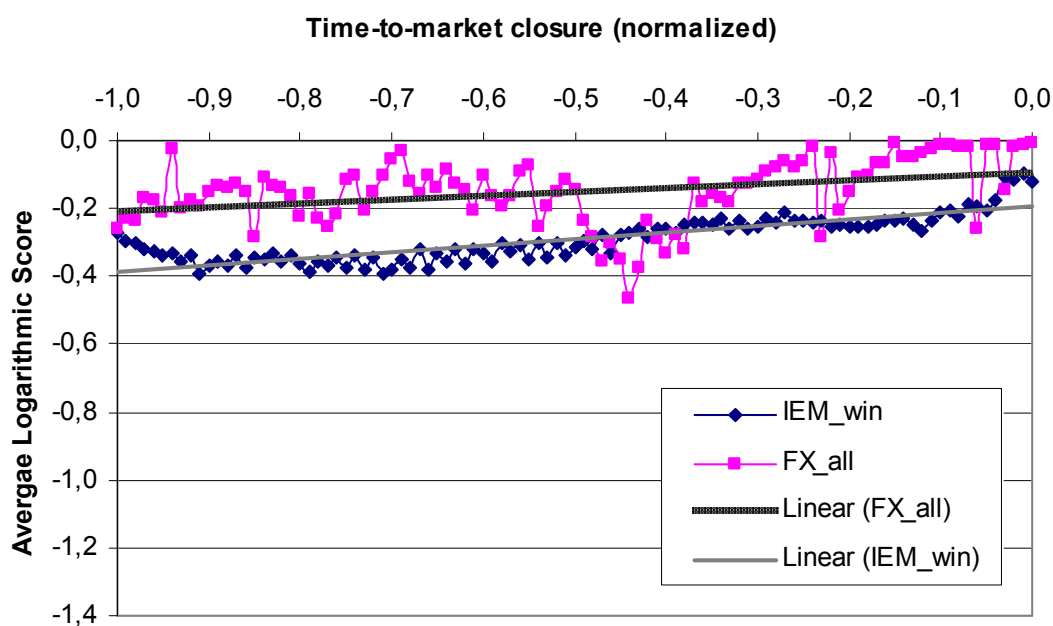


Figure 57: Comparison of Average Logarithmic Scores (ALS) for TF markets and IEM markets over normalized time

Based on Figure 57, we can make the following observations:

- Although both markets' share the same initial starting point, the TF markets swiftly outperform the IEM markets until approx. -50% before the event outcome
- From -50% to -40% prior to the outcome TF markets' ALS performance significantly worsens and underscores the IEM markets
- Thereafter, TF markets significantly outperform the IEM markets, only concerned by some fluctuations around -25% and -5% of normalized time
- A comparison of linear trend approximations for both markets' ALS performance shows a significant prominence of TF markets over IEM markets

These observations are confirmed by a comparison of average ALS vales per normalized time interval; see Table 42.

Table 42: Comparison of Average Logarithmic Scores for TF markets and IEM markets over normalized time – ALS are averages for each time segment

normalized]	[ALS]	[ALS]	%IEM	Better
Time	IEM	TF		
-1,0	-0,3292	-0,211	64%	TF
-0,9	-0,3533	-0,150	42%	TF
-0,8	-0,3645	-0,180	49%	TF
-0,7	-0,3496	-0,121	34%	TF
-0,6	-0,3262	-0,163	50%	TF
-0,5	-0,2904	-0,313	108%	IEM
-0,4	-0,2489	-0,214	86%	TF
-0,3	-0,2385	-0,148	62%	TF
-0,2	-0,2450	-0,085	35%	TF
-0,1	-0,1741	-0,059	34%	TF

Table 43: Comparison of Average Logarithmic Scores for TF markets and IEM markets over normalized time – by "worst" ALS for each time segment

normalized]	[ALS]	[ALS]	%IEM	Better
Time	IEM	TF		
-1,0	-1,2924	-1,000	77%	TF
-0,9	-1,2924	-2,000	155%	IEM
-0,8	-1,4202	-0,745	52%	TF
-0,7	-2,0969	-0,538	26%	TF
-0,6	-1,8239	-0,553	30%	TF
-0,5	-1,7447	-1,000	57%	TF
-0,4	-0,9393	-0,658	70%	TF
-0,3	-1,0458	-0,481	46%	TF
-0,2	-2,3010	-0,222	10%	TF
-0,1	-2,0000	-2,000	100%	-

Thus, we can observe that, at large, TF markets show better forecasting performance than the IEM markets.

Consequently, we conclude that the data supports the hypothesis H2 by support of the sub-hypothesis H2.2.2 in the way that AAM for TF achieve a higher average logarithmic score (ALS) on a normalized time scale than the IEM markets.

4.5 Summary and conclusions

In this chapter we presented the empirical evidence produced in the course of this thesis. After developing a research concept for the empirical investigation of the hypotheses and establishing the data used for analysis, we operationalized the hypotheses and systematically examined and discussed their support by the data.

We summarize our main findings: the first set of findings refer to the absolute performance of AAM for TF, that is, a minimum absolute performance in forecast capacity to acknowledge technological forecasts by artificial asset markets as reasonably accurate and reliable:

- All AAM for TF eventually reflected the true outcome of the underlying claim
- AAM for TF forecast the eventual outcome with a probability of >75% for at least 1,0 years or 10% of market duration in advance of market maturation, respectively, in advance of the event outcome
- AAM for TF are able to forecast the eventual outcome with a probability of >75% for up to 5 yrs or 90% of market duration in advance of market maturation, respectively, in advance of the event outcome
- On average, AAM for TF forecast the eventual outcome with a probability of >75% for approx. 2 years or 59% of market duration in advance of market maturation, respectively, in advance of the event outcome
- None of the markets instantly maintains over the full market duration a probability of >75% on the eventual outcome
- Whereas in unprocessed price data some TF markets featured major price fluctuations that distorted their forecasting performance, these fluctuations can

be put into perspective by processing the price data using regression methods such as a polynomial or a moving average. The performance distortions range from 0,5 to 2,75 years or from 10% to 70% of market duration time.

- We have found no considerable correlation between absolute or relative forecast performance of AAM for TF and selected TF market properties, such as market duration, the amount of completed trades and the number of distinct traders

As a further measure of forecasting performance, we use the logarithmic score, a proper scoring rule that is used by leading researchers in the field of AAM to evaluate absolute and comparative forecasting performance:

- AAM for TF achieve an ALS of -0,1 or better (higher) at least 1,0 years in advance – and even 2,0 years in advance if based on a moving average.
- AAM for TF achieve an ALS of -0,1 or better (higher) at least 20% of market maturation in advance of the event – and even 40% of market maturation in advance if based on a moving average.

Thus, the empirical evidence established by this research supports the hypothesis H1, that is, AAM for TF can forecast technological developments (in principle).

The second set of findings refer to the comparative performance of AAM for TF, that is, to acknowledge technological forecasts by artificial asset markets as more accurate and reliable than forecasts based on alternative methods and which are used in a comparable application context:

- By direct performance comparison, we could NOT establish sufficient empirical evidence to support AAM for TF as superior to alternative forecasting methods used in the same application context.
- However, by indirect performance comparison, we were able to establish empirical evidence to support AAM for TF as superior to alternative forecasting methods:

- TF markets show better forecasting performance on average than the IEM markets, the longest running set of prediction markets known to us and well known for their remarkable performance.
- IEM markets perform better than alternative forecasting methods used in a comparable application context.
- Consequently, TF markets perform better than alternative forecasting methods.

Thus, the empirical evidence established by this research supports the hypothesis H2, that is, AAM for TF can forecast technological developments better than alternative forecasting methods used in the same application context.

As we have established that the method TF by artificial asset markets works in principle and performs well in terms of absolute and relative accuracy and reliability, we move on to explore the design of artificial asset markets - and to identify which of the many design options are suitable for TF.

5. Design of artificial asset markets for technological forecasting

Although we have established that artificial asset markets for TF work in principle and even perform well in terms of accuracy and reliability, we learned earlier in chapter 2 that many potential pitfalls lie *in the way of realizing* information aggregation through speculative markets.

Consequently, in this chapter we systematically explore the different possible design alternatives for artificial asset markets and we evaluate the different design options for their applicability to the domain of technological forecasting.

After a brief introduction to securities and security exchanges, we start by establishing a design process for artificial asset markets. Subsequently, for each of the key steps in market design we identify a market's major elements in design and discuss for each the various design alternatives from a general viewpoint. These general discussions are followed by specific discussions of how these design choices apply to TF and which of these choices are more preferable for AAM for TF than others.

Finally, we conclude the chapter with a brief summary and the effort to describe the ideal design for an AAM for TF.

5.1 Introduction to financial instruments and financial markets

Traders seek to trade for various motives, e.g. to invest, to hedge, to speculate, etc.²⁸² See Table 44 for an overview of trader motives. For these reasons traders trade in *instruments*. Instruments represent ownership of real assets, financial assets, derivative contracts, insurance contracts, and gambling contracts.²⁸³ An overview of trading instruments is presented by Table 45.

Table 44: Motives for trading; (Harris 2002), p.33

Motives	
to invest	→ to move wealth from the present to the future
to borrow	→ to move wealth from the future to the present
to hedge	→ to reduce business operating risk
to exchange assets	→ to acquire an asset that one values more than the asset one tenders
to gamble	→ to entertain oneself
to speculate:	→ to trade on information about future price changes
to build reputation	→ to perform better than average or peers

²⁸² (Harris 2002) p.32-33

²⁸³ Financial instruments include financial assets, derivative contracts, and insurance contracts.

Real assets include physical commodities, real estate, machines, patents, other intellectual properties, and rights, such as pollution emission credits.²⁸⁴

Financial assets are instruments that represent ownership of real assets and the cash flows that they produce. Stocks and bonds are financial assets because they represent ownership of the assets of a corporation.²⁸⁵

Table 45: Overview of trading instruments; (Harris 2002), p.38

Class	Instrument	Creators
Real assets	<ul style="list-style-type: none"> • Spot commodities • Intellectual properties • Real estate • Pollution emission rights 	<ul style="list-style-type: none"> • Farmers, miners, manufacturers • Inventors and artists • Builders • Governments
Financial assets	<ul style="list-style-type: none"> • Stocks and warrants • Bonds • Trust units • Currencies 	<ul style="list-style-type: none"> • Corporate issuers • Corporate issuers, governments • Trusts • Governments, banks
Derivative contracts	<ul style="list-style-type: none"> • Futures contracts • Forward contracts • Options • Swaps 	<ul style="list-style-type: none"> • Sellers • Sellers • Seller • Sellers
Insurance contracts	<ul style="list-style-type: none"> • Insurance policies • Reinsurance contracts 	<ul style="list-style-type: none"> • Corporations • Corporations
Hybrid instruments	<ul style="list-style-type: none"> • Warrants • Index linked bonds • Convertible bonds 	<ul style="list-style-type: none"> • Corporate issuers • Corporate issuers • Corporate issuers
Gambling contracts	<ul style="list-style-type: none"> • Numerous types 	<ul style="list-style-type: none"> • Individuals, bookies, casinos, racetracks, etc.

Derivative contracts are instruments that derive their values from the values of the underlying instruments upon which they are based.²⁸⁶ They are contractual agreements between buyers and sellers that specify the exchange of certain privileges and liabilities.²⁸⁷ For example, a futures contract is a type of derivative instrument, in which two parties agree to transact a set of financial instruments or physical commodities for future delivery at a particular price.²⁸⁸ If an investor buys a futures contract, he is basically agreeing to buy something, for a set price, that a seller has not yet produced.

²⁸⁴ (Harris 2002) p.38-44

²⁸⁵ Ibid.

²⁸⁶ Ibid.

²⁸⁷ Ibid.

²⁸⁸ see (Equitrend 2004)

Derivative contracts include forward contracts, futures contracts, options, and swaps.²⁸⁹ All derivative contracts have an element of futurity: their values depend on future events. For example, the prices of futures, options, and forwards all depend on future prices of their underlying instruments.

Distinctively, derivative contracts represent no wealth because they are in *zero net supply* and do not represent ownership of real assets.²⁹⁰ In *zero net supply* the sum of all long positions²⁹¹ minus the sum of all short positions is always zero.²⁹²

Insurance contracts and gambling contracts are instruments that derive their values from the outcomes of future events. For example, the value of a fire insurance contract on a building depends on whether the building burns down. The distinction between an insurance contract and a gambling contract depends on the reasons why people buy them. People who are concerned about the loss that they would experience if some future event takes place buy insurance contracts. In contrast, gambling contracts are arranged by people who have no other financial stake in the underlying event. As derivative contracts are contracts whose value depends on future events, we can classify derivative contracts as insurance contracts or gambling contracts. In fact, many hedgers use derivative contracts to insure against risks that they face, and many traders use derivative contracts to gamble on future events in which they have no financial interest.²⁹³

Table 46: Trading instruments and instrument creation

Underlying	Instrument class	Instrument creation
Real assets	<ul style="list-style-type: none"> • Real assets • Financial assets • Derivative contracts • Insurance contracts 	by guarantee of ownership of the underlying real asset
Artificial assets	<ul style="list-style-type: none"> • Derivative contracts • Insurance contracts • Gambling contracts 	based on artificial assets, that is, by guaranteeing a payoff contingent on the realized value of a selected random variable

²⁸⁹ (Harris 2002) p.38-44

²⁹⁰ Ibid.

²⁹¹ Traders have long positions when they own something. Traders with long positions profit when prices rise. They try to buy low and sell high. Traders have short positions when they have sold something they do not own. Traders with short positions hope that prices will fall so that they can repurchase at a lower price. Short sellers profit when they sell high and buy low.

²⁹² (Harris 2002) p.38-44

²⁹³ (Harris 2002) p.38-44

Instruments in real assets, financial assets, many derivative contracts, and many insurance contracts are created on the basis of ownership of real assets.

However, some derivative contracts, some insurance contracts, and gambling contracts are created by guaranteeing a payoff contingent on the realized value of the random variable.²⁹⁴

Thus, in artificial asset markets trading instruments are created by guaranteeing a payoff contingent on the realized value of a selected random variable.

Table 47: Key processes in (financial) markets (Kambil and Heck 2002), pp.26-27

Key processes	Description
Basic trade processes	
Search	allows buyers and sellers to discover and compare trading opportunities
Pricing	helps buyers and sellers discover prices
Logistics	coordinates the transfer of physical and digital goods between buyers and sellers
Payment & settlement	transfer funds from buyer to seller
Authentication	verifies the quality of the goods sold and the credibility of the buyers and sellers
Trade context processes	
Product representation	specifies the presentation of products and services to buyers and sellers
Regulation	records and recognizes the transaction within a framework of laws and rules to signal it as legitimate and conforming to a set of market rules and social principles
Risk management	reduces buyer and seller risk in an transaction
Influence	ensures that commitments among trading partners are met
Dispute resolution	resolves conflicts among buyers, sellers, and market sponsor
Communications	enables integration of all other processes into a specific market

Trading itself is, in first place, a search problem.²⁹⁵ Buyers must find sellers, and sellers must find buyers. Exchanges design markets to solve the search problem. They usually organize markets so that everyone who wants to trade gathers at the same place. A common gathering place helps traders find those traders who will offer the best prices.²⁹⁶

²⁹⁴ see (Pennock and Wellman 2004), p.11

²⁹⁵ see (Harris 2002) p.5-7, and (Kambil and Heck 2002) p.26-27

²⁹⁶ see (Harris 2002) p.5-7

Exchanges once organized their markets exclusively on physical trading floors. Now they can do so within computerized communication networks those allow buyers and sellers to arrange their trades remotely. Electronic marketplaces have rapidly expanded as the costs of electronic communication have dropped.²⁹⁷

Five basic key processes and five support processes facilitate trade in the exchange.²⁹⁸ An overview and brief description of these processes is presented in Table 47.

Most traders want to trade in well-established markets because other traders trade there. When many traders are in the same place, arranging trade is very easy. The attraction of traders to other trades makes it hard to start new markets. However, new markets are created when old markets do not adequately meet the needs of a significant set of traders.²⁹⁹

An exchange's trading rules affect the quality of its markets. They determine the balance of power between informed traders and uninformed traders, between public traders and professional traders, and between large traders and small traders.³⁰⁰

As we have briefly introduced the nature of financial instruments and financial markets, we proceed to give an overview of artificial asset market design.

²⁹⁷ see (Harris 2002) p.5-7

²⁹⁸ see (Kambil and Heck 2002) p.26-27

²⁹⁹ see (Harris 2002) p.5-7

³⁰⁰ Ibid.

5.2 Overview of artificial asset market design – the design process

This section gives an overview of the key steps in designing and building an artificial securities market. The key steps are briefly described and their implications for market design are discussed. The key steps are shown in sequence by Figure 58.



Figure 58: The design process for artificial asset markets

As a first key step in designing and building an artificial asset market, the market purpose and content need to be established. Both are direction-setting and serve as a foundation for many of the design decisions and trade-offs that follow later in the design process. At the same time, they also serve as a basis to review and evaluate alternative design decisions as to the degree of support they provide in fulfilling the original market purpose.

Next, the information environment in which the market is supposed to operate needs to be characterized in order to understand *when* and *where* *what* kind of information is generated. Furthermore, activities in this key design step need to consider *who* the original information holders are or, more broadly, who has access to the information and how information holders can be motivated to share their information.

Subsequently, the artificial asset design is established. This design includes the selection of an instrument type, the definition of the instrument's maturity (contract expiration), the definition of the instrument's liquidation value (payoff) and the optional arrangement of multiple instruments by design of an asset structure. The specific design derived at this stage provides the artificial asset that is subject to trade, and by so, derives its value from the outcome of a selected future event.

As a next step, the market microstructure is established. Such a design involves the selection of an emission mechanism to initially place the instrument for trade, the core trading mechanism that governs the process of trade after emission, the trading rules that complement the process of trade, and the combinatorial trade mechanism that may allow traders to conduct contingent trades. The design established in this step affects market characteristics, such as liquidity, transaction costs, informative prices, volatility, and trading profits. However, in first place, it facilitates the coordination on the instruments that traders would like to trade.

Access and incentivation design involves measures concerning trader identity, trader acquisition and delimitation, the choice of a real or artificial asset value, the scope of incentivation, the source of deposit funds, prize ascertainment and prize constitution. The specific design derived at this stage supports the task of inducing people to acquire and submit the relevant information to make prices informative.

Finally, the organizational and technical system design is established. The specific design derived at this stage provides the infrastructural and operational basis for an AAM. It includes the assignment of responsibilities for key organizational tasks, such security creation, data collection, or security judging. The technical system design briefly describes the Key features and the key system elements of the IT-System that facilitates the full trading process.

As the following sections discuss each of the design steps in detail, the range of design alternatives need to be evaluated for their applicability to AAM for technological forecasting. Subsequently, we develop the framework and criteria for this evaluation.

5.2.1 Evaluation of AAM design alternatives for TF markets

As we systematically explore the different possible design alternatives for TF markets, we wish to evaluate the different design options for their applicability to the domain of technological forecasting. Consequently, for evaluation we need to develop some criteria.

Table 48: Criteria for evaluation the applicability of AAM design alternatives to TF markets

Criteria	Specification	Design evaluation
<i>Market efficiency</i>	<ul style="list-style-type: none"> Do asset prices at any time reflect all available information? 	<ul style="list-style-type: none"> Does the design promote or discourage market efficiency of TF markets?
<i>Financial cost and risk</i>	<ul style="list-style-type: none"> What is the operational cost of maintaining the market? What is the exposure to financial risk? 	<ul style="list-style-type: none"> Does the design incur or impede financial cost of TF markets? Does the design promote or discourage financial risk (e.g. by promoting or discouraging legal risk) of TF markets?

Most fundamentally, asset markets are evaluated for their market efficiency³⁰¹. Essentially, a market is efficient if prices at any time reflect all available information.³⁰² Many measures are used to gauge market efficiency, among the most popular are market transparency and market liquidity (Smant 2003).

Transparency reflects the degree of disclosure of information on any transaction. Typically, transparency is limited to detailed disclosure of transaction details for each trader and a daily summary for the market.

Liquidity reflects the exchange's offer to trade (i) instantly and (ii) for a more or less known price. There are different dimensions of liquidity, e.g. market depth which translates into the number of contracts that can be traded at a given bid-ask spread; or market width which represents the bid-ask spread at a given number of contracts to be traded.

Whatever the measure used to gauge market efficiency, the design alternatives need to be evaluated in the light of promoting or discouraging market efficiency of TF markets.

³⁰¹ see (Madhavan 2000; Harris 2002; Smant 2003)

³⁰² see also section 3.1

Another fundamental criterion used to evaluate design alternatives for TF markets is the financial cost and risk brought upon by the design. Thus, main concerns are what the operational cost and financial risk of maintaining the market in the respective design is. Financial risk may be a consequence of a design promoting legal risk or of a design producing unintentionally high liabilities.

As we have established the criteria for evaluating AAM design alternatives for TF markets, we move on to discuss the market design process in more detail.

5.3 General guidelines for the design of artificial asset markets

Prior to discussion of the first step in the design process for artificial asset markets, we establish some general guidelines for the design of AAM. An overview of these guidelines is presented by Table 49.

Table 49: General guidelines for the design of AAM; adapted from (NetExchange 2002)

No.	Guideline
1	Augment Current Processes
2	From General to Specific
3	Consistent Applicability
4	Involve a wide range of participants
5	Being right must be valuable to traders

Subsequently, the general design guidelines are briefly discussed.

Augment Current Processes. Markets are not ends-in-themselves; rather, they are one of several means through which the participants in commerce do business. The basic liquidity that makes a market a dependable place for information discovery comes from the use of the market as a day-to-day tool. Thus, a TF market must be designed to fit into the process of technological forecasting.

From General to Specific. Technological forecasting is built up from the observation of underlying fundamentals and the expert consideration of interrelationships among these fundamentals. The TF market must begin to engage the technological forecasting business from the general perspective of predicting the evolution and interaction of fundamental technological developments. As trends and interactions coalesce into perceptions of specific relevant events, TF markets must facilitate the inclusion and further refinement of these.

Consistent Applicability. The nature, issuance, maturity, and transaction of securities in TF markets must be based on publicly-understood rules and procedures that change rarely, if at all.

Involve a wide range of participants. The purpose of TF markets is to aggregate expertise across different sources of expertise, academic, governmental, and

commercial. Therefore, TF markets must fit the operational modes, deal with the topics of interest, guard the information privacy, and accommodate the concerns of a wide range of participants.

Being right must be valuable to traders. Markets are group processes that function effectively if participants provide valuable insight in the form of transactions. In return, all participants in the market receive information that is of higher quality than they could have attained through some other process. "Free riding" will render a market useless if the private gain from providing insightful orders is not greater than the private gain of just watching. Thus, to get participants to provide orders that reflect valuable insight, the participants must know that they will profit from the orders if the future substantiates their insight.

Next, as we have established some general guidelines for the design of artificial asset markets, we proceed to discuss the first step of the design process.

5.4 Step 1: Market purpose and content

As a first key step in the process of designing a new informative artificial asset market, the market purpose and objectives need to be established. This design step serves as a foundation for many of the design decisions and trade-offs that follow later in the design process. At the same time, the outcome of this design step also serves as a basis to review and evaluate alternative design decisions as to the degree of support they provide in fulfilling market purpose and objectives.

Initially, the prime purpose for establishing an AAM was to research such markets' ability to collect and aggregate information in the laboratory and in the field respectively, and to study under which circumstances these markets' failed to function. Meanwhile, the pervasion of the mass-connecting internet and relatively cheap information technology has motivated various efforts to establish AAMs for other purposes than pure research.³⁰³

Table 50: Motives (commercial) for creating asset markets – and their applicability to financial markets (FM) and to AAMs

Motives	FM	AAM
to create a market in pursuit of trader motives ³⁰⁴	X	(X)
to profit from facilitating trade: by arranging trades or by supplying liquidity	X	(X)
to utilize market prices as forecasts		X
to utilize market data and/or trader data for marketing purposes		X
to entertain people and to build a community respectively		X

As asset markets can serve many different needs of traders, such as to invest, to borrow, to exchange assets, to hedge risks, to distribute risks, to gamble, to speculate, and to deal, so can artificial asset markets serve these needs.³⁰⁵ For example, the Economic Derivatives market, an artificial asset market run by Goldman Sachs and Deutsche Bank, trades in the outcome of macro-economic data, such as (un-)employment statistics, and, thus, allows traders to hedge risks.³⁰⁶ Thus, the primary purpose of this AAM appears to be to create a market in pursuit of trader motives (e.g.

³⁰³ see also sections 3.3 and 3.4

³⁰⁴ see also Table 85

³⁰⁵ see (Harris 2002), p.176

³⁰⁶ see information provided at <www.economicderivatives.com> as of October 2004

to distribute risk) and to profit from facilitating trade by arranging trades or by supplying liquidity.

However, in general, the prime purpose of establishing an AAM may be to utilize market prices as forecasts, to utilize market data and/or trader data for marketing purposes, or to simply entertain people and to build a community respectively. See Table 50 for a summary of motives of establishing asset markets.

Table 51: Examples of AAM content

Theme	Specific content
Politics	Which candidate will win the 2004 U.S. Presidential elections?
Sports	Which team will win the Soccer Confederations Cup 2005?
Movies	What will be the box-office income of the 1 st weekend for the movie Toy story 3?
News	Will the US catch Osama bin Laden while Bush is US president?
Futurist	Will a dinosaur be recreated by 2050?
Technology	Will hybrid powered cars supersede conventional engine cars? When?

The intention to establish a market typically comes in combination with a certain theme in mind. This theme determines the market's content and ultimately determines the information environment in which the market will operate.

The content of the market may be as diverse as tomorrow's weather, next quarter's US interest rate, the outcome of a political election, the box office sales of new movies, or the specificity of some technological progress.³⁰⁷ Table 51 provides an overview of possible themes and content of AAM.

Consequently, an AAM for technological forecasting will feature technological development as theme and specific technological forecasts as content.

³⁰⁷ see also sections 3.3 and 3.4

5.5 Step 2: Characterization of the information environment

As a basis for the design of an informative artificial asset market, the information environment in which the market operates needs to be characterized in order to understand how the information may find its way into the market and this process can be facilitated and promoted. As a starting point for the discussion, FIX displays a conceptual model of the general flow of information about an event outcome from its generation to its inclusion to a forecast.

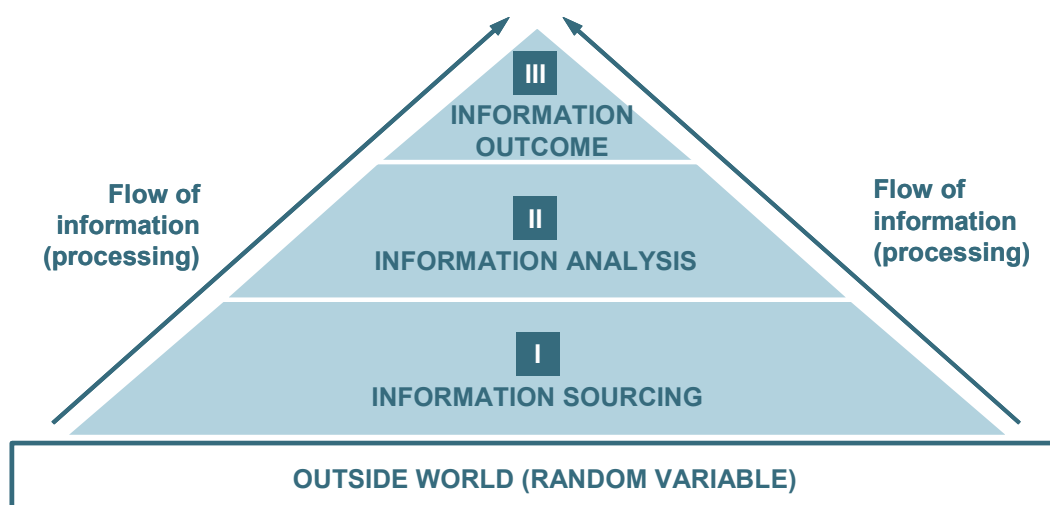


Figure 59: Conceptual model of the general flow of information

As indicated in the figure above, three principle stages in the flow of information can be distinguished: the stage of information sourcing, the stage of information analysis, and the stage of information outcome. However, the information also features some general properties which relate to the forecasted event. Subsequently, we discuss the characteristics of each of these stages and their implications for AAM design. A summary is provided by Table 52.

Table 52: Characterization of the information environment: Criteria, descriptions, examples, and implications for design

Criteria	Description	Example: Sports event	Implications for market design
0 – Random variable			
<i>Outcome solution space</i>	describes the possible outcomes of the event	Game win/draw/lose	➤ Security design
<i>Outcome affectability</i>	describes how strongly the event outcome can be arbitrarily influenced under regular conditions (thus, indicates the randomness of the event)	Low	➤ Market objectives, trading rules ➤ Access & Incentivation design
<i>Duration</i>	describes the typical forecast horizon for the type of event	Half-year to 1 day	➤ Access & Incentivation design
I – Information sourcing			
<i>Private / Public information</i>	describes if the nature of the relevant information input is rather private or public – indicates motives to join for trade in market	Public, widely known	➤ Asset value & market currency ➤ Access & Incentivation design
<i>No. of inputs</i>	indicates the number of different factors influencing the outcome of the event	Few	➤ Asset value & market currency ➤ Access & Incentivation design
<i>Frequency of input changes (Time-based spread)</i>	indicates if the majority of factors influencing the outcome of the event stay stable or decisively change frequently	Very frequent	➤ Prize ascertainment design ➤ Trading rules, e.g. trade hours
<i>Geographic spread</i>	describes how the first-hand information holders are geographically distributed	Very local	➤ Access & Incentivation design ➤ Trading rules, e.g. trade hours
<i>Demographic spread</i>	describes how the first-hand information holders are distributed among the population in demographic terms	Broad	➤ Asset value & market currency ➤ Access & Incentivation design
II – Information analysis			
<i>Task balance</i>	describes if the balance of the individual analysis task emphasizes the utilization of private info (-> info collection) or rather the evaluation of publicly available info (-> opinion formation)	Opinion formation	➤ Asset value & market currency ➤ Access & Incentivation design
<i>Complexity – effort</i>	describes the complexity of the task for an individual to consolidate and interpret the information sources for assessing event outcome	Low	➤ Asset value & market currency ➤ Access & Incentivation design
<i>Complexity – degree of insight (overall vs. partial insight)</i>	indicates how likely an individual will have an overall insight or a partial insight into what is driving the event outcome	Overall insight	➤ Core trade mechanism
III – Information outcome			
<i>Solution space ambiguity</i>	how (un)ambiguous the event outcomes can be described	Clear	➤ Security design
<i>Outcome verifiability</i>	describes how easily the outcome is publicly verifiable ex-post	Easy	➤ Organizational design

Subsequently, we discuss the criteria for the characterization of the information environment and their implications for AAM design.

Stage 0 – Random variable

Information relating to the outcome of an event features some general properties which are discussed below.

Outcome solution space describes the possible outcomes of the event; the solution space may be binary, discrete or continuous. For example, the solution space for the outcome of a soccer match can be described as "Team A wins/Team B loses", "Team A loses/Team B wins", "Draw", or "Cancelled". The corresponding implications for AAM design are discussed in Instrument type design (5.6.1).

Outcome affectability describes how strongly the event outcome can be arbitrarily influenced under regular conditions; thus, this characteristic indicates the randomness of the event. For example, the outcome of a sports game cannot be arbitrarily changed under regular conditions. However, the magnitude of a company's earnings may be arbitrarily changed to a certain degree due to the leeway given by accounting rules.

An AAM that covers an outcome that is decisively changeable, needs to consider the participation of individuals who might change the outcome due to the benefits provided by his participation.³⁰⁸ In such a context, access and incentivization design can be designed accordingly to provide a reduced level of incentive (5.8), trading rules may impose position limits (5.7.3), or concerned individuals may be excluded from trade by respective market objectives design (5.4) and trader identity design (5.8.1).

Duration describes the typical forecast horizon for the type of event, which may range from hours (e.g., sports events) to a multi-year horizon (e.g., technological development). Accordingly, traders need to be motivated to endure the time horizon; the corresponding implications for AAM design are discussed in access and incentivization design (5.8).

³⁰⁸ such a behavior is known as "moral hazard": it describes the risk that one party in a contract will alter its behavior due to the existence of the agreement. For example, taking less precautions against accidents after an insurance policy is put in place (Equitrend 2004)

Stage I – Information sourcing

As information relevant for the event outcome is generated at information sources, it diffuses through private and public channels to an individual who may actively or passively acquire the information. The information is private if it is material information about the event outcome that is not available to public – and which is not yet considered in the forecast. Private information loses its status only when it becomes available to the public. For example, after a firm releases information relating to its performance to the public through a broadly distributed press release or a public filing, the information is publicly available.

Private/public information. Individuals holding private information are likely to expect a higher utility or return on their information than individuals holding public information. As a consequence, individuals holding private or public information may need a different type and level of incentivitation in order to be willing to pass on their information. The corresponding implications for AAM design are discussed in the various sections of access and incentivitation design (5.8).

No. of inputs. A further information characteristic is the number of different inputs influencing the outcome of the forecasted event. This characteristic serves as a proxy for individual effort: in general, the higher the number of inputs, the higher the effort for an individual to cover the inputs. As a consequence, individuals exercising more effort to cover more event-driving inputs may need a different type and higher level of incentivitation to pass on their information than individuals requiring less effort to do so. The corresponding implications for AAM design are discussed in the various sections of access and incentivitation design (5.8).

Frequency of input changes. A complement to the above information characteristic is the frequency of input changes, that is, if important factors which influence the event outcome stay stable or decisively change frequently. Analog to the number of different inputs, the more frequent the change, the higher the effort for an individual to try to process these changes. As a consequence, individuals exercising more effort to cover more event-driving inputs may need a higher level of incentivitation to pass on their information than individuals requiring less effort to do so. Furthermore, individuals should be enabled to use their frequent information in a timely manner. The corresponding implications for AAM design are discussed in prize ascertainment design (5.8.6) and in trading rules design (5.7.3, trading hours).

Geographic spread describes to what degree the information and information holders are geographically distributed. They may be geographically dense or globally dispersed – in any case the market needs to sufficiently cover the potential trader base by designing market access and incentivitation (5.7.4) accordingly. Furthermore, the geographic spread of potential traders needs to be considered in asset value market design, as real-money markets operating in multiple jurisdictions and in different money transfer infrastructures may impose over-proportionally higher installation and operating costs (5.8.3).

Implicitly, the geographic spread of information holders also affects trading rules (specifically, trading hours; see 5.7.3) as different time zones may need to be covered.

Demographic spread describes to what degree the information and information holders are distributed among the population in demographic terms. Analogue as for the geographic spread, the information holders may be demographically dense (e.g., company staff in specific functions) or dispersed – in any case the market needs to sufficiently cover the potential trader base by designing market access and incentivitation (5.8) accordingly.

Furthermore, the demographic spread of potential traders needs to be considered in asset value market design, as information holders of different demographic segments may need a different type and level of incentivitation in order to be willing to pass on their information. (5.8.3).

Stage II – Information analysis

As an individual has actively or passively acquired information relevant for the event outcome, it tries to consolidate and interpret the information in how it may influence the event outcome. Subsequently, we discuss the characteristics of the information at this process stage and their implications for AAM design.

Task balance describes if the individual analysis task emphasizes the utilization of private information or rather the evaluation of publicly available information. If the event outcome is deterministic, that is, clearly and easily determinable by private information, the analysis rather emphasizes the acquisition of this private information; as it leaves little room for interpretation. For example, the outcome of who will the Nobel Prize is

elected privately by a committee – a collection of the private opinions of the committee members will yield the Nobel Prize winner.

If the event outcome is non-deterministic, that is, there is no private information relevant to the event outcome, the analysis rather emphasizes the evaluation of the available public information; as it leaves considerable room for interpretation. For example, under regular conditions the result of a soccer game cannot be known upfront, as there is an element of chance – the pooling of various informed opinions will yield the best estimate of what the outcome will be.³⁰⁹

The corresponding implications for AAM design are discussed in the various sections of access and incentivization design (5.8).

As noted earlier, individuals holding private information are likely to expect a higher utility or return on their information than individuals holding public information. As a consequence, individuals holding private or public information may need a different type and level of incentivization in order to be willing to pass on their information. The corresponding implications for AAM design are discussed the various sections of access and incentivization design (5.8).

Complexity of causal relations describes the complexity of the task for an individual to consolidate and interpret the information sources for assessing the event outcome. This characteristic serves as a proxy for individual effort: in general, the higher the complexity, the higher the effort for an individual to perform the analysis task. For example, an analysis to forecast a country's GDP growth is likely to be more complex than the analysis to forecast the outcome of a soccer game.

As a consequence, individuals exercising more effort to cover more complex relations may need a different type and higher level of incentivization to pass on their information than individuals requiring less effort to do so. The corresponding implications for AAM design are discussed in the various sections of access and incentivization design (5.8).

Degree of insight also describes the complexity of the task for an individual to recognize causal relations between event-driving inputs and the event outcome. However, this characteristic uses as a proxy an individual's likely degree of insight into the sum of causal relations. In general, the higher the complexity of causal relations, the lower the probability of an overall insight and the more likely a partial insight of an individual into these relations.

³⁰⁹ see also section 3.3 or (Armstrong 2001b)

For example, for the rather complex analysis associated with forecasting a country's GDP, an individual may have a high degree of partial insight into the future development of the country's exports and its impact on GDP, but the individual may be unsure about other factors contributing to GDP development.

As a consequence, individuals with overall insight are likely to produce a better estimate of the overall event outcome than individuals with a partial insight. However, the consolidation of different partial insights may yield as good a forecast of the event outcome as one that is based on overall insights.³¹⁰

The corresponding implications for AAM design are discussed in asset structure design (5.6.4) and combinatorial trade design (5.7.4).

Stage III – Information outcome

Finally, the individual's evaluation of the information is transformed into the solution space of the event outcome. The individual then compares his result to the market forecast and may take consequential trading action to create or adjust the forecast of the event outcome. Subsequently, we discuss the characteristics of the information at this process stage and their implications for AAM design.

Solution space ambiguity indicates the general degree of ambiguity in describing the possible outcomes of the specific event type. For example, the solution space for the outcome of a soccer match can be described unambiguously as "Team A wins/Team B loses", "Team A loses/Team B wins", "Draw", "Cancelled".

In another example, however, the description of possible outcomes for a technology to establish as "Technology establishes", "Technology does not establish" is rather ambiguous. How is "establishment" defined? There are many possible definitions, e.g., a 25% share in global new unit sales of a class of device utilizing the technology.³¹¹

An individual providing information about the outcome of an event must understand how the various outcomes are defined. The corresponding implications for AAM design are discussed in artificial asset design (5.6).

Outcome verifiability complements the above criteria by indicating how easily the outcome is publicly verifiable ex-post. To continue the previously given example, it is relatively easy for an individual to verify the outcome of a soccer game ex-post, as such

³¹⁰ see also sections 3.3 and 5.6.4 for a more detailed discussion of the theoretical background

information is typically covered by a broad range of public media. Moreover, there is likely to be no dispute between individuals over the outcome of the event.

However, whether a new technology has established by reaching a 25% share in global new unit sales of a class of device utilizing the technology may not be easy to verify in a timely fashion through public media. Moreover, certain parts of the given definition may dispute, for example, how the market is comprised to calculate the market share. As a consequence, an objective party may be required to judge whether the event has or has not occurred by applying the given definition.

The corresponding implications for AAM design are discussed in artificial asset design (5.6) and in organizational design (5.9).

Next, we review the application of the discussed criteria to TF markets.

³¹¹ see section 5.6

Application to TF markets

Based on the review of the process of technological development provided in section 2.3, the application of criteria that characterizes the information environment for TF markets is summarized in Table 53. In addition, the implications for AAM design are included in the table.

Table 53: General characterization of the information environment for TF markets

Criteria	TF info environment	Implications for market design
0 – Random variable		
<i>Outcome solution space</i>	Technology performance or prevalence	➤ Security design to cover continuous variable
<i>Outcome affectability</i>	Low	➤ "Insiders" allowed to trade
<i>Duration</i>	Multi-year horizon	➤ Long-term incentives (status!)
I – Information sourcing		
<i>Private / Public information</i>	Public, <u>not</u> widely known	➤ Principle asset value: open ➤ A&I: anonymity of traders!
<i>No. of inputs</i>	Many	➤ Optional: standardized commerce
<i>Frequency of input changes</i>	Infrequent	➤ Annual prize ascertainment
<i>Geographic spread</i>	Global	➤ Global trader base ➤ continuous trade, 24/7
<i>Demographic spread</i>	Small distinct group + "coverage" industry	➤ Peer acknowledgement: rank-order-tournament
II – Information analysis		
<i>Task balance</i>	Opinion formation	➤ Peer acknowledgement: rank-order-tournament
<i>Complexity – effort</i>	High	➤ Principle asset value: open ➤ Access & Incentivation design
<i>Complexity – degree of insight (overall vs. partial insight)</i>	Partial insight	➤ Combinatorial trade mechanism with standardized commerce
III – Information outcome		
<i>Solution space ambiguity</i>	Ambiguous	➤ Detailed, peer-reviewed security definitions
<i>Outcome verifiability</i>	Difficult	➤ Use of judges

Subsequently, we briefly discuss the generalized characterization of the information environment for TF markets and their implications for market design.

Stage 0 – Random variable

The outcome solution space for technological development typically describes a dimension of technology performance or prevalence. For example, the outcome solution space for the maximum performance of white LEDs in 2005 can be described in terms of

lumens per watt. As a consequence, security design needs to consider the coverage of a continuous variable solution space.

The affectability of the outcome of technological developments is typically low³¹², thus, the potential for moral hazard is low. Hence, market policy may support "insider trading". The duration of technology developments typically takes a multi-year horizon.³¹³ As a consequence, a TF market needs a long-term incentive and reward design, e.g., such as a status-building system.³¹⁴

Stage I – Information sourcing

From the multi-year perspective of technological developments the information is of public nature, although it is typically not widely known. However, to protect traders that would like to utilize classified information, TF market design should allow for an anonymous trader identity.

The large numbers of factors that typically drive a technological development allow the use of standardized commerce to provide special insight. The infrequent change of these event-driving factors suggests that an annual prize ascertainment may be sufficient.

As technological development is typically a result of global effort³¹⁵, TF markets should ideally cover a global trader base. Furthermore, a global reach covering all or many time zones suggests a continuous trading session without stoppages.

The demographic spread of information holders encompasses a typically relatively small group of researchers and developers and another, larger group of analysts of an own industry that covers such technological developments. Such a demographic spread suggests for TF market design that the use of a system that enhances peer acknowledgement may provide sufficient incentivization. For example, a rank-order-tournament prize ascertainment design would support such a system.

As an understanding of the potential participants is crucial for market design, we subsequently discuss the diffusion of information on technological developments in greater detail.

³¹² see also sections 2.3 and 2.5.1

³¹³ Ibid.

³¹⁴ see section 5.8.7 for a more detailed discussion of such an incentive measure

³¹⁵ see also sections 2.3 and 2.5.1

Diffusion of information on technological development. As a technology develops, information on the technology's development diffuses from researchers and developers to the general public by a pattern indicated by Figure 60.

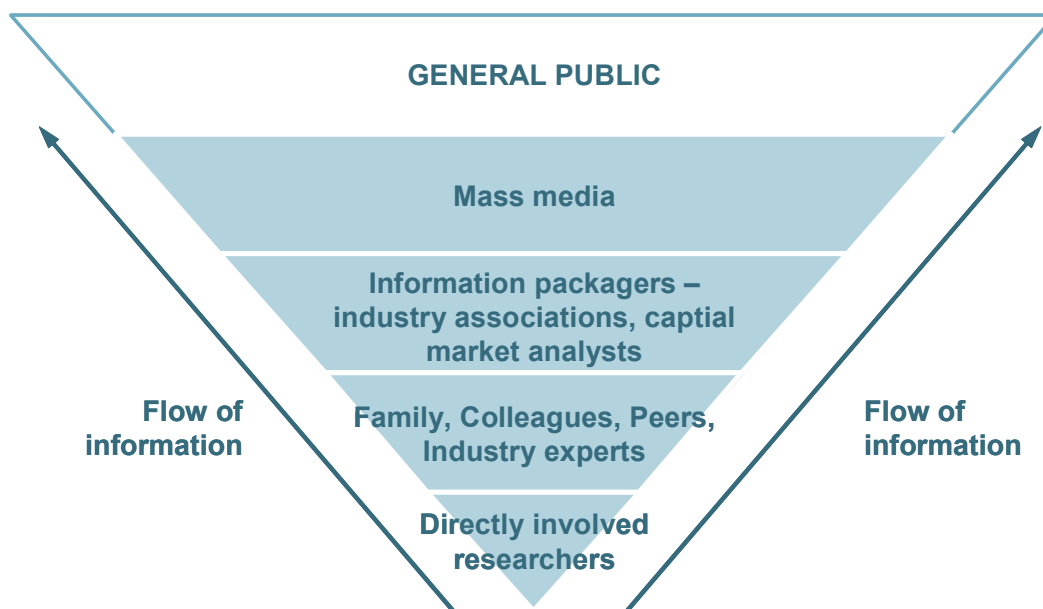


Figure 60: Diffusion of TF information; adapted from (Sherden 1998), p.162

The information on current technological development and commentary on likely future development originates from researchers and developers who are directly occupied with the technological development they report on.

Next, (parts of) the information diffuses to colleagues (professional and private) and peers, including scientists working on the development of competing technologies and various other projects at universities or corporate labs, as well as government-sponsored studies at think-tanks such as the "Rand Corporation". This group also includes industry experts and numerous commercial firms that specialize in an industry.^{316,317} Large commercial enterprises that conduct their own specialized technology intelligence also operate on this level. Table 54 summarizes the most important information sources at this stage.

³¹⁶ see (Sherden 1998), p.163

³¹⁷ For example, Frost & Sullivan, IDC, Dataquest, Forrester, Gartner Group, etc.

Table 54: Most important TF information sources for large commercial enterprises conducting technology intelligence; adapted from (Lichtenthaler 2003), p. 9

Source	Delivery medium
Formal <ul style="list-style-type: none"> • research programs • research articles • patents • conference proceedings • etc. 	<ul style="list-style-type: none"> • journals, newsletters • offline-databases • online-databases • internet-Archives • etc.
Informal <ul style="list-style-type: none"> • competitors • customers • suppliers • start-ups, VC funds • universities • industry institutions • etc. 	<ul style="list-style-type: none"> • regular meetings • memberships • visitations, visits • phone calls • Interviews • casual meetings, small talk • etc.

In the next tier are the TF information packagers, including industry associations and capital market analysts. These organizations cannot afford to process TF information and to develop their own forecasts, but instead they buy them from tier 1 informants.

Finally, the (mass) news media report on technological progress and offer their commentary on future development to the general public in tier 5.

As a conclusion, in order to achieve a high degree of informational efficiency, a TF market design should address the needs of tier 1 and tier 2 information holders, as these segments have access to (1) the earliest and (2) least processed (and most information-rich) information on a specific technological development. Notably, operational consequences for access, incentivitation and interface design (technical design) should be considered.

Stage II – Information analysis

The task balance of information analysis emphasizes opinion formation and pooling rather than information collection, as a majority of information concerning TF development is publicly available and known among peers. Such a task balance also suggests the use of a peer acknowledgement system, as described above.

The complexity for an individual to perform the information analysis is typically high due to the complex, non-trivial process of technology development.³¹⁸ Consequently, the

³¹⁸ see also sections 2.3 and 2.5.1

effort for individuals who do not know about the technological development and need to acquire the information is high. If such individuals are supposed to engage in TF markets as well, access and incentivation design will need to provide considerable incentives that justify the individual effort.

Due to the complex nature of technological development, the likely degree of insight into this process will be partial rather than overall. Such an environment of partial insight suggests the use of a standardized commerce in combination with a combinatorial market mechanism.

Stage III – Information outcome

The solution space for technological developments is typically ambiguous; detailed definitions are necessary to describe a specific outcome of a technological development. As a consequence, security design needs to utilize such detailed definitions to provide clarity about contract (liquidation) values. As a measure to assist security design in this respect, security definition may be scrutinized by extensive peer-review.

Induced by the ambiguity of the solution space for, the outcomes of technological developments suffer from a lack of verifiability. This characteristic suggests the use of an objective third party to verify the outcome of technological developments and to resolve disputes as a result of remaining ambiguity in security design.

To conclude, this evaluation is a generalized characterization of the information environment of technological development. For the coverage of a specific (range of) technological development this evaluation may not be appropriate for all criteria; however, a majority of the generalized evaluation will still apply. Thus, we recommend a reevaluation of the given characterization of the information environment in the course of designing a new TF market.

For comparison, we provide without further discussion an overview of characterizations of different information environments, including sports events, political elections, Nobel Prize awards, public company earnings, in contrast to technology developments (see Table 55).

Table 55: Comparison of information environment characterizations for different events

Criteria	Sports	Political elections	Nobel prize winners	Public companies	Tech developments
0 – Random variable					
<i>Outcome solution space</i>	Game win/draw/loose	Election win/loose, share, seats	Nominees win/loose	Quarterly company earnings	Technology performance or prevalence
<i>Outcome affectability</i>	Low	Low	High	Medium	Low
<i>Duration</i>	Half-year to 1 day	Half-year horizon	Half-year horizon	3 month horizon	Multi-year horizon
I – Information sourcing					
<i>Private / Public information</i>	Public, widely known	Public, widely known	Private (high info asym.)	Public, Private (high info asym.)	Public, <u>not</u> widely known
<i>No. of inputs</i>	Few	Many	Few	Many	Many
<i>Frequency of input changes</i>	Very frequent	Infrequent	Infrequent	Frequent	Infrequent
<i>Geographic spread</i>	Very local	Local	Local (!)	varies by company	Global
<i>Demographic spread</i>	Broad	Broad	Small distinct group	Small distinct group + "coverage" industry	Small distinct group + "coverage" industry
II – Information analysis					
<i>Task balance</i>	Opinion formation	Opinion formation	Info collection	Info collection	Opinion formation
<i>Complexity – effort</i>	Low	Medium	Low	Medium	High
<i>Complexity – degree of insight</i>	Overall insight	Overall insight	Overall insight	Partial insight	Partial insight
III – Information outcome					
<i>Solution space ambiguity</i>	Clear	Clear	Clear	Ambiguous	Ambiguous
<i>Outcome verifiability</i>	Easy	Easy	Easy	Easy	Difficult

5.6 Step 3: Artificial asset design

As the purpose of informative artificial asset markets is to collect and aggregate dispersed public and private information regarding the outcome of some specific future event,³¹⁹ the artificial assets traded in such markets need to be instruments that derive their values from the outcomes of those future events. Formally, instruments are defined by a fundamental and the terms of contract liquidation, that is, contract expiration and the payoff scheme. If the design of single instruments is arranged in way that their date of issuance or maturity and their underlying fundamentals are related to each other, such an arrangement is a design of asset structure.

Table 56: Artificial asset design: key design elements and principle design alternatives

Key design elements	Key design options	Principle design alternatives
Fundamental & Instrument type	<p><i>Fundamental</i></p> <ul style="list-style-type: none"> ○ Technology establishes or de-establishes in the market ○ Technology meets a performance target <p><i>Instrument type</i></p> <ul style="list-style-type: none"> ○ Single compound ○ State contingent 	<ul style="list-style-type: none"> ● single compound security which pays a dividend in proportion to the outcome of the random variable ● complete set of multiple, stage contingent securities the space of possible outcomes is partitioned into a finite number of subsets. Each subset is “tied” to a security. The “winning” security pays off a fixed amount; all other securities pay nothing.
Contract expiration	<ul style="list-style-type: none"> ● Time-driven (end-of-period) ● Event-driven 	
Payoff	<ul style="list-style-type: none"> ● Function <ul style="list-style-type: none"> ○ Binary ○ Linear ○ Other 	
Asset structure		<ul style="list-style-type: none"> ● Event-specific commerce ● Standardized commerce

An overview of these key design elements, their corresponding design options and the principle design alternatives is given by Table 56. In the subsequent sections each of the key design elements and the final principle design are discussed and developed for their application to a TF information market.

³¹⁹ see also section 3.3

5.6.1 Instrument type

A four step process is provided for choosing the type of instrument for the artificial asset, see Figure 61. This process comprises steps to establish the random variable as security fundamental, to establish the outcome solution space, to select the security state space, and to select the instrument type. Subsequently, we provide a discussion of these tasks.

First, the security fundamental needs to be established. The fundamental consists of some statistic or set of statistics which can be objectively measured; the statistic represents the random variable that is subject to the forecast. For example, the fundamental for a technological development may be the year in which the technology reaches a certain performance. The fundamental for a sports game may be the result of the game.

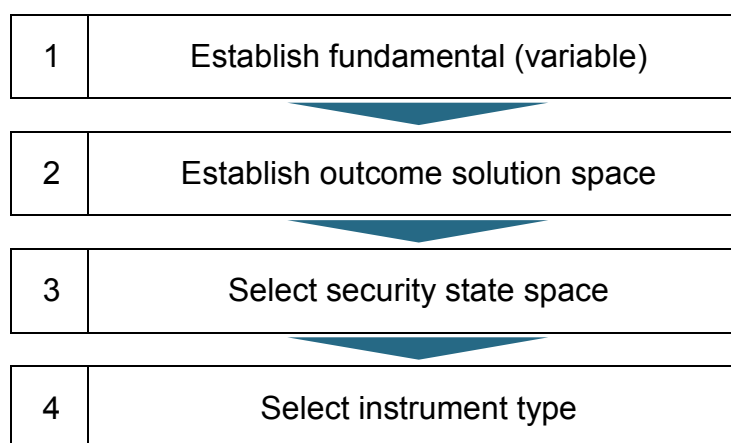


Figure 61: Key steps in instrument type design

Consequently, the outcome solution space of the fundamental needs to be established. The outcome solution space describes the possible outcomes of the fundamental, the range of possible values it may contain. The solution space may be binary, discrete or continuous. For example, the solution space for the outcome of a soccer match can be described as "Team A wins/Team B loses", "Team A loses/Team B wins", "Draw", or "Game cancelled". Obviously, such a solution space is discrete.

Next, as the outcome solution space has been established, it needs to be mapped against the desired security state space. Same as the outcome solution space, the security state space may be binary, discrete or continuous.

Outcome solution space		Security state space
binary	→	binary
discrete	→	discrete
continuous	→	continuous

Figure 62: Mapping of Outcome solution space to Security state space

In general, the format of the security state space will be the same or of lower order than the outcome solution space, see Figure 62. However, for reasons of e.g. scale or resolution some other mapping may be chosen. An important consideration for design must be if traders are sufficiently able to understand and discern the chosen mapping. Table 58 illustrates the mappings for three examples. Ultimately, the selection of a security state space is a matter of choice.

However, in an AAM of standardized commerce with a combinatorial trade mechanism³²⁰, security state space design should consider a set of recommendations; these recommendations are summarized in Table 57.

Table 57: Security state space design recommendations for a market design using a standardized commerce/combinatorial trade mechanism

Base securities should feature a 3-state security space: each state representing a rise, a stagnation, or a decline by X points in the underlying fundamental – because:

- by defining the security with a discrete number of states, rather than as a continuous item, it is much easier to construct composite securities from different states of the basic securities
- the very broad range of conceivable paths for a data series need not be considered explicitly, only the period-to-period movement
- if a participant is interested in a path, then an intersection that explicitly represents the path can be constructed from these states

As the security state space has been established, the final step is to select the instrument type. Two principle options present themselves, a single compound security

³²⁰ In such a principle market model, a standardized commerce uses base securities that track basic fundamentals that drive events. A combinatorial trade mechanism allows traders to express their special, partial insight by constructing composite securities from the standardized base securities. See also sections 5.6.4 and 5.7.4

or a contract set. A mapping of which instrument is able to cover which security state space is illustrated in Figure 63.

Table 58: Examples of mappings of Outcome solution space to Security state space for different events

Event	Possible outcomes	Outcome solution space	Security state space
Sports playoff game	win/loose	binary	binary
Year in which technology X will establish?	2005, 2006, ..., 2020+	discrete	discrete
Public company earnings	Between 1,0 Mrd. and 1,6 Mrd	continuous	continuous

A single compound security covers the space of possible outcomes with a single contract; thus, such an instrument type has a continuous state space by definition. For example, by covering the continuous range of a public company's earnings between USD 1,0 Billion and 1,6 Billion, a single compound security may have a value that corresponds to USD 1,0 Billion and 1,6 Billion.

However, the continuous state space may be transformed into a discrete or binary state space by a partitioning into the respective scale. For example, by covering a soccer playoff game, a single compound security value of 0 to 50 units may correspond to "Team A wins/Team B loses" and a security value of 51 to 100 units accordingly to "Team A loses/Team B wins".

Hence, a single compound security may be chosen for any of the three principle security state space types.

Laboratory experiments have shown that single compound securities have had performance difficulties.³²¹ Plott and Sunder (1988) consequently recommend not to use single compound securities but to choose the alternative instrument type instead.

Security state space	Instrument type		
binary	single compound security		contract set
discrete			
continuous			

Figure 63: Mapping of security state space to instrument type

³²¹ see (Plott and Sunder 1988)

In contrast, a contract set covers the space of possible outcomes with multiple contracts; the coverage of the outcome solution space is achieved by associating each discrete outcome with a separate security. Thus, such an instrument type has a discrete state space by definition. For example, by covering whether a technology X may establish within 2005 to 2020, each year would be represented by an own security.

Hence, a contract set may be chosen for a binary or a discrete security state space. For a contract set to cover a continuous outcome solution space, the solution space would need to be transformed into a discrete security state space first.

Laboratory experiments have demonstrated that contract sets have consistently performed well as instrument type.³²² Plott and Chen (1998) consequently recommend employing contract sets as instrument type.

Subsequently, we review the application of instrument type selection to TF markets.

Application to TF markets

We apply the four step-process illustrated in Figure 61 to explore the type of instrument needed for TF markets. Specifically, these steps are to establish the random variable as security fundamental, to establish the outcome solution space, to select the security state space, and to select the instrument type. Subsequently, we provide a discussion of these tasks.

As suggested above, the first step in selecting the appropriate security instrument is to establish the fundamental, the random variable for TF markets. In technological forecasting there is not only one, but a range of random variables that may be of interest. A specific interest will also suggest a specific fundamental. However, in section 2.3 we have established as common forecast needs either one of the following:

- the event of when a new technology or the corresponding new application domain establishes
- the position of a technology's performance plateau (at which performance? when will it be reached?)

³²² see (Plott 2000)

- the event of when an established technology will be superseded

The identified information needs suggest either (1) a time or (2) a performance level as possible fundamentals for TF markets. We transform the information needs into forecasting questions and develop for each a continuous/discrete and a binary variable format – see Table 59 and Table 60.

Table 59: Instrument type design: application to TF markets – Time-based fundamentals in continuous/discrete and binary format

Continuous/discrete format	Binary format
When will technology A establish?	Will technology A establish before/after time t ?
When will technology B reach its performance plateau?	Will technology B reach its performance plateau before/after time t ?
When will technology C be superseded?	Will technology C be superseded before/after time t ?

Table 60: Instrument type design: application to TF markets – Performance-based fundamentals in continuous/discrete and binary format

Continuous/discrete format	Binary format
At which performance will technology A establish?	Will technology A establish below/above performance p ?
At which performance will technology B reach its performance plateau?	Will technology B reach its performance plateau below/above performance p ?
At which performance will technology C be superseded?	Will technology C be superseded below/above performance p ?

As noted above, the choice of a fundamental and its outcome solution space depends on the specific need and interest. As both are established, the security state space can be selected.

However, to conclude, we advocate the use of a discrete outcome solution space and a discrete security state space for a range of reasons. Among those, a discrete solution space present traders with more than one choice (as a binary space), but also limits the choice to a range of discrete possible outcomes. Furthermore, a discrete state space facilitates the use of a contract set as instrument type. Thus, we also advocate to follow the recommendation by Plott and Chen (1998) to utilize contract sets as instrument type for TF markets.

A note on contract ambiguity

The solution space for technological developments is typically ambiguous; detailed definitions are necessary to describe a specific outcome of a technological development. For example, the description of possible outcomes for a technology to establish as "Technology establishes", "Technology does not establish" is rather ambiguous. How is "establishment" defined? Different parties are likely to disagree on what they perceive as "established" technology.

As we review the suggested choice of TF market fundamentals (Table 59 and Table 60) for ambiguity, we identify a range of uncertainties which we summarize in Table 61.

Table 61: Instrument type design: application to TF markets – Typical uncertainties in TF market fundamentals

Uncertainties	Sources of uncertainty
"technology A, B, C"	<ul style="list-style-type: none"> • Which criteria separate a technology being A,B,C from not being A,B,C
"to establish"	<ul style="list-style-type: none"> • Which criteria separate an established technology from a technology that has not yet established?
"to reach the performance plateau"	<ul style="list-style-type: none"> • Which criteria separate a technology that has reached its PP from a technology that has not?
"to be superseded"	<ul style="list-style-type: none"> • Which criteria separate a technology that is superseded from a technology that is not?

To trade, an individual providing information about the outcome of an event must understand how the various outcomes are defined – moreover, all traders should share the same understanding. As a consequence, security design needs to utilize such detailed definitions to provide clarity about contract validation and liquidation value. Table 62 summarizes a set of suggestions for resolving the identified uncertainties for TF markets.

Table 62: Instrument type design: application to TF markets – Resolution of typical uncertainties in TF market fundamentals

Uncertainties	Suggestions for resolution
"technology A, B, C"	<ul style="list-style-type: none"> • criteria that separates a technology from being A,B,C from not being A,B,C
"to establish"	<ul style="list-style-type: none"> • per anno shipment of >X units (national, global) • (market share of >X%)

	<ul style="list-style-type: none"> • used by a number of industry leaders
"to reach the performance plateau"	<ul style="list-style-type: none"> • total performance increase <3% over 4 consecutive yrs
"to be superseded"	<ul style="list-style-type: none"> • market position drops from leading to second • (market share of <X%) • per anno shipment of <X units (national, global) • discontinued by set of industry leaders in favor of competitor technology

For example, to resolve the uncertainty of a fundamental covering if a technology will establish, "technology establishment" may be specified as an annual global shipment of 100.000 new units of a class of device utilizing the technology of interest.

To support the clarity of a security definition and to resolve any remaining uncertainties, security definition proposals may be scrutinized by extensive peer-review or by some similar means.

5.6.2 Expiration

By definition, the type of security instrument typically used in artificial asset markets pays off at a future point in time a certain value corresponding to a specific event outcome.³²³ Thus, security contracts have an expiration date at which their liquidation values are determined, paid off, and contracts are liquidated.

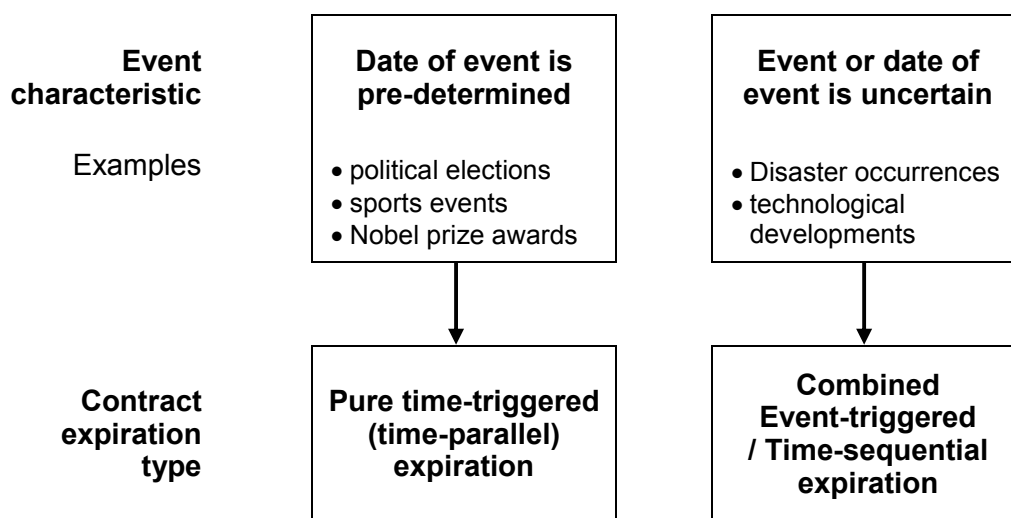


Figure 64: Selection of contract expiration type

The terms of contract expiration depend on the type of event covered by the security, see Figure 64. Two principle design alternatives present themselves for contract expiration, a purely time-triggered or time-parallel expiration and a combined event-triggered/time-sequential expiration. Subsequently, the design alternatives and their corresponding key characteristics are discussed – see Table 63 for a summary.

Time triggered expiration. If the event occurrence itself and the time of the occurrence are pre-determined, a purely time-triggered or time-parallel expiration contract type is appropriate. Pre-determined events are, for example, political elections, sports events, and Nobel Prize awards; political elections are held on previously specified dates. Sports events are scheduled. Nobel Prize winners are announced every year in October.

³²³ see, for example, the artificial asset markets described in sections 3.5 and 3.6

Table 63: Contract expiration design: overview and characterization

Principle design alternatives	
<p>Purely time-triggered</p> <ul style="list-style-type: none"> • for coverage of events with pre-determined occurrence • typically used to cover different outcomes of the event • all contracts covering the same event are issued at a common time • all contracts covering the same event expire at a common time – contracts have a common expiration time • requires <u>no</u> ongoing contract maintenance 	<p>Combined event-/time-triggered</p> <ul style="list-style-type: none"> • for coverage of events of uncertain occurrence • typically used to cover different occurrence times for an uncertain event (a specific outcome) • all contracts covering the same uncertain event may be issued either <ul style="list-style-type: none"> – at the same time – sequentially following an interval until the event occurs or coverage is terminated • all contracts covering the same uncertain event expire sequentially following an interval until the event occurs or coverage is terminated – contracts have the different expiration dates • requires ongoing contract maintenance <ul style="list-style-type: none"> – periodic review if event has occurred – periodic new contract issuance

In an asset structure which uses a time triggered expiration, all contracts covering the same event are issued at a common time and they expire at another common time. Thus, contracts of such an expiration type have a common expiration time.

In addition, contracts of this type need no ongoing contract maintenance, that is, they need to be reviewed for expiration only once and no periodic new contract issuance is necessary.

Typically, such a contract design is used by a set of multiple contracts to cover different outcomes of the same event.

Examples of AAMs that feature such a contract expiration type include the markets TU/Siemens, CalTech/HP Sales, IEM, HSX, FX, Tradesports, and Newsfutures.³²⁴

Combined event-/time-triggered expiration. If the occurrence itself and the occurrence time of the event are uncertain, a combined event-triggered/time-sequential expiration contract type is the appropriate choice. Uncertain events are, for example,

³²⁴ see sections 3.5 and 3.6

disaster occurrences (e.g., avalanches, floods, etc.), political events (e.g., resign of a government), or technological developments (e.g., medical nanorobots).

In an asset structure which uses a combined event-/time-triggered expiration, the contracts covering the same event expire sequentially by some interval (see FX, middle) until the event occurs or until the coverage is terminated and no (new) contract is issued that would cover a further time period. Thus, the contracts feature different expiration times, separated by a chosen time interval.

The issuance for contracts of this type may be done at a common time or they may be issued sequentially as the contract of the previous period has expired (see FX, right).

Furthermore, contracts of this type need considerable ongoing contract maintenance, that is, they need to be reviewed for expiration in every interval (to verify whether the event has or has not occurred) and new contracts need to be issued periodically until the event has occurred.

Typically, such a contract design is used by a set of multiple contracts to cover different possible occurrence times for an uncertain event.

Examples of AAMs that feature such a contract expiration type include the markets Tradesports and HSX.³²⁵

Subsequently, we review the application of contract expiration design to TF markets.

Application to TF markets

We apply contract expiration design to TF markets. As noted above, technological developments are events of uncertain occurrence.³²⁶ Thus, coverage of this type of event suggests a combined event-/time-triggered contract expiration.

We review the security fundamentals for TF markets suggested in the previous section and develop the corresponding contract expiration designs. See Table 64 and Table 65 for a summary for time-based and performance-based fundamentals, respectively.

Table 64: Contract expiration design: application to TF markets – Time-based fundamentals in continuous/discrete and binary variable format

TF market fundamentals	Contract expiration design
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³²⁵ see sections 3.5 and 3.6

³²⁶ see also sections 2.3, 2.5.1, and 5.5

<i>Continuous/discrete variable format</i>	
When will technology A establish?	Combined event-/time-triggered <i>Event expiration criteria:</i> <ul style="list-style-type: none"> • as defined by forecast question (left) <i>Time expiration criteria:</i> <ul style="list-style-type: none"> • time range covering likely event occurrence
When will technology B reach its performance plateau (PP)?	
When will technology C be superseded?	
<i>Binary variable format</i>	
Will technology A establish before/after time t?	Combined event-/time-triggered <i>Event expiration criteria:</i> <ul style="list-style-type: none"> • as defined by forecast question (left) <i>Time expiration criteria:</i> <ul style="list-style-type: none"> • any time threshold point of interest
Will technology B reach its performance plateau before/after time t?	
Will technology C be superseded before/after time t?	

Table 65: Contract expiration design: application to TF markets – performance--based fundamentals in continuous/discrete and binary variable format

TF market fundamentals	Contract expiration design
<i>Continuous/discrete variable format</i>	
At which performance will technology A establish?	Combined event-/time-triggered <i>Event expiration criteria:</i> <ul style="list-style-type: none"> • as defined by forecast question (left) <i>Time expiration criteria:</i> <ul style="list-style-type: none"> • end point of time range of likely occurrence
At which performance will technology B reach its performance plateau?	
At which performance will technology C be superseded?	
<i>Binary variable format</i>	
Will technology A establish below/above performance p?	Combined event-/time-triggered <i>Event expiration criteria:</i> <ul style="list-style-type: none"> • as defined by forecast question (left) <i>Time expiration criteria:</i> <ul style="list-style-type: none"> • end point of time range of likely occurrence
Will technology B reach its performance plateau below/above performance p?	
Will technology C be superseded below/above performance p?	

For the suggested time-based TF market fundamentals of the continuous/discrete variable format the event expiration criteria is defined by the definition of the fundamental itself, whereas the time expiration criteria is defined by arbitrarily selected time range that most likely covers the time of event occurrence.

For TF market fundamentals of the binary variable format the time expiration criteria differs from that of the continuous/discrete variable format by a setting of any time threshold point of interest.

For the suggested performance-based TF market fundamentals of the continuous/discrete variable format the event expiration criteria is again defined by the definition of the fundamental itself, whereas the time expiration criteria is arbitrarily set at a point in time at the end of the time range that most likely covers the time of event occurrence.

The contract expiration criteria for TF market fundamentals of the binary variable format do not differ from the design for the continuous/discrete variable format.

5.6.3 Payoff function

As securities are issued, the sellers guarantee a certain payoff at security expiration, whereby the payoff is a function of the final outcome.³²⁷ By this mechanism the trading value of securities should at any time reflect their liquidation values.³²⁸

Three principle options present themselves for a security payoff design, a binary payoff function, a linear payoff function, and some other type of payoff function. Table 93 summarizes the characteristics of the three principle design options.

Table 66: Contract payoff design: overview and characterization

Principle design alternatives		
Binary	Linear	Other
<ul style="list-style-type: none"> • pays / liquidation value is <ul style="list-style-type: none"> ○ a specific fixed amount for a security representing the final outcome ○ and 0 for all other securities 	<ul style="list-style-type: none"> • pays / liquidation value is <ul style="list-style-type: none"> ○ a multiple of the final outcome • typically used to cover outcomes measured in % 	<ul style="list-style-type: none"> • payout / liquidation value is determined by some other arbitrary function, e.g. <ul style="list-style-type: none"> ○ pays out a specific fixed amount for each different security state

Subsequently, the design options and their corresponding key characteristics are introduced and discussed.

Table 67: Contract payoff design: overview and characterization

	Binary payoff	Linear payoff	Other payoff

³²⁷ see section 5.1

³²⁸ see sections 5.1 and 3.1

single contract asset structure	Binary solution space	Continuous solution space	Discrete solution space
multiple contract asset structure	Discrete solution space	N / A	N / A

Binary payoff function.

If the event occurrence itself and the time of the occurrence are pre-determined, a purely time-triggered or time-parallel expiration contract type is appropriate. Pre-determined events are, for example, political elections, sports events, and Nobel Prize awards; political elections are held on previously specified dates. Sports events are scheduled. Nobel Prize winners are announced every year in October.

By employing a binary payoff function each security will have a liquidation value that is binary to the fundamental variable at contract expiration (Spann 2002).

$$d_{i,T} = \begin{cases} \nu & \text{if the fundamental variable expires at a pre - defined value} \\ 0 & \text{if else than above} \end{cases} \quad (\nu > 0, i \in I)$$

$d_{i,T}$ payoff for market i at time T

ν absolute payoff

The combination of multiple, state contingent contracts with a binary payoff function is known as an Arrow-Debreu security: An instrument with a fixed payout of one unit in a specified state and no payout in other states (Equitrend 2004). Another frequently used term for such an instrument is a "Winner-takes-all" contract set (Forsythe, Nelson et al. 1992).

Linear

By employing a linear payoff function each security will have a liquidation value that is linear to the fundamental variable at contract expiration (Spann 2002).

$$d_{i,T} = \rho \cdot Z_{i,T} \quad (\rho > 0, i \in I)$$

$d_{i,T}$ payoff for market i at time T

- ρ payoff multiplier
- $Z_{i,T}$ value of the fundamental for market i at time T

Other

Other payoff functions include logarithmic payoff, dividends, or options.

In principle, any arbitrary payoff function may be utilized. But as the payoff function becomes more complex, it becomes more difficult for traders to understand – and may ultimately lead to less price efficiency by deterring traders from trading or inducing misperceptions about payoff (Spann 2002).

Correspondingly, binary and linear payoff functions are the most common payoff functions among implemented experimental markets.

5.6.4 Asset structure

If the design of single instruments is arranged in way that their date of issuance or maturity and their underlying fundamentals are related to each other, this arrangement is a design of asset structure. The principle design alternatives of asset structure design are summarized by Table 68.

Table 68: Asset structure design: Overview and characterization

Principle design alternatives	
<p>Event-specific commerce</p> <ul style="list-style-type: none"> • a security that is typically unrelated to other securities issued parallel or serial • to track a selected event • typically confronted with a high, if not infinite, number of potential events • may serve as a basis to trade on correlation of events 	<p>Standardized commerce</p> <ul style="list-style-type: none"> • a series of securities, identical except for their for their date of issuance and maturity which are synchronized to sequentially cover an extended time horizon without leaving any time gaps • to track fundamentals that drive a range of specific events • typically serves as a basis to trade on a correlation of fundamentals (>> combinatorial trade)

Subsequently, both design alternatives are briefly discussed.

Event-specific commerce. An event-specific asset structure covers specific events, the outcomes of which can be enumerated as a set of mutually exclusive states that span all possible outcomes of the event. For example, a security set covering the event of an artificial kidney proving successful in the year 2005 would need to cover the outcomes "yes" and "no".

Examples of AAMs that feature such an event-specific asset structure design include the markets TU Vienna/Siemens, HP sales, IEM, HSX, FX, TradeSports, Newsfutures, and Economic Derivatives.³²⁹

Standardized commerce. An alternative option is to standardize a futures commerce by establishing multiple security series that track some fundamental issues. These fundamental issues must be represented by data indices that are somewhat objectively measurable. Each security series is composed by a string of securities that are identical except for their date of issuance and maturity which are synchronized to sequentially cover an extended time horizon without leaving any time gaps; see Figure 65 for an illustration. The securities covering the different data indices may be defined as single compound securities or as multiple state-securities; see section 5.6.1 for the definition and details.

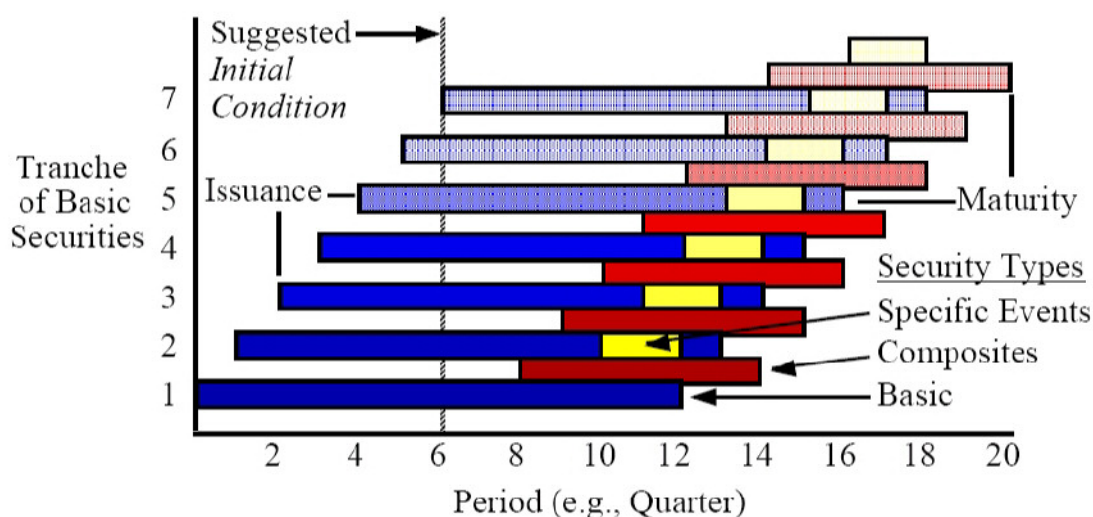


Figure 65: Illustration of a standardized asset structure (NetExchange 2002), p.4

As an example, in order to forecast the share of residential homes using solar energy for space heating and hot water, three security series may track as fundamental issues (i) the price of fossil fuel, (ii) the performance of solar technology for a given cost of

³²⁹ see sections 3.5 and 3.6

installation and operation, and (iii) the amount of capital spent on R&D for solar home-heating technology.³³⁰ These fundamental issues must be expressed as data indices; for example, the price of fossil fuel may be expressed in terms of its 2005 average price level. Finally, the security series covering the data indices development may be defined as three state-securities, indicating for a given time period a data index increase by 10 points, a decrease by 10 points, or a stable development in-between. Currently, the only example of an AAM we know of that featured such a standardized asset structure design was the Policy Analysis Market; this market only existed as a prototype until it was abandoned due to political reasons.³³¹

Next, we examine the suitability of both principle asset structures for TF markets.

Application to TF markets

In general, the principle asset structure is largely driven by the market purpose and objectives under consideration of the information environment. Both alternatives are viable options, as summarized by Table 69.

Whereas an event-specific commerce may cover both, selected events across different technological fields (automotive, telecommunications, etc.) and within a specific technological field (e.g. biotechnology), a standardized commerce is more appropriate for the coverage of a specific technological field.

The market efficiency of an event-specific commerce is, in general, non-discernible to a standardized commerce. However, the attractiveness of a simple and clear event-specific nature may, over time, be more than offset by the fading appeal due to the infrequent security renewal. The opposite is true for a standardized commerce.

In terms of financial cost and risk an event-specific commerce is likely to cost less than a standardized commerce. Whereas the latter requires the creation and maintenance of data indices by a trusted (third) party, an event-specific commerce' maintenance effort is more limited.

³³⁰ based on example given by (Martino 1993); p.146

³³¹ see (Wolfers and Zitzewitz 2004), p.1 and (NetExchange 2003a)

Table 69: Principle asset structure: Application to TF markets

Design alternative.	Market efficiency	Financial cost/risk to operator
<i>Event-specific commerce</i>	<p><i>Non-discriminable / Lower</i></p> <ul style="list-style-type: none"> • may cover selected events across different technological fields (automotive, telecommunications, etc.) • may cover selected events within a specific technological field (e.g. biotechnology) • higher base liquidity due to attractiveness of simple and clear event-specific nature • but infrequent security renewal may induce less activity and, thus, lower total liquidity 	<p><i>Lower (relatively)</i></p> <ul style="list-style-type: none"> • maturity maintenance typically requires relatively less effort – but if frequent renewal of securities is required (typically non-automatable), this incurs higher total costs
<i>Standardized commerce</i>	<p><i>Non-discriminable / Higher</i></p> <ul style="list-style-type: none"> • rather for coverage of a specific technological field (or industry) • lower base liquidity due to lower attractiveness of abstract nature • but frequent security renewal may induce more activity and, thus, higher total liquidity 	<p><i>Higher (relatively)</i></p> <ul style="list-style-type: none"> • requires creation and maintenance of data indices by a trusted (third) party • required periodic maturity inspection requires little ongoing effort (automatable) • extensive periodic renewal of securities (typically automatable) incurs less relative cost

5.7 Step 4: Trading mechanism design

To trade, traders must coordinate on the instruments they will trade as well as on when to trade those instruments. This coordination is facilitated by the trading mechanism of the exchange. It affects market characteristics, such as liquidity, transaction costs, informative prices, volatility, trading profits. However, the trading mechanism ultimately determines what a trader can do and what they can know. It therefore affects trading strategies, the power relationships among different types of traders, and ultimately trader profitability. Thus, the trading mechanism refers to the set of rules governing the trading process. As there are many trading mechanism design choices, a discussion of all these choices is beyond the scope of this thesis. However, we discuss the key

design elements that are most relevant for the design of artificial asset markets. An overview of these key design elements and the respective principle design alternatives is given in Table 70 below.

Table 70: Trading mechanism design: key design elements and principle design alternatives

Key design elements	Principle design alternatives
Asset emission mechanism	<ul style="list-style-type: none"> • IPO style emission • Unit portfolio emission
Core trading mechanism	<ul style="list-style-type: none"> • Continuous double auction (CDA) • Continuous double auction with market maker (CDAwMM) • Market scoring rule (MSR) • Dynamic pari-mutuel market (DPM)
Trading rules	<ul style="list-style-type: none"> • Trading hours • Order types • Short selling • Caps
Combinatorial trade	<ul style="list-style-type: none"> • Simple or Non-combinatorial trade • Combinatorial trade

When trading instruments are sold to traders for the first time, the asset emission mechanism design determines how the instruments are emitted to the market. In principle, there are two mechanisms, an IPO-style emission and a unit portfolio emission.

The core trading mechanism design determines how the flows of demand (buy orders) and supply (sell orders) interact to produce transaction volume and transaction prices. Markets use many different types of trading systems based on several characteristics. Beyond the core trading mechanism design, many other trade procedures are necessary to help traders coordinate on which assets they will trade and when to trade those assets. Thus, trading rules are necessary for organizing the end-to-end trading process.

The final key design element addresses that it is common that traders have composite interests. If the trader is able to express this conditional interest through a single trade, such a trade is a combinatorial trade.

In the subsequent sections each of the key design elements and the corresponding principle design alternatives are discussed and evaluated for their application to a TF information market.

5.7.1 Asset emission mechanism design

When trading instruments are sold to traders for the first time, the instruments are emitted to the market. In principle, there are two mechanisms how new instruments are emitted to the market, an IPO-style emission and a unit portfolio emission. Table 44 gives an overview of both emission mechanism designs.

Table 71: Primary market mechanism design: principle design alternatives and key characteristics

Principle design alternatives	Key characteristics
IPO-style emission	<ul style="list-style-type: none"> • all instruments (a specified volume) are sold at a set price (range) at market initiation • number of circulated instruments is fixed • in net supply, that is, the issuer raises money • subsequent trading is only possible between traders, not between issuer and traders
Unit portfolio emission	<ul style="list-style-type: none"> • instruments can be continuously sold and redeemed as part of a complete contract set at a price equivalent to the set's fixed aggregate payoff (>>unit portfolio) • in zero net supply, that is, for every long position there is a short position • number of outstanding instruments is variable • trading is either possible in unit portfolios (with issuer) or in single contracts (with other traders)

Subsequently, the principle design alternatives and their corresponding key characteristics are introduced and discussed.

IPO-style emission. This emission mechanism distributes at market initiation a limited volume of securities at a set price to investors. In such a mechanism instruments are supplied in zero net supply as common in financial markets where the primary goal is to raise money from investors. Investors who do not acquire securities at emission have to turn to other traders and wait for them to sell the desired security.

The initial give-away price can be set "IPO-style" – in reference to an Initial Public Offering (IPO) common in financial markets – by producing a price estimate by a somewhat arbitrary valuation method.

Another method of setting the initial price is by employing an auction (see also section 5.1). Of course there are many variations of auctions: e.g., in a "Dutch" auction, bids

are accepted starting with the highest and moving down until all available securities are sold. All winning bidders then pay the lowest successful bid price. An "English" auction begins with the lowest acceptable price – the reserve price – and proceeds to solicit successively higher bids from the bidders until no one will increase the bid. Acceptance of bids start with the highest and move down until all available securities are sold. All winning bidders then pay the lowest successful bid price.

Unit portfolio emission. The alternative emission mechanism design is to offer complete contract sets (portfolios) at a fixed price at any time. Thus, contracts are issued by means of "unit portfolios." A unit portfolio consists of one of each of the contracts in the market and has a price equal to the guaranteed aggregate payoff of this contract set. In this way, the issuer neither gains nor loses money by issuing contracts; instruments are supplied in zero net supply.

Contracts are placed in circulation by traders through the purchase of these unit portfolios from the market institution. Similarly, contracts can be withdrawn from circulation through the sale of a unit portfolio to the market institution. The price at which these unit portfolios can be purchased or redeemed is determined by the sum of the liquidation values of all the contracts in the portfolio. Note that because contracts can be placed into or removed from circulation only by the purchase and sale of unit portfolios, there will always be an equal number of each contract in a set in circulation at any point in time.

For example, a unit portfolio for month m in the market "When will technology X establish?" consists of one of each of the four contracts ≤ 2005 , 2006, 2007 and ≥ 2008 . The purchase or sale price of each of these unit portfolios is 100 currency units, which equals the sum of the liquidation values for one share each of ≤ 2005 , 2006, 2007 and ≥ 2008 , regardless of which has the highest return in month m .

Across the participants in an information market, the securities constitute a zero-sum game. The securities have monetary value only because the traders have invested in them, investments which each trader knows will, with certainty, neither grow nor shrink across the whole system, but which may grow or shrink for each trader depending on the trades each trader makes.

Next, we evaluate the principle design alternatives of the emission mechanism for their utilization in a TF.

Application to TF markets

In terms of market efficiency, an IPO-style emission mechanism may be less efficient as it requires a broad trader base at a specific point in time – at emission – to distribute the securities among many information providers and to prevent few traders from controlling all securities. Moreover, if traders did not acquire shares during the emission they may have to wait until other traders are willing to sell, a property that further decreases liquidity.

The alternative mechanism design develops market activity and liquidity as traders join the market. This mechanism provides the market with continuous liquidity in unit portfolios, so thereby, traders do not have to wait for other traders to sell – which represents a significant advantage.

See Table 88 for a summary of our evaluation of the application of the emission mechanism design alternatives to TF markets.

Table 72: Design of emission mechanism design: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>IPO-style emission</i>	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • requires a broad trader base at emission to prevent few traders from controlling all securities • traders may have to wait until other traders are willing to sell 	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • can be used to raise money for artificial assets with open value • however, such a money-raising design may be exposed to higher legal and thus financial risk
<i>Unit portfolio emission</i>	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • the market and market liquidity develops as traders join the market • provides continuous liquidity • traders do not have to wait for other traders to sell – traders can broaden the market offering 	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • is supplied in zero net supply, that is, the market operator does not raise money by selling unit portfolios

In terms of financial cost and risk an IPO-style emission mechanism may provide the advantage of raising money for artificial assets with open value. However, such a money-raising design may be exposed to higher legal and thus financial risk. In contrast, the alternative design mechanism supplies unit portfolios that come to the

market in zero net supply. Thus, there is no financial imbalance in this emission transaction that would expose the market operator to legal or financial risk.

To conclude, a unit portfolio emission appears better suited for application in TF markets, as it provides continuous liquidity and does not expose the market operator to financial risk.

5.7.2 Core trading mechanism design

In this section we provide a brief introduction to trading mechanism characteristics first, before we discuss the principle design alternatives which come as a package of the introduced characteristics.

Brief introduction to trading mechanism characteristics

Trading or pricing systems determine how the flows of demand (buy orders) and supply (sell orders) interact to produce transaction volume and transaction prices (Smart 2003). Markets/exchanges use many different types of trading systems based on several characteristics, see Table 73.

Table 73: Secondary market mechanism design: Trading/pricing system characteristics – design alternatives

No.	Alternative 1		Alternative 2
1.	Floor trading (open outcry)	vs.	Electronic trading (screen based)
2.	Batch / Periodic / Call	vs.	Continuous
3.	Auction	vs.	Dealer
4.	Order-driven	vs.	Quote-driven
5.	Non-automated	vs.	Automated
6.	Open / public order book	vs.	Closed order book

Subsequently, we provide a brief description of these characteristics.

Floor trading - open outcry: Trading occurs at a central, physical location and with open outcry traders who signal their buy/sell orders by shouting and signaling.

Electronic trading - screen based: Trading occurs decentralized using an electronic/computer system where traders enter their orders and receive information about buy and sell orders.

Batch/periodic/call (auction) markets: Collects subscriptions for desired price-quantity combinations to buy and sell. Periodic transactions at the point of intersection between demand and supply curves.

Call markets allow traders to avoid frequent monitoring and allow orders to accumulate giving participants a higher number of contra-side orders when the deals are made. But they require participants to be more precise about their own estimates, a comparative judgment is not enough.

Continuous markets: Continuous flow of orders. Transactions take place any time when demand from buyers meets supply from sellers.

Continuous markets sometimes require participants to monitor markets often to see if prices have changed (this can often be avoided with limit orders), but allow rapid predictable trade execution when one does pay attention and the market is thick enough. Also participants need only consider whether their estimate is higher or lower than a current available price in order to decide whether to trade or not.

Auction markets: Buyers and sellers trade with each other directly (usually implicitly through the intermediation of the exchange) and their buy and sell orders determine transaction prices.

Dealer markets: Buyers and sellers trade with a dealer who acts as intermediary in both buy and sell transactions and the dealer sets buy (bid) and sell (ask) prices.

Order-driven markets: Buyers and sellers specify the quantity/volume of their order (and normally a limit to the maximum buy or minimum sell price, limit orders). Transactions occur when demand and supply cross. Quantity of orders is predetermined, prices are uncertain.

Quote-driven markets: Buyers and sellers specify the buy (bid) and sell (ask) price (normally for a standard quantity/volume order) at which they are willing to trade. Opposite parties select the quantity they desire to sell or buy at specified bid and ask prices. Price of orders is predetermined, quantities are uncertain.

Non-automated: or manual markets allow a specialist/market-maker to handle and manipulate orders to facilitate an “orderly” market.

Automated: A computer system collects all buy and sell orders and determines automatically all transactions, using a predetermined rulebook.

Open (public) order book: Unfulfilled (limit) orders are visible to all parties, who may therefore adjust their own orders. Order flows may signal new information, or available limit orders may affect the price of your own buy/sell order.

Closed order book: only the specialist/market-maker can see remaining orders in the system.

As we have introduced some basic characteristics of trading mechanisms we proceed to discuss the alternatives for trading mechanism design.

Principle trading mechanism designs

There are four principle design alternatives for the core trading mechanism of an artificial asset market. Table 74 provides an overview with a brief description. Subsequently, we introduce and discuss the principle design alternatives and their corresponding key characteristics.

Continuous double auction (CDA). A CDA constantly matches orders to buy an asset with orders to sell. If at any time one party is willing to buy one unit of the asset at a bid price of p_{bid} , while another party is willing to sell one unit of the asset at an ask price of p_{ask} , and p_{bid} is greater than or equal to p_{ask} , then the two parties transact (at some price between p_{bid} and p_{ask}). If the highest bid price is less than the lowest ask price, then no transactions occur.

In a CDA, the bid and ask prices rapidly change as new information arrives and traders reassess the value of the asset. Since the auctioneer only matches willing bidders, the auctioneer takes on no risk. However, buyers can only buy as many shares as sellers are willing to sell; for any transaction to occur there must be a counterparty on the other side willing to accept the trade.

As a result, when few traders participate in a CDA, it may become illiquid, meaning that not much trading activity occurs. The spread between the highest bid price and the lowest ask price may be very large, or one or both queues may be completely empty, discouraging trading. Hence, a successful CDA must overcome a chicken-and-egg problem: traders are attracted to liquid markets, but liquid markets require a large number of traders.

Markets operating with a CDA mechanism have been shown to be good enough to produce forecasts more accurate than alternative methods, even if they are susceptible to liquidity problems (Pennock, Lawrence et al. 2000; Berg, Forsythe et al. 2001). Active speculative markets, such as NASDAQ and CBOT, are most commonly structured as continuous double auctions, where buyers and sellers can offer and trade at any time.

Table 74: Core trading mechanism design: principle design alternatives and key characteristics

Principle design alternatives	Key characteristics
Continuous double auction (CDA)	<ul style="list-style-type: none"> • constantly matches orders to buy an asset with orders to sell; buyers can only buy as many shares as sellers are willing to sell and vice versa • when few traders participate in a CDA, it may become illiquid, meaning that not much trading activity occurs
Continuous double auction with market maker (CDAwMM)	<ul style="list-style-type: none"> • same as CDA, but additionally provides a market maker who is willing to accept a large number of buy and sell orders at particular prices • increased liquidity, but market maker is exposed to risk
Market scoring rule (MSR)	<ul style="list-style-type: none"> • maintains a probability distribution over all outcomes • an automated market maker is always willing to accept a trade on any event at some price • requires a patron to subsidize the market • avoids the problem of thin markets or illiquidity
Dynamic pari-mutuel market (DPM)	<ul style="list-style-type: none"> • hybrid between a pari-mutuel market and a CDA • market institution changes the price for particular outcomes based on the current state of wagering • market maker always willing to accept buy orders, but not sell orders • selling is accomplished via a standard CDA mechanism

Continuous double auction with market maker (CDAwMM). One way to induce liquidity is to provide a market maker who is willing to accept a large number of buy and sell orders at particular prices. This mechanism is called a CDA with market maker (CDAwMM). Conceptually, the market maker is just like any other trader, but typically is willing to accept a much larger volume of trades. The market maker may be a person, or may be an automated algorithm. Adding a market maker to the system increases liquidity, but exposes the market maker to risk. Now, instead of only matching trades, the system actually takes on risk of its own, and depending on what happens in the future, may lose considerable amounts of money.

Market scoring rule (MSR). The new mechanism of a market scoring rule (MSR) has been proposed by Hanson (2003) and has so far only been tested in the laboratory. An MSR can be conceptualized as an automated market maker always willing to accept a trade on any event at some price. The mechanism requires a patron to subsidize the

market. The patron's final loss is variable, and thus technically implies a degree of risk, though the maximum loss is bounded.

An MSR maintains a probability distribution over all events. At any time any trader who believes the probabilities are wrong can change any part of the distribution by accepting a lottery ticket that pays off according to a scoring rule (e.g., the logarithmic scoring rule; see also 4.3.3), as long as that trader also agrees to pay off the most recent person to change the distribution.

In the limit of a single trader, the mechanism behaves like a scoring rule, suitable for polling a single agent for its probability distribution. In the limit of many traders, it produces a combined estimate.

Since the market essentially always has a complete set of posted prices for all possible outcomes, the mechanism avoids the problem of thin markets or illiquidity.

Dynamic pari-mutuel market (DPM). The new mechanism of a market scoring rule (MSR) has so far only been tested in the laboratory. A DPM can be thought of as a hybrid between a pari-mutuel market and a CDA.

A DPM is indeed pari-mutuel in nature, meaning that it acts only to redistribute money from some traders to others, and so exposes the market institution to no volatility (no risk). A DPM has the infinite liquidity of a pari-mutuel market: traders can always purchase shares in any outcome at any time, at some price automatically set by the market institution. A DPM is also able to react to and incorporate information arriving over time, like a CDA. The market institution changes the price for particular outcomes based on the current state of wagering. If a particular outcome receives a relatively large number of wagers, its price increases; if an outcome receives relatively few wagers, its price decreases.

DPM prices do reflect current information, and traders can cash out in an aftermarket to lock in gains or limit losses before the event outcome is revealed. While there is always a market maker willing to accept buy orders, there is not a market maker accepting sell orders, and thus no guaranteed liquidity for selling: instead, selling is accomplished via a standard CDA mechanism. Traders can always "hedge-sell" by purchasing the opposite outcome than they already own.

Next, we evaluate the principle design alternatives of the core trading mechanism for their utilization in a TF.

Application to TF markets

In terms of market efficiency, CDAwMM and MSR design are likely to be more efficient than the alternative designs, especially when operated with relatively few traders as it is likely the case with TF markets. Whereas a CDAwMM mechanism features a market maker who increases liquidity, the MSR mechanism always has a complete set of posted prices for all possible outcomes and, thus, avoids the problem of illiquidity. With medium relative efficiency, the DPM mechanism comes next, as it offers infinite one-sided liquidity (buy-side) but no guaranteed liquidity for selling. Least efficient is the CDA mechanism if only few traders trade, as such a market may quickly become illiquid, further discouraging trading.

An overview of our evaluation of the application of core trading mechanism design alternatives to TF markets is summarized in Table 75.

Table 75: Principle trade mechanism: Application to TF markets

Design alternative.	Market efficiency	Financial cost/risk to operator
Continuous double auction (CDA)	<i>Contextual / Lower</i> <ul style="list-style-type: none"> • If only few traders trade, such a market may become illiquid, meaning that not much trading activity occurs, further discouraging trading 	<i>Contextual / Lower</i> <ul style="list-style-type: none"> • does not need any market subsidization
Continuous double auction with market maker (CDAwMM)	<i>Contextual / Higher</i> <ul style="list-style-type: none"> • features a market maker who increases liquidity against a simple CDA 	<i>Contextual / Higher</i> <ul style="list-style-type: none"> • needs a market maker to subsidize the market – exposure to financial risk and cost • a more complex operation that may incur higher maintenance costs
Market scoring rule (MSR)	<i>Contextual / Higher</i> <ul style="list-style-type: none"> • always has a complete set of posted prices for all possible outcomes, thus, avoids the problem of thin markets or illiquidity 	<i>Contextual / Medium</i> <ul style="list-style-type: none"> • needs a patron to subsidize the market – exposure to limited financial risk and cost • a more complex operation that may incur higher maintenance costs
Dynamic pari-mutuel market (DPM)	<i>Contextual / Medium</i> <ul style="list-style-type: none"> • offers infinite one-sided liquidity (buy-side) but no guaranteed liquidity for selling 	<i>Contextual / Lower</i> <ul style="list-style-type: none"> • does not need any market subsidization

In terms of financial cost and risk, however, the CDA and DPM mechanisms are best, as both do not need any market subsidization. As the next best choice, a MSR mechanism needs a patron to subsidize the market which, however limited, features exposure to limited financial risk. Finally, as a CDAwMM mechanism features a market maker, this agent comes at cost and may incur significant financial risk by subsidizing the market. The market maker may also incur higher maintenance costs if it needs adjustment to operate smoothly under varying market conditions.

To conclude, in our view the DPM mechanism is preferable to all other mechanisms, as it provides the optimal balance between market efficiency and financial cost and risk.

5.7.3 Trading rules

Beyond the core trading mechanism, many other trade procedures are necessary to help traders coordinate on which assets they will trade and when to trade those assets. Thus, trading rules are necessary for organizing the end-to-end trading process (Smart 2003). A discussion of the full range of trading rules is beyond the scope of this work, thus, we will briefly discuss only the most important trading rules. An overview of these key trading rules is shown in Table 76.

Table 76: Trading mechanism design – trading rules: overview of key design issues

Key design issues	Description
Trading hours	determines the daily, weekly, monthly, and annual time in which trade is possible
Order types	allows traders to place conditional orders based on price, time, or other criteria
Short selling	sale of a security where the seller does not own the stock, but is only borrowing it. The seller is then committed to purchasing the stock back at a later time
Caps	upper limits on orders, shareholding, or portfolio size

Subsequently, the key design issues of trading rules are discussed and consequently evaluated for their application to a TF information market.

Trading hours

Trading hours determine the daily, weekly, monthly, and annual time in which trade on the exchange is possible. On one hand, it is desirable to have a generous trading schedule – to the extreme of 24/7, always open, never closed – to minimize conflict with other activities and to allow the market to incorporate new information with minimum delay.

On the other hand, it is not desirable to leave the market open for long periods as participants may often find a lack of activity in the market and, over time, lose interest in engaging in trade.³³² Moreover, the market sponsor may wish to restrict trading hours to periods outside of typical business hours, as the sponsor may not want participants being preoccupied with the trading during the work day when other, more pressing issues of daily operation need attention – this is especially true in a business context.³³³

For utilization in a TF information market, due to the nature of information discovery in a global and relatively long-term technological development we advocate trading hours of 24/7. We acknowledge that such TF markets will probably suffer from a lack of activity, and therefore suggest the development of counter-measures to reduce the adverse effect on traders' interest to trade.

Order types

Different order types allow traders to place conditional orders based on price, time, or other criteria. The use of different order types by exchanges facilitates the organization of trade, the maintenance of price stability/liquidity, and the prevention of abuse of advance information.³³⁴

Orders types can be grouped according to certain characteristics of price and timing:

Price-based orders:

- Market order: Order to execute immediately against the best available price, which consequently becomes the next market price. In other words: an order that will be executed against the next market price.

³³² see (Plott and Chen 2002)

³³³ See section 3.5.2 for an example of such a design

³³⁴ see (Smant 2003)

- Limit order: Order to execute against a price below (buy order) or above (sell order) the stated limit price.
- Sans forcer: Order to execute at the discretion of the broker, in such a way as not to influence the price in a significant way.
- Stop orders: Orders to execute when the market price crosses certain levels:
 - Stop-loss sell order: (a) limit below current price- execute when limit is reached or prices below, (b) limit above current price- execute when limit is reached or lower price after price first moved above limit;
 - Stop-loss buy order: (a) limit above current price- execute when limit is reached or prices higher, (b) limit below current price- execute when limit is reached or higher price after price first moved below limit.

Time-based orders:

- Open or continuous order: Order remains valid until cancelled (good-till-cancelled).
- Day order: Order to be executed at stated day, otherwise automatically cancelled.
- Fill-or-kill order: To be executed immediately or otherwise cancelled automatically.
- All-or-nothing order: To be executed in its entirety, or otherwise cancelled automatically.

By other criteria:

- Round-lot/odd-lot order: Some exchanges use standard quantities to be traded (round-lots, for example, 100 shares). Trading other quantities must be specially indicated

For utilization in a TF information market, a market order and a limit order should comprise the minimum of order types. If the remaining order types are implementable at a low marginal cost (e.g. in automated, electronic exchanges) they should be offered

as well – but these functionalities should be presented in a way that they don't confuse and spoil the trading experience of unsophisticated traders.

Short selling

"Short selling" refers to the sale of a security where the seller does not own the stock, but is only borrowing it. The seller is then committed to purchasing the stock back at a later time, hoping for a lower price. Thus, "short selling" is a way to invest directly against a particular outcome that the short seller does not believe to occur.

If this feature is used, the exchange needs to make sure that the short seller indeed has enough cash to buy the contracts back later at whatever price. So, for each contract that is short, the exchange needs to store away the maximum price of a contract from the short seller's cash, to be used only when the short seller eventually decides to do the buy-back – or to let the exchange do it for him or her at the market's closing.

For utilization in a TF information market, we advocate the possibility of short selling, as gives investors more freedom and flexibility in making their investment decisions, promotes more market activity, and increases the market's liquidity.

Caps

Caps represent upper limits on orders, shareholding, or portfolio size. For reasons of market power balance, a market sponsor may decide to impose a cap on the holdings of different securities. This way, an investor can not accumulate a shareholding beyond the cap to exert his or her market power for whatever reason.

For utilization in a TF information market, we do not recommend the use of caps as TF markets are expected to feature only few traders of whom some will inevitably control large stakes.

5.7.4 Combinatorial trade design

In 5.1 we have learned that traders seek to trade for various motives. They may seek to invest, to hedge, to speculate, etc. In their desire to trade traders may have simple interests or composite interests. A trader expresses his simple interest by acquiring an unconditional instrument. For example, if a trader believes in the success of a specific

technology, he may invest in an instrument that correlates directly with this technology's success. Such a trade is a simple or non-combinatorial trade.

Table 77: Combinatorial trade design: Overview and characterization

Principle design alternatives	
Simple or Non-combinatorial trade	Combinatorial trade
<ul style="list-style-type: none"> • limits traders to express unconditional interests • ordering is simple • does not provide insight on correlation of different underlying fundamentals • appropriate if items of interest are NOT inter-connected 	<ul style="list-style-type: none"> • allows traders to express composite interests • ordering is complex • provides insight on correlation of different underlying fundamental • suitable if items of interest are inter-connected

However, it is common that traders have composite interests. For example, the chance of establishment of technology A (e.g. hybrid cars) given that costs of raw material B (oil) rises – and especially decision-contingent estimates such as of the chance of war given that we elect a particular person for president, the stock price of a company given that we cancel the development of technology B, or a technology's future performance development given that a lead developer dies (following the speculation that in the 1960ties the Soviet Union lost the race to the moon after the leading aerospace engineer Sergej Koroljow died). If the trader is able to express this conditional interest through a single trade, such a trade is a combinatorial trade.

Table 77 gives an overview of both principle design alternatives for combinatorial trade design.

Thus, the trade of instruments may be organized in a way to allow for composite trades.³³⁵ Composite trades facilitate the trade of composite securities as an expression of a trader's composite interests. Composite securities define relationships among base securities, thus, composite securities are derived from basic securities by allowing traders to structure multi-item orders by themselves.

A simple composite is an intersection between two basic securities. For example, the probability that a decrease in fossil fuel prices will coincide with a decrease of the share

³³⁵ see, e.g., (NetExchange 2002), pp.4

of residential homes using solar energy; or that an increase in the number of video-rent stores offering DVDs will correspond to an increase in DVD (player) sales.

The purpose of the composite type of security is to provide traders, who have an insight into interrelations among basic securities, with a means of expressing their insight and benefiting from the expression if correct.

Table 78: Illustration of composite interests; based on (NetExchange 2003a), p.27

		<i>DVDs will establish</i>		Price
		A	$\sim A$	
<i>DVDs are available in Video-rent stores</i>	B	AB 0.30	$\sim AB$ 0.20	\$0.50
	$\sim B$	A $\sim B$ 0.05	$\sim A\sim B$ 0.45	\$0.50
Price		\$0.35	\$0.65	

Table 78 provides an example for the illustration of composite interests, the establishment, or not, of DVDs (A and $\sim A$) and the availability, or not, of DVDs in video-rent stores (B and $\sim B$).

Around the outside of the table, prices are given for each of the two states of each event; e.g., \$0.35 for A and \$0.50 for B. Knowing that there is a 35% chance that DVDs will establish does not help to predict why it might establish and thus provides no insight that might guide development and business strategy if developers wish to pursue that event.

Prices for each of the four intersection securities (AB, $\sim AB$, A $\sim B$, $\sim A\sim B$) conform to the prices for A, $\sim A$, B, and $\sim B$. For example, the composite probability for AB of 0,3 indicates that the probability of DVDs to establish rises to 30% if DVDs are available in video-rent stores. By contrast, this probability falls to 5% if DVDs are not available in video-rent stores. Thus, the insight provided by such composite probability offers guidance to development and business strategy.

Whereas simple event-specific securities can only represent the states of A, $\sim A$, B, and $\sim B$, only composite securities are able to represent the four intersections (AB, $\sim AB$, A $\sim B$, $\sim A\sim B$).

As noted above, the purpose of composite securities is to provide traders, who have an insight into interrelations among basic securities, with a means of expressing their

insight. To continue the above example, a video-rent chain administrative may want to place an order on the pure event B (whether DVDs will be available in video-rent stores), without bothering about event A (whether DVDs will establish) that is outside his expertise. Thus, the video-rent chain administrative will want to buy or sell B vs. $\sim B$. In contrast, a business analyst of the entertainment industry may have a very strong belief about the impact of video-rent store DVD availability on DVD establishment, but have no strong perception of video-rent store plans to introduce DVDs. The business analyst will want to buy or sell AB vs. $\sim AB$ while being shielded of $\sim B$ happening (video-rent store do not introduce DVDs).

Neither of these participants can be satisfied with a market mechanism that restricts them to orders for individual intersections. Buying (selling) the package AB and $\sim AB$ is equivalent to buying (selling) B. Similarly, selling (buying) the package $A\sim B$ and $\sim A\sim B$ is equivalent to selling (buying) $\sim B$. Thus, the military video-rent chain administrative wants to trade packages that contain all the individual independent joint outcomes involving the event in which he is interested. The business analyst of the entertainment industry wants to swap AB and $\sim AB$, which is also a package trade.

A number of trading and commerce systems have evolved to explicitly process composite trades when the underlying liquidity is too low for serial trading to support the fulfillment of composite interests. Figure X below illustrates the basics of a combinatorial process in the context of an AAM.

A combinatorial exchange process identifies multilateral deals among orders that require specific combinations of securities, or packages. This is achieved by the addition of Gates that serve to decompose orders into base security packages and then recombine matched trades back into composites. Since trades are found at the base security level and are identified multilaterally, a combinatorial exchange process can bring realized market liquidity much closer to its fundamental liquidity than could a process that focused on bilaterally matching orders for composite securities.

Currently, the only example of an AAM that featured such a standardized asset structure design was the Policy Analysis Market; this market only existed as a prototype until it was abandoned due to political reasons.³³⁶

³³⁶ see (Wolfers and Zitzewitz 2004), p.1 and (NetExchange 2003a)

Next, we examine the application of combinatorial trade design to TF markets.

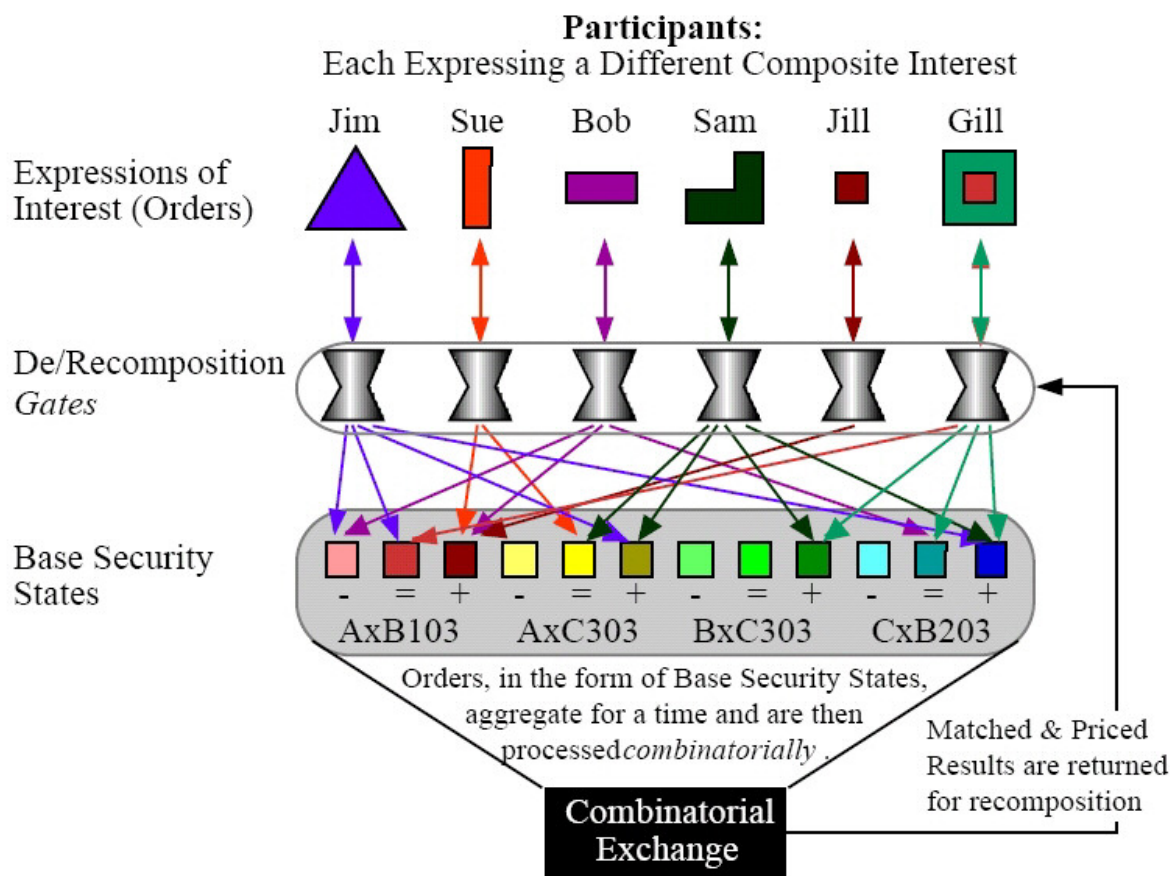


Figure 66: Logic of a combinatorial exchange (NetExchange 2002), p.9

Application to TF markets

As for the principle asset structure, the principle trade mechanism is largely driven by the market purpose and objectives under consideration of the information environment. Again, both alternatives are viable options, as summarized by Table 79.

The market efficiency of a serial market mechanism may be relatively lower than for a combinatorial market mechanism. The spread of trader interest over multiple serial markets may result in a lower base liquidity per market; moreover, informational specialists may be deterred as they are not able to express composite interests.

In contrast, a combinatorial market mechanism allows trader interest to focus and express all his composite interests, which is likely to attract more informational specialists to submit their knowledge through trade.

In terms of financial cost and risk, a combinatorial market is likely to come at a higher cost than a serial market. Whereas a serial market does not inherently require a liquidity-providing mechanism that needs financial subsidies, the opposite is true for a combinatorial market. Furthermore, the more complex mechanism of a combinatorial market is more likely to lead to higher system acquisition and maintenance costs than for a more simple serial market.

Table 79: Principle trade mechanism: Application to TF markets

Design alternative.	Market efficiency	Financial cost/risk to operator
<i>Serial market</i>	<p><i>Lower (relatively)</i></p> <ul style="list-style-type: none"> • lower base liquidity per market • informational specialists may be deterred as they are not able to express composite interests • relative simplicity of trade mechanism may attract less skilled traders 	<p><i>Non-discriminable / Lower</i></p> <ul style="list-style-type: none"> • does not require liquidity-providing mechanism that requires financial subsidies • less complex trade mechanism may incur lower acquisition and maintenance costs
<i>Combinatorial market</i>	<p><i>Higher (relatively)</i></p> <ul style="list-style-type: none"> • higher base liquidity per market • ability to express composite interests attracts more informational specialists • relative complexity of trade mechanism may deter less skilled traders 	<p><i>Non-discriminable / Higher</i></p> <ul style="list-style-type: none"> • typically requires some liquidity-providing mechanism to complete composite trades – which may require financial subsidies (for market makers) • more complex trade mechanism may incur higher acquisition and maintenance costs

5.8 Step 5: Access and Incentivation design

As efficient markets with informative prices depend on a continuous flow of information relevant to the underlying of the instrument – from wherever this information becomes available – the general task at stake is to induce people to acquire and reveal information relevant to estimating the variables of the specific event covered by the instrument. Consequently, any person with potential access to the relevant information should be given access to the information market and should be motivated by incentives to acquire and submit the relevant information. These aims are addressed

by access design and incentivisation design; see Table 80 for an overview of the key design elements and the principle design alternatives.

Table 80: Access and Incentivisation design: Key design elements and design alternatives

Domain	Key design elements	Principle design alternatives
<i>Access</i>	Trader identity	<ul style="list-style-type: none"> • Revealed identity • Anonymous identity
	Trader base shaping	<ul style="list-style-type: none"> • Private access (active acquisition) • Public access (passive acquisition)
<i>Incentivisation</i>	Asset value & market currency	<ul style="list-style-type: none"> • Real money • Play money
	Incentivisation scope	<ul style="list-style-type: none"> • Market-specific • Cross-market
	Trader subsidization	<ul style="list-style-type: none"> • Self deposit • Endowment
	Prize ascertainment	<ul style="list-style-type: none"> • Non-performance-based • Performance-based
	Prize constitution	<ul style="list-style-type: none"> • Tangible • Intangible

Whereas access design tries to ensure that the most significant potential information holders can access the market, incentivisation design attempts to get the appropriate level and type of effort out of these information holders at the lowest cost.³³⁷ Because of the costs to participants to learn and manage trading, the incentive to participate must be significant. In the subsequent sections each of the key design elements and the corresponding principle design alternatives are discussed and evaluated for their application to a TF information market.

5.8.1 Trader identity

The identity of traders is concerned as it may be concealed or disclosed to the market institution and it may be concealed or disclosed to other traders, e.g., by supplying trader identity with transaction data. As noted earlier³³⁸, the prototypical market microstructure model considers two principle classes of agents: informed traders who

³³⁷ see (Jeffrey 2002), pp.12

³³⁸ see section 5.1

possess private information about future asset values and uninformed traders who are liquidity motivated.³³⁹ Revelation of trader identity has effects on both groups motivation and thus affects trade.³⁴⁰ Consequently, we discuss the effects of trader identity for both principle trader groups.

Informed traders with access to classified information may not want to trade, if their identity is revealed because of many reasons, e.g., because of not wanting observers to make conclusions about the traders' occupation or knowledge, or because the traders fear punishment by the owner of the classified information (e.g. the employer). The latter might be especially true for technology developers in large commercial enterprises. Indeed, many studies demonstrate that too much transparency can actually reduce liquidity because traders are unwilling to reveal their intentions to trade.³⁴¹

Whereas these arguments may be especially true for disclosure of trader identity to other traders or outsiders observing the market, traders might view the disclosure of their identity solely to the market institution somewhat relaxed.

Furthermore, if the chosen principle market model employs a play-money market³⁴², a primary source of motivation for informed traders may be to relate his performance to other traders, secretly but most often also publicly.³⁴³ In this case informed traders may not object to some partial reveal of their identity through the use of pseudonyms. This way, the disclose of pseudonyms with transaction and performance data allows informed traders their motivation.

Liquidity traders may be attracted to trade, if they are able to observe the trades of informed traders. Such traders adjust prices based on the net order imbalance (i.e., the difference between buy and sell share volume) observed. Several studies show that information on traders' motivations can significantly affect asset prices.³⁴⁴

Thus, liquidity traders prefer disclosed trader identities, even if that means that their own identity is disclosed as well.

³³⁹ These traders trade anonymously and market makers (or representative liquidity providers) adjust prices based on the net order imbalance (i.e., the difference between buy and sell share volume) observed.

³⁴⁰ see (Madhavan 2000), p.236

³⁴¹ see (Madhavan 2000), pp.236-241

³⁴² see section 5.8.3

³⁴³ see section 5.8.7

To conclude, the literature almost uniformly agrees that traders who trade on private information signals will prefer anonymous trading systems while liquidity traders, especially those who can credibly claim their trades are not information-motivated, prefer greater disclosure.³⁴⁵ Examples of AAMs that feature such an anonymous trader identity design include the markets IEM, HSX, FX, TU Vienna/Siemens, and HP sales.³⁴⁶ We know of no field-deployed AAM that uses the alternative disclosed identity design.

From the viewpoint of the market institution, a full disclosure of trader identity does not appear necessary for operational reasons. But the institution may typically wish that one trader can only open and control one account and not open multiple accounts to distort market power or market prices. To avoid the latter, the institution may require a partial disclosure of trader identity.

Furthermore, the disclosure of trader identity to the market institution may be required by regulation if the chosen principle market model employs a real-money market.³⁴⁷

Application to TF markets

Our evaluation of the application of trader identity design alternatives to TF markets is summarized in Table 81.

As identified in section 5.5, TF markets are likely to attract only a relatively small number of traders. As liquidity traders are attracted to highly active markets³⁴⁸, such traders will very unlikely engage in TF markets. Thus, a TF market design in respect to trader identity should focus on the needs of informed traders.

In terms of market efficiency, an anonymous trader identity design is likely to be more efficient than a market design with disclosed trader identity. For the reasons given above, many informed traders may be deterred by a requirement to fully reveal their identity. Furthermore, the process of establishing the true identity may require a relatively high effort by potential traders, and, thus, keep them from joining the market. The opposite is true for a market design that conceals trader identity.

³⁴⁴ see, e.g., (Forster and George 1992)

³⁴⁵ see (Madhavan 2000), p.241

³⁴⁶ see sections 3.5 and 3.6

³⁴⁷ see section 5.8.3

³⁴⁸ see (Madhavan 2000), p.241

Table 81: Trader identity design alternatives: application to TF markets

Design alternative.	Market efficiency	Financial cost/risk to operator
<i>Disclosed identity</i>	<p><i>Lower</i></p> <ul style="list-style-type: none"> • may deter many informed traders who prefer to stay anonymous in order to mask their source of private information • process of establishing true identity of globally dispersed traders may deter traders because of required initial effort • may attract liquidity traders who observe and act on informed traders' activities 	<p><i>Significantly higher</i></p> <ul style="list-style-type: none"> • cost of establishing true identity – like in financial markets – is very high; especially true for globally dispersed traders • may be a requirement for real-money markets
<i>Anonymous identity</i>	<p><i>Higher</i></p> <ul style="list-style-type: none"> • attracts informed traders who prefer to stay anonymous in order to mask their source of private information • low initial effort in joining the market may lead to more traders • liquidity traders may be attracted if pseudonyms of informed traders are supplied with transaction data 	<p><i>Significantly lower</i></p> <ul style="list-style-type: none"> • no cost of establishing true identity

In terms of financial cost and risk a market that requires the establishment of true trader identity bears a very significant cost, whereas a market without this requirement bears no such cost. The former is even truer, if the identification of traders concerns a globally dispersed trader population.

Note, that if the selected principle market model is a real-money market, the disclosure of trader identity and the consequential costs may be required by regulation.

To conclude, the above evaluation suggests the use of a market design with an anonymous trader identity. In order to satisfy the motivational source of informed traders, a pseudo-identity should be supplied with selected transaction and performance data. Furthermore, in order to avoid or minimize that a trader uses multiple identities and multiple account some minimum identity information, such as a private e-mail address, should be recorded.

5.8.2 Trader base shaping

Security prices depend on a continuous flow of information relevant to the underlying commodity from wherever this information becomes available³⁴⁹. Thus, in principle, it is in the interest of the market institution (i) to promote awareness among potential information holders that they can capitalize on their information in an information market, and (ii) to rely on market forces to discipline self-selected traders to trade profitably and thus advance external efficiency (that prices reflect all available information).³⁵⁰

Two principle design options present themselves for shaping a market's trader base, a private market access (typically, by active acquisition) and a public market access (typically, by passive acquisition). Table 82 summarizes the characteristics of both alternatives.

Table 82: Trader base shaping: Overview and characterization

Principle design alternatives	
<p>Private access (active acquisition)</p> <ul style="list-style-type: none"> • potential traders must be eligible to join market • eligibility is defined by some trader identity characteristic, e.g. organizational belonging, demographics • typically, by invitation only; thus, regulated (distorted) self-selection of traders • markets and prices are observable to traders only and NOT to the public 	<p>Public access (passive acquisition)</p> <ul style="list-style-type: none"> • anybody willing to trade may join market (self-supply of funds may be required) • pure self-selection • markets and prices are observable to the public

Subsequently, both design alternatives and their corresponding key characteristics are discussed.

Private access. In such a design only eligible traders may participate in trade. Eligibility of traders is defined by some trader identity characteristic, such as the belonging to a specific organization, or some other demographic statistic. Typically,

³⁴⁹ see section 5.1

³⁵⁰ see also section 3.1

eligible traders are invited to join the market; thus, traders are not purely self-selected, but are typically motivated to participate in trade, even if they do not trade successfully, that is, profitably. Thus, active means of awareness creation are used, that rely on the state-of-the-art in marketing, e.g. target group-specific meetings, presentations, direct mail, etc.

In a private access design, markets and market prices are observable and accessible only to eligible traders, but not to the open public. Thus, such a design supports the concealed trade in classified information. Such a characteristic may be desired, e.g. by commercial enterprises interested in internal information. Indeed, Hewlett-Packard, a computer firm, has chosen such a private access design for its sales forecast AAM.³⁵¹ Another firm, Siemens, an electronics and electrical-engineering conglomerate, chose the same design for the forecast of punctuality in meeting a project deadline.³⁵²

Public access. In such a design anybody may participate in trade, there is no restriction by trader identity characteristics. Typically, passive means of awareness creation are used, that essentially rely on random discovery by traders and word-of-mouth proliferation. Thus, such a design supports the principle of pure trader self-selection.³⁵³ Furthermore, in a public access design markets and market prices are, in principle, fully observable to the public.

Examples of AAMs that feature such a public access design include the markets IEM, HSX, and FX.³⁵⁴

To conclude, the choice of a private or public access design is largely driven by the market purpose and objectives and the information environment. If the market purpose and objectives demand to conceal trade in classified information, or if the information environment suggests that only selected participants have relevant information, a private access design is appropriate.

If the market purpose and objectives and information environment suggest no such restrictions, a public access design may be more appropriate.

³⁵¹ see section 3.5.2

³⁵² see section 3.5.1

³⁵³ see sections 3.1, 3.3, and 5.1

³⁵⁴ see section 3.6

Application to TF markets

Our evaluation of the application of trader base shaping alternatives to TF markets is summarized in Table 83. As noted above, the choice of a private or public access design is largely driven by the market purpose and objectives and the information environment. Thus, the market efficiency of both designs depends on if the design matches the purpose. For example, if a TF market access is limited to members of a company that operates only in Europe, information beyond these boundaries may not be reflected in the market.

A private access design may lead to good market efficiency if it holds only traders likely to have access to the best possible information sources. But these traders may not be skilled at trading and may not be sufficiently motivated to improve or trade at all. Such a design undermines the principle of trader self-selection.³⁵⁵ Furthermore, a comparably low number of traders may result in less market liquidity.

In contrast, a public access design is open to all traders, including those traders who may possess no information, may trade irrationally, and may significantly bias or distort market prices. But such a design supports the principle of pure trader self-selection, which relies on market forces to discipline traders to trade profitably and thus advance market efficiency. Moreover, a comparably high number of traders may result in higher market liquidity.

Table 83: Trader base shaping: application to TF markets

Design alternative.	Market efficiency	Financial cost/risk to operator
<i>Private access (active acquisition)</i>	<i>Contextual</i> <ul style="list-style-type: none"> • market access is likely to be restricted to traders with best information • acquired traders may not be most skilled traders • acquired traders may not be motivated to trade • undermines the principle of trader self-selection • lower number of traders may result in lower market liquidity 	<i>Higher (relatively)</i> <ul style="list-style-type: none"> • targeting, acquisition, verification and retention of traders may require considerable effort • level of incentivization may need to be relatively high
<i>Public access (passive acquisition)</i>	<i>Contextual</i> <ul style="list-style-type: none"> • market access is open to all 	<i>Lower (relatively)</i> <ul style="list-style-type: none"> • little effort required for

³⁵⁵ see sections 3.1, 3.3, and 5.1

<p>traders, including those who may possess no information and who may distort prices</p> <ul style="list-style-type: none"> • supports the principle of trader self-selection • higher number of traders is likely to result in higher market liquidity 	<p>targeting and acquisition of traders</p> <ul style="list-style-type: none"> • no verification and retention of traders is required • level of incentivization does not need to be relatively high
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In terms of financial cost and risk a private access design is likely to cost more than its alternative. The effort for targeting, acquiring, verifying and retaining selected traders may be considerable. Furthermore, the level of incentivization needed to sufficiently motivate selected traders to trade is likely to be higher and, thus, to come at a higher cost.

The opposite is true for a public access design, as there is only relatively little effort required acquiring traders and no verification of traders is necessary. In addition, the level of incentivization need not to be as high as for a private design, as traders decide on their participation by pure self-selection.

To conclude, given the considerable effort and financial cost associated with a private access design for a debatable improvement in market efficiency, we suggest the use of a public access design for TF markets. However, we recognize that it may be desirable for the rapid establishment of a narrow-focus TF market to initially use a private access design to secure a knowledgeable trader base from the very beginning of trade.

5.8.3 Asset value and Market currency: Real vs. Artificial

As assets are exchanged in a market, they trade at a certain value which is denoted in the market's currency. The initial value assigned to securities when they are traded for the first time is determined by the institution that issues the securities – in the case of an AAM this is done by the market sponsor. In financial terms, this value may be real or it may be artificial (that is, fictitious). Table 84 summarizes the characteristics of both alternatives.

Table 84: Asset value and market currency: Overview and characterization

Principle design alternatives	
<p>Real money</p> <ul style="list-style-type: none"> • legal tender and, thus, of material value in the real world defined by other than the market institution – value is "predetermined" • typically higher risk/reward for investors than play money design • money itself directs incentivization of investors • subject to tight legal regulation and associated costs • market institution has no control of currency policy • spendings by market institution comes at real cost; limited flexibility for other design decisions, e.g. endowments 	<p>Play money</p> <ul style="list-style-type: none"> • artificial currency without any material value in the real world; its value is defined by the market institution – value is subject to other design decisions • typically lower risk/reward for investors than play money design • money derivatives direct incentivization of investors, e.g. bragging rights, or trade for prizes • subject to no or relaxed legal regulation • market institution as issuer has full control of currency policy • spendings by market institution comes at NO real cost; full flexibility for other design decisions, e.g. endowments

Subsequently, both design alternatives and their corresponding key characteristics are discussed.

Real money is a legal tender and, thus, of material value in the real world defined by other than the market institution – thus, the value of holding real money currency is externally determined. The use of real money as market currency typically involves a higher risk/reward-investment trade-off than a play money currency design. The clear prospect of winning or losing money, thus, the real money itself directs the incentivization of investors to engage in trade.

As a legal tender issued by other than the market institution, real money is subject to regulation by the authorities of the currency-issuer's jurisdiction.

The use of real money as currency in games is considered as gambling. In many countries gambling is outlawed, subject to a state-run monopoly, or subject to licensing. The involvement of real money in the process of purchasing securities requires the purchased securities and the securities exchange to be under regulation of a respective authority, e.g. in the USA this authority is the Securities and Exchange Commission.

Thus, the distinction between "gambling" and "trading" in prediction markets, while not well-grounded in economics, is important for the legality of a specific prediction market.

In both cases setting up an operation based on real-money necessarily incurs very significant technical, regulatory, and fiduciary costs.³⁵⁶

Finally, the use of real money typically places limits on the flexibility of other market design decisions, as money spending by the market institution comes at a real cost. Such an affected design decision is e.g. the option of granting an endowment as source of investor funds.

Examples of AAMs that feature such a real-money market design include the markets TU Vienna/Siemens, HP sales, IEM, TradeSports and Economic Derivatives.³⁵⁷

Play money is an artificial currency without any material value in the real world; its value is defined by the market institution – thus, the value of holding play money currency is subject to other market design decisions. A play money currency is usually created to facilitate a game of entertainment.

The use of play money as market currency typically involves a lower risk/reward-investment trade-off than a real money currency design. The consequences of winning or losing play money are not as obvious as for real money, as play money derivatives, such as bragging rights or bidding points for prizes auctions, direct the incentivization of investors to engage in trade.

The use of play money eludes itself from the jurisdiction that applies to real money currencies and gives the issuer full control over currency policy.

Finally, the use of play money gives full flexibility for making other market design decisions, as money spending by the market institution comes at no real cost. As noted above, such an affected design decision is e.g. the option of granting an endowment as source of investor funds.

Examples of AAMs that feature such a play-money market design include the markets HSX, FX, and Newsfutures.³⁵⁸

³⁵⁶ The IEM as a real-money market has been able to avoid regulation. Although the IEM is under the regulatory purview of the Commodity Futures Trading Commission (CFTC), it is not regulated by, nor are its operator registered with, the CFTC or any other regulatory authority. This exception may be rooted in the research purpose of the market reflected also by the omission to charge commissions or transaction fees, by the limited financial risk of USD 500 that traders can expose themselves, and by the first-mover advantage in gaining such an exception from regulation.

³⁵⁷ see sections 3.5 and 3.6

Table 85: Motives for trading and their applicability to financial markets (FM) and AAMs; adapted from (Harris 2002), p.33

Motives	FM	AAM
to invest: to move wealth from the present to the future	X	
to borrow: to move wealth from the future to the present	X	
to hedge: to reduce business operating risk	X	X
to exchange assets: to acquire an asset that one values more than the asset one tenders	X	
to gamble: to entertain oneself	X	X
to speculate: to trade on information about future price changes	X	X
to build reputation: to perform better than average or peers		X

Empirical evidence

As noted above, the choice of a real vs. an artificial asset value affects the incentivisation of (potential) traders. A clear implication is that markets where traders risk their own money should produce better forecasts than markets where traders run no financial risk.

However, the relative efficiency of real-money versus play-money markets is an relatively open empirical question, as there is currently only one study that has directly compared the accuracy of actual- and virtual-currency markets in a real-world setting (Servan-Schreiber, Pennock et al. 2004). This study has found, perhaps surprisingly, that play-money markets performed as well as or even better than the real-money markets.

The authors of the study argue, in a real-money market, the weights given to each person's opinion reflect the amount that they are willing to bet, which might be largely affected by their wealth levels. Thus, in real-money markets, trader opinion likely reflects the distribution of wealth which can often reflect returns to skills other than predictive ability.

By contrast, the only way to amass wealth in a play-money exchange is by a history of accurate predictions. As such, it seems plausible that play-money exchanges offset their missing or negligible financial incentive by producing more efficient opinion weights.

A summary of the findings of this study can be found in section 5.8.3.

³⁵⁸ see sections 3.5 and 3.6

Application to TF markets

Our evaluation of the application of real vs. artificial asset values to TF markets is summarized in Table 86. In terms of market efficiency, common belief suggests that real-money markets will be more efficient than play-money markets. But, as noted above, the only empirical study so far that has compared the performance of real-money vs. play-money markets has found that both may perform equally well.

An implication would be that for "technologists", people with knowledge or an interest in technological developments, appreciation through demonstration of knowledge and skill may be as strong an incentive as the prospect to improve financial wealth.

In addition, play money markets still offer the opportunity to enhance their attractiveness by the award of material incentives (prizes) based on play money values.

Table 86: Real vs. artificial asset value: Application to TF markets

Design alternative.	Market efficiency	Financial cost/risk to operator
<i>Real money</i>	<p><i>Non-discriminable / Higher</i></p> <ul style="list-style-type: none"> • in general, financial incentivization may attract more traders • but for "technologists" financial incentivization may be not as important as appreciation through demonstration of knowledge and skill • a study shows that real money markets are not more efficient than play-money markets (Servan-Schreiber, Pennock et al. 2004) 	<p><i>Considerably higher</i></p> <ul style="list-style-type: none"> • compliance with required regulation incurs very significant technical, regulatory, and fiduciary costs • increased legal risk • change of asset value is difficult and comes at cost • award of endowments comes at considerable cost
<i>Play money</i>	<p><i>Non-discriminable / Lower</i></p> <ul style="list-style-type: none"> • in general, non-financial incentives may attract less traders • but for "technologists" appreciation through demonstration of knowledge and skill may be strongest incentive • material incentives (prizes) may still be awarded based on play money value • a study shows that play money markets perform as good as real-money markets (Servan-Schreiber, Pennock et al. 2004) 	<p><i>Considerably lower</i></p> <ul style="list-style-type: none"> • as no regulation is required there are no consequential costs • relatively low legal risk • flexibility in (change of) valuation of asset value • flexibility in awarding endowments

In terms of financial cost and risk a real money market costs considerably more than a play-money market. Whereas the latter enjoys shelter from regulation a consequential costs, the former bears very significant technical, regulatory, and fiduciary costs. Moreover, a later change of asset value or a supply of endowments comes at a significant cost only to real-money markets. Whereas real-money markets are exposed to considerable legal risk, this risk is rather limited for play-money markets.

To conclude, given the considerable financial cost and risk associated with real-money markets and the evidence that play-money markets may perform equally well in terms of market efficiency, we suggest the use of artificial asset values for TF markets.

5.8.4 Incentivation scope design: Market-specific vs. Cross-market

Most fundamentally, the motivation of traders to engage in an AAM is to achieve some goal.³⁵⁹ Engaging in trade comes to traders at a cost, e.g., putting self-provided funds at risk, learning to trade and to improving on it, or the opportunity cost of trading instead of doing something else. Thus, the design of the set incentives must consider which goal is provided to traders (>>Prize constitution design), by which activities they are able to reach those goals (>>Prize ascertainment design), and how the costs to engage in trade may be minimized (>>Trader subsidization).

However, the motivation of traders to engage in an AAM may vary by the different, parallel conducted markets on the exchange. For example, whereas one trader may have an interest in and knowledge of technological development in the automotive sector, another trader may prefer to engage in markets covering the medical technology sector. Whether traders are incentivized on a market-by-market basis or over all markets is addressed by incentivization scope design. Table 93 summarizes the characteristics of both principle design alternatives of incentivization scope design.

Table 87: Scope of prize ascertainment: overview and characterization

Principle design alternatives	
market-specific	cross-market
<ul style="list-style-type: none"> • trader subsidization, prize ascertainment and prize constitution are designed market-by-market <ul style="list-style-type: none"> ○ traders may receive a subsidy in every market, but the subsidy is non-transferable to other markets ○ traders may win prizes in every market • thus, each market is provided with an independent set of incentives • supports parallel markets of relatively diverse information themes by providing independent incentives to a trader base with different interests and unrelated information 	<ul style="list-style-type: none"> • a design of trader subsidization, prize ascertainment and prize constitution covers all markets on the exchange <ul style="list-style-type: none"> ○ traders may receive only one subsidy to engage in any of the markets – the subsidy is transferable between markets ○ traders may win prizes in every market • thus, a single set of incentives is offered across all markets • supports parallel markets of relatively similar information themes by providing overall incentives to a trader base with relatively similar interests and complementary information

Subsequently, the principle design alternatives and their corresponding key characteristics are introduced and discussed.

³⁵⁹ see sections 3.1, 5.1, and 5.8.3

Market-specific incentivisation scope. In such a design, incentivisation design domains, such as trader subsidization, prize ascertainment, and prize constitution, are designed market-by-market. For example, traders may receive a subsidy in every market, but the subsidy is non-transferable to other markets. Furthermore, traders may win (different) prizes in every market.

Hence, in a market-specific incentivisation scope design each of the markets on the exchange is provided with an independent set of incentives. Such a design supports parallel markets of relatively diverse information themes by providing independent incentives to a trader base with different interests and unrelated information.

In principle, a market-specific incentivisation scope design is applicable to real-money markets as well as to play-money markets, although it is infrequently used for real-money markets. Examples of AAMs that feature such a trader funding design include the play-money markets of Newsfutures.³⁶⁰

Cross-market incentivisation scope. In such a design, incentivisation design domains, such as trader subsidization, prize ascertainment, and prize constitution, are designed once to cover all parallel markets on the exchange. For example, traders may receive a subsidy, but only one for all markets, that is, the subsidy is transferable between parallel markets.

Thus, in a cross-market incentivisation scope design a single set of incentives is offered across all parallel markets on the exchange. Such a design supports parallel markets of relatively similar information themes by providing overall incentives to a trader base with relatively similar interests and complementary information.

A cross-market incentivisation scope design is applicable to real-money markets as well as to play-money markets. Examples of AAMs that feature such an incentivisation scope design include the play-money markets of HSX and FX.³⁶¹

Subsequently, we review the application of incentivisation scope design alternatives to TF markets.

Application to TF markets

Our evaluation of the application of incentivisation scope design alternatives to TF markets is summarized in Table 88.

³⁶⁰ see sections 3.5 and 3.6

³⁶¹ Ibid.

In terms of market efficiency, a market-specific design may be more efficient than a cross-market design. Whereas the former design option incentivizes traders "to be right" about the outcome in every parallel market, the cross-market design incentivizes traders to perform well overall but not necessarily "being right" in specific markets. Thus, while a market-specific design suggests that "being right" is more important than trading skills, a cross-market design values trading skills at least as important as "being right" about the outcome.

In a market-specific design traders do not need to consider activities in all parallel markets – trader attention may focus on specific markets without limiting their chances of performing well. Furthermore, as subsidies are provided to each trader in every parallel market, these markets enjoy sufficient base liquidity as traders join.

In a cross-market design, however, traders need to consider activities in all markets – trader attention may broaden in order to maintain chances of performing well. Furthermore, markets of such a design may suffer a total lack of liquidity as investment capital is typically transferred and allocated to the most liquid markets.

Table 88: Design of scope of prize ascertainment: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>market-specific</i>	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • incentivizes traders "to be right" in every parallel market >> "being right" is more important than trading skills • traders do not need to consider activities in all parallel markets – trader attention may focus • base liquidity in every market as traders join 	<p><i>Higher</i></p> <ul style="list-style-type: none"> • set of incentives needs to be provided for each market <ul style="list-style-type: none"> ○ trader subsidies need to be provided in each market to each trader ○ prizes need to be provided for each market
<i>cross-market</i>	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • incentivizes traders to perform well overall, but not necessarily being right in specific markets >> trading skills are at least as important as "being right" • traders need to consider activities in all markets – trader attention may broaden • markets may suffer a total lack of liquidity as investment capital is typically transferred to most liquid markets 	<p><i>Lower</i></p> <ul style="list-style-type: none"> • set of incentives needs to be provided only once across all markets <ul style="list-style-type: none"> ○ trader subsidies need to be provided only for each trader ○ prizes need to be provided only once across all markets

In terms of financial cost and risk a market-specific incentivisation scope design costs significantly more than the cross-market design alternative. For example, a market-specific scope design may need to provide subsidies in every parallel market to every trader, as well as it may need to provide a prize in every parallel market. A cross-market scope design, however, needs to provide trader subsidies and prizes only once across all markets.

To conclude, the choice of an incentivisation scope design is largely driven by the diversity of themes covered by the TF market³⁶² and financial constraints on supplying financial incentives³⁶³. Thus, it is not sensible to recommend a general design for the incentivisation scope for TF markets.

5.8.5 Trader subsidization

Traders need funds or, respectively, a starting capital in order to be able to trade. Two principle options present themselves for sources from which these funds are supplied, the first option being the self-supply in which traders bring their own funds to the market and the alternative option being an endowment of funds to traders by the market sponsor. Table 89 summarizes the characteristics of both alternatives.

A further key design aspect includes the scope of parallel markets that are considered for trader subsidization. A discussion of this design has been provided earlier, see section 5.8.3.

Subsequently, both design alternatives and their corresponding key characteristics are discussed.

Self-supply. In such a design traders are required to supply their own funds as capital for trade. In principle, this design option is only applicable to markets with a real-money market design. Traders can choose how much of their own funds they want to invest and, thus, to which level of financial risk they want to expose themselves.

³⁶² which is in turn determined by the market purpose and content; see also section 5.4

³⁶³ which is in turn determined by the choice of a real-money vs. play-money market; see also 3.7.5

Examples of AAMs that feature such a trader funding design include the real-money markets TU Vienna/Siemens³⁶⁴, IEM, TradeSports and Economic Derivatives.³⁶⁵

Table 89: Trader subsidization design: overview and characterization

Principle design alternatives	
<p>Self-supply</p> <ul style="list-style-type: none"> • in principle, only applicable to real-money markets • traders are required to invest self-supplied funds • traders are exposed to financial risk (at a level of their choice) 	<p>Endowment</p> <ul style="list-style-type: none"> • traders receive endowment by the market sponsor • purpose of endowment is to stimulate trade or to simply supply starting capital • endowment may be given as one-time grant and/or as regular allowance • endowment may be given as cash (stimulus to join, but not to trade) or as security portfolio (stimulus to join+trade) • endowment may or may not be withdrawn from market by traders • applicable to real- and play-money markets
<p>Scope</p> <p>defines the scope of parallel markets considered for trader funding</p>	<ul style="list-style-type: none"> • market-specific • cross-market

Endowment. In such a design traders receive endowments by the market sponsor. In combination with a real-money market design, the purpose of such endowments is to stimulate trading activity and, ultimately, to advance market efficiency. In combination with a play-money market design, the purpose of endowments is to necessarily supply traders with some starting capital of artificial value.

Endowments may be given as a one-time grant (typically, as a trader joins the market) and/or as a regular allowance to provide an ongoing stimulus to engage in trade, even after traders have experienced trading losses.

Furthermore, endowments may be given in cash or as a portfolio of securities. Whereas an endowment in cash gives traders full flexibility in choosing when to trade as cash typically does not lose in value, an endowment of a portfolio of securities provides an incentive to eventually engage in trade as the value of securities changes with ongoing market activity. Thus, while a cash endowment provides a stimulus to join

³⁶⁴ this market employed a combined self-supply/endowment design, see also section 3.5.1

³⁶⁵ see section 3.6

the market, but little stimulus to promptly engage in trade, an endowment of securities also provides a strong stimulus to trade.

The stimulus to trade may even be increased by designing the endowment in securities as an unbalanced portfolio, that is, an unequal number of a range of available securities.³⁶⁶

Furthermore, the endowment may be designed in a way that it may not be withdrawn from the market. In this case, the endowment serves as an interest-free loan which only needs to be repaid as the trader ends his engagement in the market and has sufficient currency to pay back the loan.

Endowments are typically used in small real-money markets with few traders (< 200 traders) or in play-money markets. Examples of AAMs that feature such a trader funding design include the play-money markets HSX, FX, and Newsfutures, but also the small scale real-money markets TU Vienna/Siemens³⁶⁷, and HP sales.³⁶⁸

Application to TF markets

Our evaluation of the application of trader funding design alternatives to TF markets is summarized in Table 90. As indicated above, the choice of a source of trader funds design is largely driven by the selection of the principle market model, namely, the choice of a real-money or a play-money market design.

In terms of market efficiency, a self-supply design may be less efficient than an endowment design, as the latter may provide a stronger stimulus to traders to join the market and engage in trade. Furthermore, such a design eases the market's reliance on sufficiently wealthy traders and allows also meager or risk-averse traders to test and compete on their information and skills.

However, traders that receive endowments may trade less carefully and rationally than traders investing their own funds.³⁶⁹

In terms of financial cost and risk an endowment design for a real-money market costs significantly more than a self-supply design, as endowments need to be supplied to each trader. A self-supply design incurs no such costs, however, the processes of real-money deposit and withdrawal may be subject to regulation and may incur some costs.

³⁶⁶ Such a design has been used, e.g., in the HP sales market; see section 3.5.2

³⁶⁷ this market employed a combined self-supply/endowment design, see also section 3.5.1

³⁶⁸ see sections 3.5 and 3.6

³⁶⁹ this does not necessarily result in decreased market efficiency – see also section 3.7.5

Table 90: Trader subsidization design: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>Self-supply</i>	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • traders exposed to real financial risk may trade more rationally³⁷⁰ • distribution of wealth may affect which traders join the market and which do not – knowledgeable subjects may not want to or be able to join • due to exposure to financial risk less traders may join the market which may result in less market liquidity 	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • as traders supply their own funds, no subsidy to stimulate trade is required • the processes of real-money deposit and withdrawal may be subject to regulation and may incur significant costs
<i>Endowment</i>	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • distribution of wealth does not strongly affect which traders join the market – meager or risk-averse, but knowledgeable traders are more likely to join the market • eased trader exposure to real financial risk may induce more traders to join the market which may result in higher market liquidity • stimulates traders to join the market and may specifically stimulate to engage in trade 	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • cost/risk for a real-money market is higher than a self-deposit design • cost/risk for a play-money market is zero

To conclude, the choice of a trader subsidization design is largely driven by the market purpose and objectives, the consequential selection of the principle market model, namely, the choice of a real-money or a play-money market design, and by the financial constraints on supplying all traders with endowments. Thus, it is not sensible to recommend a general design for source of funds for TF markets.

5.8.6 Prize ascertainment

Most fundamentally, the motivation of traders to engage in an AAM is to achieve some goal.³⁷¹ A market sponsor may offer such a goal by rewarding traders for some specific

³⁷⁰ this does not necessarily result in decreased market efficiency – see also section 3.7.5

trading activities. The principles of how traders may become eligible for such explicit rewards are determined by a market's prize ascertainment design. Two principle alternatives present themselves for this design, a performance-based and a non-performance-based prize ascertainment. Table 91 summarizes the characteristics of both design options.

Common for both principle design alternatives are further key design aspects, including the scope of parallel markets and the time horizon of trader activities that are considered for prize ascertainment. Whereas the design of the scope of parallel markets has been discussed earlier³⁷², a discussion of the design of time horizon of trader activities considered for prize ascertainment is provided at the end of this section.

Table 91: Prize ascertainment design: overview and characterization

Principle design alternatives	
Performance-based	Non-performance-based
<ul style="list-style-type: none"> • prize ascertainment is based on the development (increase/decrease) of trader investment • common design alternatives: <ul style="list-style-type: none"> ○ based on absolute performance <ul style="list-style-type: none"> – linear – quote-based ○ based on relative performance <ul style="list-style-type: none"> – rank order tournament (ROT) 	<ul style="list-style-type: none"> • prize ascertainment is based on some other criteria than the development of trader investment • common design alternatives: <ul style="list-style-type: none"> ○ lottery – unconditional ○ lottery – conditional
<p>Scope defines the scope of parallel markets considered for prize ascertainment</p>	<ul style="list-style-type: none"> • market-specific • cross-market
<p>Time horizon defines the time period for which trader activities are considered for prize ascertainment</p>	<ul style="list-style-type: none"> • market-specific (at market maturity) • periodic

Subsequently, the design alternatives and their corresponding key characteristics are discussed.

³⁷¹ see sections 3.1, 5.1, and 5.8.3

³⁷² see section 5.8.3

Performance-based prize ascertainment. In such a design, prize ascertainment is based on the development, e.g., increase or decrease, of a trader's investment in absolute or relative terms.

Thus, in principle, the base for performance evaluation in such a design is the absolute net worth of an investment at a given point in time. The net worth of the investment held by the investor in his account is constituted by the sum of cash plus the market value of all securities at a given time. A trader's investment has decreased, if the net worth of his investment at a later point in time is smaller than the net worth of his investment at an earlier point in time. Conversely, a trader's investment has increased, if the net worth of his investment at a later point in time is greater than the net worth of his investment at an earlier point in time.

As indicated above, a performance-based prize ascertainment design may reward traders for increasing their investment to a specific value (absolute performance) or for increasing their investment relative to other traders (relative performance) – several key options present themselves. A detailed characterization of these design options and an evaluation of their application to TF markets is provided later in this section.

An example of an AAM that features such a performance-based prize ascertainment design includes the market Newsfutures.³⁷³

Non-performance-based. In such a design, prize ascertainment is based on some other criteria than the development of trader investment. Two common designs are used in a non-performance-based prize ascertainment, an unconditional and a conditional lottery. The unconditional lottery entitles every trader registered at the market exchange to participate in a pure game of chance. Thus, regardless of individual investor performance, every investor has an equal chance of winning a prize. In a conditional lottery investors need to meet certain pre-defined criteria first, in order to participate in the lottery. Such criteria may be performance-oriented or rather based on participation only, e.g. required minimum of account net worth, of number of trades, or of participation time. Only after a trader has met the pre-defined criteria, he or she is entitled to participate in a lottery with other eligible investors, who then all have an equal chance of winning a prize.

An example of an AAM that features such a conditional lottery prize ascertainment design includes the market "Nobelpreisboerse".³⁷⁴

³⁷³ see sections 3.5 and 3.6

Subsequently, we review the application of prize ascertainment design alternatives to TF markets.

Application to TF markets

Our evaluation of the application of prize ascertainment design alternatives to TF markets is summarized in Table 92.

Table 92: Prize ascertainment design: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>Performance-based</i>	<p><i>Higher</i></p> <ul style="list-style-type: none"> • rewards knowledge and insight and punishes unfamiliarity and irrationality • provides traders with a stimulus to trade actively in order to increase their investment through trade and even reach a specific goal • likely to lead to higher trading activity which may result in higher market liquidity 	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • if prize ascertainment rewards absolute performance, risk is higher as more traders may qualify for prizes >> design details determine volume of prize-winning traders and consequential costs • if prize ascertainment rewards relative performance, cost/risk is comparable to non-performance based design, e.g., lottery
<i>Non-performance-based</i>	<p><i>Lower</i></p> <ul style="list-style-type: none"> • rewards some specific trader activity, e.g., joining the market • does not reward increase of investment through trade, thus, does not award incorporation of appropriate information • does not necessarily provide a stimulus to trade actively – and if it does, it may not incentivize to trade rationally 	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • typically lower cost/risk, as limited number of few traders are rewarded with prizes, e.g. lottery

In terms of market efficiency, a performance-based design is likely to be more efficient than a non-performance-based design. Whereas the former design option rewards a trader's knowledge and insight and punishes his unfamiliarity and irrationality, a non-performance-based design does not reward a trader's increase of investment through

³⁷⁴ see <www.nobelpreisboerse.de> as of October 2004

trade, but acknowledges some other trader activity, e.g., simply joining the market. Thus, while a performance-based design provides traders with a stimulus to trade actively in order to increase their investment through trade and even reach a specific goal, the alternative design does not necessarily provide a stimulus to trade actively – and if it does, it may not incentivize to trade rationally.

The financial cost and risk of a prize ascertainment design is contextual and largely depends on the design details of both principle design alternatives. However, a performance-based prize ascertainment design is likely to bear a higher financial risk and cost to the market sponsor, as typically more traders are likely to qualify for a prize than in a non-performance-based prize ascertainment. This is especially true, if absolute performance is rewarded.

If prize ascertainment rewards relative performance, the financial risk and cost is limited and, thus, typically comparable to a non-performance based design, e.g., a lottery.

To conclude, a performance-based design is likely to lead to higher market efficiency, but does not necessarily lead to a higher financial risk and cost, if designed accordingly. Thus, we recommend the use of a performance-based design for TF markets. As such a principle design alternative offers further design options to choose from, we subsequently review these options in more detail.

Performance-based prize ascertainment design

As identified above, a performance-based prize ascertainment design offers further design options which are principally based on a trader's absolute or relative performance. Specifically, three design alternatives present themselves, a linear, quote-based, or rank-order-tournament-based prize ascertainment. Table 93 summarizes the characteristics of both alternatives.

Subsequently, the design options and their corresponding key characteristics are introduced and discussed.

Linear prize ascertainment. A performance-based, linear prize ascertainment transforms an account's net worth (in market currency) by a linear function into prize value. A higher account net worth directly translates into a higher prize value. Thus, a

linear prize ascertainment rewards on absolute investor performance irrespective how of this performance relates to others.

Such a basic prize ascertainment is typically used for real money markets, in which an account's net worth directly translates into real money. Examples of AAMs that feature such a linear prize ascertainment design include the real-money markets TU Vienna/Siemens, IEM, TradeSports and Economic Derivatives.³⁷⁵

Table 93: Performance-based prize ascertainment design: overview and characterization

Performance-based design alternatives		
Linear (absolute performance)	Quote-based (absolute performance)	Rank-order-tournament (relative performance)
<ul style="list-style-type: none"> • higher performance directly translates into a higher prize value 	<ul style="list-style-type: none"> • if a pre-defined level of performance is met, the trader becomes eligible for a prize • multiple, performance-increasing levels may translate into value-increasing prizes 	<ul style="list-style-type: none"> • ranks all traders by their performance and entitles investors to prizes based on their ranking, e.g., top 25

Quote-based prize ascertainment. A performance-based, quote-based prize ascertainment uses a step function to transform an account's net worth (in market currency) into prize value. Only if a pre-defined level of net worth is met does the account holder become eligible for a prize. Consequently, a higher account net worth does not automatically translate into a higher prize value. Thus, a quote-based prize ascertainment rewards on absolute investor performance irrespective of how this performance relates to others.

Furthermore, more than one net worth level may be defined at which an investor becomes eligible for a prize.

Examples of AAMs that feature such a quote-based prize ascertainment design include the play-money markets HSX, FX, and Newsfutures, but also the small scale real-money markets TU Vienna/Siemens³⁷⁶, and HP sales.³⁷⁷

Rank order tournament (ROT). A performance-based, rank order tournament prize ascertainment ranks all traders on the exchange by their account's net worth and

³⁷⁵ see sections 3.5 and 3.6

³⁷⁶ this market employed a combined self-supply/endowment design, see also section 3.5.1

³⁷⁷ see sections 3.5 and 3.6

entitles investors to prizes based on their ranking. Consequently, a higher account net worth does not automatically translate into a higher prize value. Only if an increase in net worth leads to surpass the net worth of an other investor's account does this improve the outperformer's ranking and translate into another prize eligibility. Thus, a rank order tournament prize ascertainment rewards on relative investor performance irrespective of how good or bad absolute performance is.

As a change of prize eligibility with every different ranking may be impractical, certain ranges of ranking can be consolidated into groups and associated with different prize eligibility. E.g. the top 3 investors each receive the top prize, the next 7 investors each receive a runner-up prize and the top 20 to 50 each receive a consolation prize.

Examples of AAMs that feature such a ROT design include the play-money markets HSX, FX, and Newsfutures.³⁷⁸

Application to TF markets

Our evaluation of the application of performance-based prize ascertainment design alternatives to TF markets is summarized in Table 94. The support of market efficiency by the various performance-based prize ascertainment designs will be different in different context. As noted above, the choice for a real-money market model is likely to be a linear design, while the choice for a play-money market model may be a quote-based or a rank-order-tournament design.

A linear prize ascertainment provides traders with a stimulus to trade actively in order to maximize prize value, but at the same time it typically does not provide a stimulus to reach a specific target.

A quote-based design provides traders with a stimulus to trade actively as to reach the (next higher) level at which they will become eligible for a (higher-value) prize. In this design traders receive the opportunity to follow a strategy of small steps in increasing their performance. Typically, a relatively large circle of traders becomes eligible for prizes, albeit of different value.

A rank-order-tournament design provides traders with a stimulus to trade actively as to outperform other traders. However, as the competition for the top-ranks is typically very intense, not few traders may view their chance to rise to those ranks as unreasonable and may in turn lose their motivation to trade.

Table 94: Performance-based prize ascertainment design: application to TF markets

³⁷⁸ see sections 3.5 and 3.6

Design alternative	Market efficiency	Financial cost/risk to operator
<i>Linear (absolute performance)</i>	<p><i>Contextual / Medium</i></p> <ul style="list-style-type: none"> • higher performance directly translates into a higher prize value • specifically provides an incentive to be right about the security's liquidation value (=forecasted outcome) • provides a stimulus to trade actively to maximize prize value – but typically does not provide a stimulus to reach a specific target 	<p><i>Contextual / Highest</i></p> <ul style="list-style-type: none"> • bears highest risk and uncertain costs as number of traders who may qualify for prizes is least limited and uncertain
<i>Quote-based (absolute performance)</i>	<p><i>Contextual / High</i></p> <ul style="list-style-type: none"> • if a pre-defined level of performance is met, the trader becomes eligible for a prize • multiple, perf.-increasing levels may translate into value-increasing prizes • specifically provides an incentive to be right about the security's liquidation value (=forecasted outcome) • provides a stimulus to trade actively as to reach next level – strategy of small steps • typically rewards a large circle of traders 	<p><i>Contextual / High</i></p> <ul style="list-style-type: none"> • depends on design details, but if designed properly, bears limited risk but still uncertain costs
<i>Rank-order- tournament (relative performance)</i>	<p><i>Contextual / High</i></p> <ul style="list-style-type: none"> • ranks all traders by their performance and entitles investors to prizes based on their ranking, e.g., top 25 • provides a stimulus to trade actively as to outperform other traders – but may also demotivate traders with "hopeless" ranking • typically rewards a small circle of traders • in contrast to alternative designs, does not specifically provide an incentive to be right about the security's liquidation value (=forecasted outcome) – "only" to be better than others 	<p><i>Contextual / Lowest</i></p> <ul style="list-style-type: none"> • bears no risk and certain costs as number of traders who may qualify for prizes is certain

In terms of financial cost and risk, a rank-order-tournament appears to be the performance-based prize ascertainment design with the lowest cost and risk.

A linear prize ascertainment design bears the highest risk and uncertain costs as the number of traders who may qualify for prizes is the least limited of all designs and uncertain. In a quote-based design traders need to, at least, achieve a minimum performance in order to be eligible for a prize. Thus, such a design, if designed properly, bears a somewhat limited risk but still uncertain costs.

In contrast, a rank-order-tournament design bears no financial risk and has certain costs as number of traders who may qualify for prizes is pre-determined and certain.

To conclude, a rank-order-tournament design is likely to lead to relatively high market efficiency at limited, pre-determined and certain costs.

Given our earlier-made choice of a play-money market model for TF markets³⁷⁹, we recommend the use of a rank-order-tournament design for TF markets. However, we recognize that a combined design may produce the most effective support of market efficiency at limited costs.

Specifically, we suggest using a combination of a rank-order-tournament and a quote-based design. Whereas a quote-based design provides a continuous stimulus to a large circle of traders, including novices, to eventually improve their performance, an additional rank-order-tournament provides a stimulus to the most active traders to match their knowledge and skill and hereby especially rewards top-performance.

Time horizon of prize ascertainment

As noted earlier in the introduction to this section, a prize ascertainment design also needs to consider the time horizon for which specific trader activities are considered for prize ascertainment. Two principle design options present themselves, a market maturity-specific design and a periodic design. Table 95 summarizes the characteristics of both alternatives.

Subsequently, the design options and their corresponding key characteristics are introduced and discussed.

³⁷⁹ see section 5.8.3

Table 95: Time horizon of prize ascertainment: overview and characterization

Principle design alternatives	
market maturity-specific <ul style="list-style-type: none"> • prize ascertainment is performed at market maturity • only a one-time prize event • timing of prize ascertainment coincides with market and contract liquidation • in parallel markets, prize ascertainment timing is typically not synchronic 	periodic <ul style="list-style-type: none"> • prizes are awarded on a periodic basis, e.g. weekly, monthly, quarterly, annually • multiple prize events • timing of prize ascertainment is independent from market and contract liquidation • in parallel markets, prize ascertainment timing is typically synchronized

Market maturity-specific prize ascertainment design. In such a design prize ascertainment is performed at market maturity, as markets and their contracts are liquidated. Consequently, there is only a single prize event. Furthermore, in parallel markets, prize ascertainment timing is typically not synchronic as market maturities are not synchronic.

An example of an AAM that features such a market maturity-specific design of the time horizon of prize ascertainment includes the play-money market "Nobelpreisboerse".³⁸⁰

Periodic prize ascertainment design. In such a design prize ascertainment is performed on a periodic basis, independent from when markets mature. Consequently, there are multiple prize events. Furthermore, in parallel markets, prize ascertainment timing is typically synchronized.

An example of an AAM that features such a market maturity-specific design of the time horizon of prize ascertainment includes the play-money markets of Newsfutures.³⁸¹

Subsequently, we review the application of a prize ascertainment's time horizon design alternatives to TF markets.

Application to TF markets

Our evaluation of the application of time horizon design alternatives for prize ascertainment to TF markets is summarized in Table 96.

In terms of market efficiency, a market-maturity-based prize ascertainment design is likely to be less efficient than a periodic prize ascertainment design. A market-maturity-based prize ascertainment design provides only once a stimulus to trade and only a

³⁸⁰ see <www.nobelpreisboerse.de> as of October 2004

³⁸¹ see sections 3.5 and 3.6

single chance for traders to reach prize eligibility. Moreover, it provides rather "late" a stimulus to trade, that is, at market termination – for TF markets this may be several years (!) until prize ascertainment is performed.

A periodic prize ascertainment design, however, provides multiple times a stimulus to trade and offers multiple chances for traders to reach prize eligibility. In contrast to the other design alternative, a periodic time horizon provides an early and regular stimulus to trade – for TF markets of typically long market duration this may be already several years in advance to maturity.

Table 96: Prize ascertainment – time horizon design: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>at market-maturity</i>	<p><i>Lower</i></p> <ul style="list-style-type: none"> • provides only once a stimulus to trade – only a single chance for traders to reach prize eligibility • provides rather "late" a stimulus to trade, at market termination – for TF markets this may be several years 	<p><i>Lower</i></p> <ul style="list-style-type: none"> • prizes need to be provided only once for each market
<i>periodic</i>	<p><i>Higher</i></p> <ul style="list-style-type: none"> • provides multiple times a stimulus to trade – multiple chances for traders to reach prize eligibility • provides already "early" and regular a stimulus to trade – for TF markets this may be several years in advance 	<p><i>Higher</i></p> <ul style="list-style-type: none"> • prizes typically need to be provided multiple times for each market

In terms of financial cost and risk a periodic prize ascertainment design costs typically clearly more than a market maturity-based prize ascertainment design. Whereas in the latter design prizes need to be provided only once for each market, a periodic prize ascertainment design typically needs to provide prizes multiple times, that is, periodically, for each market.

To conclude, given the typically relatively long duration of TF markets (typically, a couple of years)³⁸², we recommend the use of a periodic prize ascertainment design with a maximum period of one year.

5.8.7 Prize constitution

While the previous section discussed the principles of how traders may become eligible for prizes, this section treats what may constitute such explicit rewards.

Two principle alternatives present themselves, a tangible and an intangible prize constitution design. Table 91 summarizes the characteristics of both design options.

As identified in section 5.1, traders in AAMs are very likely to be utilitarian traders, who expect to receive some benefit from trading besides monetary profits. In fact, of the identified AAM trader motives hedging, gambling, learning trading, and building credentials only hedging against risks necessarily requires the use of "real" money – and at the same time makes the need for prizes dispensable.

Consequently, an AAM market design should serve the identified AAM trader motives to attract and incentivize traders to engage in trade.

Table 97: Prize constitution design: overview and characterization

Principle design alternatives	
<p>Tangible prizes</p> <ul style="list-style-type: none"> • prizes of material value <p>further principle design options:</p> <ul style="list-style-type: none"> ○ monetary ○ non-monetary <ul style="list-style-type: none"> – merchandise, gift certificates – event-related (e.g. dinner, vacation) 	<p>Intangible prizes</p> <ul style="list-style-type: none"> • prizes of no or unseizable material value <p>further principle design options:</p> <ul style="list-style-type: none"> ○ private acknowledgement, e.g. <ul style="list-style-type: none"> – private message, meeting, etc. – anonymous ranking ○ peer or public acknowledgement, e.g. <ul style="list-style-type: none"> – public ranking, trader status level – award (event) – article, public interview, etc.

Subsequently, the design alternatives and their corresponding key characteristics are discussed.

³⁸² see also sections 2.3 and 2.5.1

Tangible prizes are prizes of material value. They include monetary (cash) and non-monetary prizes, such as merchandise, gift certificates or event-related prizes, such as a dinner or a vacation.

Intangible prizes are prizes of no or unseizable material value. They include forms of private or public acknowledgement, such as an acknowledging message, a ranking of participants, the grant of a formal status, a symbolic award, or a winner's interview in a magazine article.

Subsequently, we review the application of a prize ascertainment's time horizon design alternatives to TF markets.

Application to TF markets

Our evaluation of the application of time horizon design alternatives for prize ascertainment to TF markets is summarized in Table 98.

The support of market efficiency by both design alternatives depends largely on the type of traders that are supposed to join the market, which in turn depends largely on type of information that is covered by the AAM. As discussed in section 5.5, TF markets that specialize deeply in a specific technological field are likely to attract and focus on specialists, who may be stronger motivated by intangible prizes, such as forms of peer acknowledgement, than by tangible prizes.

TF markets that do not specialize deeply and rather cover technological developments which have a broad socio-economic impact and are visible to a broad public are likely to attract non-specialists, who may be more motivated by tangible prizes. Accordingly, whereas tangible prizes rather support the non-specialist traders' motive of gambling and the associated entertainment, intangible prizes rather support the specialist traders' motive of credibility building.

In addition, the fading attraction value of (unchanging) tangible prizes rather supports a short-term, one period engagement of traders. In contrast, intangible prizes that build on trader acknowledgement rather supports a long-term, multiple period engagement.

In terms of financial cost and risk, tangible prizes typically cost more than intangible prizes. Whereas tangible prizes typically involve considerable material values, the opposite is true for the design alternative.

Table 98: Prize constitution design: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>Tangible prizes</i>	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • the prospect of winning tangible prizes rather attracts non-professionals • may have a "trophy" value • tangible prizes may not be as strong a motive as acknowledgement may be a for professionals/specialists • rather supports traders' motive of gambling • rather supports trader short-term, one period engagement 	<p><i>Higher</i></p> <ul style="list-style-type: none"> • typically higher cost/risk, as significant material values are involved
<i>Intangible prizes</i>	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • acknowledgement may be a stronger motive for professionals/specialists than tangible prizes • cannot be bought by cash – may have special "trophy value" • rather supports traders' motive of credibility building • rather supports trader long-term, multiple period engagement 	<p><i>Lower</i></p> <ul style="list-style-type: none"> • typically lower cost/risk, as NO significant material values are involved

To conclude, the choice of a prize constitution design is largely driven by the market purpose and objectives, and the consequential selection of type of traders that are supposed to join the market. However, as TF markets typically span multi-year horizons, we recommend the use of intangible prizes designed to support a long-term engagement of traders.

We recognize that a combined design may produce the most effective support of market efficiency at reasonable costs. Specifically, we suggest using a combination of non-monetary incentives and a public acknowledgement. Whereas a public acknowledgement design provides a long-term stimulus to a small circle of specialist traders, regular non-monetary incentives may provide a stimulus to a larger circle of non-specialist traders.

5.9 Step 6a: Organizational design

Finally, the organizational and technical system design is established. The specific design derived at this stage provides the infrastructural and operational basis for an AAM. It includes the assignment of responsibilities for key organizational tasks, such as security creation, data collection, or security judging – see also the illustration by Figure 67.

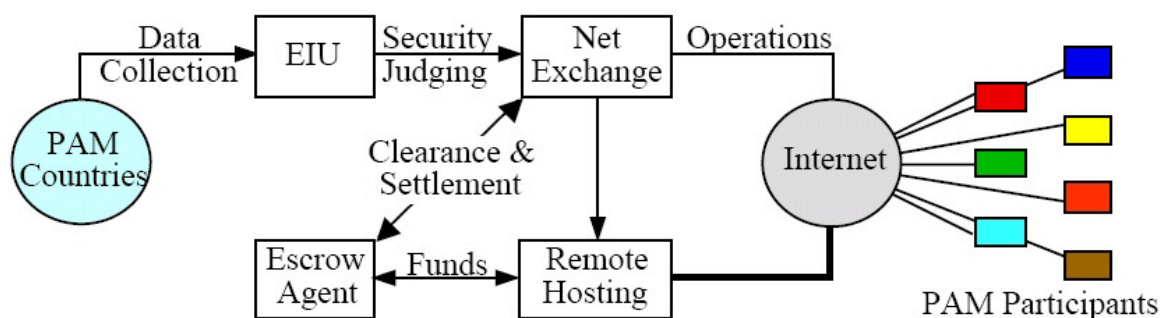


Figure 1. Policy Analysis Market Service Structure

Figure 67: Illustration of the key elements for organizational design of artificial asset markets

The key organizational tasks and main design alternatives for the corresponding organization of those tasks are summarized by Table 99.

Table 99: Organizational design: Key organizational tasks and main design alternatives for the corresponding organization of those tasks

Organizational tasks	Organizational design alternatives
<i>Trading</i>	<ul style="list-style-type: none"> • by traders – see section 5.7.4, trader access and incentivisation design for a discussion of design alternatives
<i>Security creation</i>	<ul style="list-style-type: none"> • security is created by third party (market sponsor) • security is created by traders/individuals
<i>Data collection</i>	<p><i>If contract type is Event-specific commerce (data point):</i></p> <ul style="list-style-type: none"> • by third party (credible institution) • by market sponsor • by traders <p><i>If contract type is Standardized commerce (data series)</i></p> <ul style="list-style-type: none"> • by third party (credible institution) • by market sponsor
<i>Security judging</i>	<ul style="list-style-type: none"> • by third party (credible institution) • by market sponsor • by traders
<i>Market operation &</i>	<ul style="list-style-type: none"> • by market sponsor

<i>maintenance</i>	<ul style="list-style-type: none"> • by dedicated platform operator
<i>Funds management</i>	<p><i>If market currency is play money:</i></p> <ul style="list-style-type: none"> • no funds management required <p><i>If market currency is real money</i></p> <ul style="list-style-type: none"> • by third party (credible institution) • by market sponsor

Subsequently, we discuss each of the design aspects and alternatives in detail.

Organizational design for security creation

The organizational design of security creation offers two principle options based on who is responsible for proposing securities. The two options are a security creation by the market sponsor and a security creation by individual traders. Table 100 summarizes the characteristics of both alternatives.

Table 100: Organizational design alternatives for security creation: overview and characterization

Organizational design alternatives for security creation	
by market sponsor	by traders/individuals
<ul style="list-style-type: none"> • a third party with an interest in a specific topic to be forecasted suggests a forecast • the market operator creates a security/a market based on the suggested topic • theme-push-/directed approach: market sponsor may suggest themes that are outside the interest of the established trader community 	<ul style="list-style-type: none"> • traders (or unregistered individuals) may suggest topics of their interest to be forecasted • suggested topic may be discussed in discussion forum; market operator chooses suggested topics based on interest display in forum and creates a respective security/market • user-driven approach; traders drive themes that may reflect unanticipated topics • tendency to loose focus may be contained by imposing theme limits

Subsequently, the design options and their corresponding key characteristics are introduced and discussed.

Security creation by a market sponsor. In such a design, the market sponsor suggests the topic of the forecast and proposes a respective security.

Such a market sponsor-driven security creation is the more commonly used of both market designs. Examples of AAMs that feature such a security creation design include

the real-money markets IEM, TradeSports and Economic Derivatives and play money markets such as HSX and Newsfutures.³⁸³

Security creation by individual traders. In such a design, individual traders suggest the topic of the forecast and propose a respective security. By some mechanism a proposal is selected and a security is released.

Such a user-driven security creation is the less commonly used of both market designs. An example of an AAM that features such a design includes the play money market Foresight Exchange.³⁸⁴

Application to TF markets

Our evaluation of the application of organizational design alternatives for security design to TF markets is summarized in Table 101. The support of market efficiency by both designs will be different in different context. However, as a sponsor-driven security creation may not fully meet trader interest, such a design may lead to lower trading activity and lower market efficiency. Correspondingly, a user-driven security creation may lead to higher trader interest and to higher market efficiency.

Table 101: Organizational design for security creation: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>by market sponsor</i>	<i>Contextual / Lower</i> <ul style="list-style-type: none"> • sponsor-driven securities may not meet trader interest and thus lead to lower trading activity 	<i>Contextual / Lower</i> <ul style="list-style-type: none"> • A simple, low cost security creation mechanism is sufficient
<i>by traders/individuals</i>	<i>Contextual / Higher</i> <ul style="list-style-type: none"> • user-driven securities may better meet trader interest and thus lead to higher trading activity 	<i>Contextual / Higher</i> <ul style="list-style-type: none"> • The mechanism to allow for security creation by traders may involve higher costs

In terms of financial cost and risk, a market sponsor-driven security creation is likely to carry lower costs than the design alternative, as for the former a simple, low cost security creation mechanism is sufficient, whereas a trader-driven security creation requires a more complex mechanism which may involve higher costs.

³⁸³ see sections 3.5 and 3.6

³⁸⁴ Ibid.

To conclude, none of the design options is obviously ideally suited for TF markets. Thus, the design decision discussed above is primarily driven by the purpose of the TF market.

Organizational design for data collection and security judging

Three options present themselves for the organizational design of data collection and security judging: by a third party, by a market sponsor, or by traders and a judge or jury. Below, Table 102 summarizes the characteristics of the three alternatives.

Table 102: Organizational design for data collection & security judging: overview and characterization

Organizational design alternatives for data collection & security judging		
by third party	by market sponsor	by traders + judge/jury
<ul style="list-style-type: none"> • a trusted third party collects the real world data underlying the security fundamental • consequently, the third party determines the outcome of the event • a third party that is compensated irrespective of security values is expected to act as the most objective of the design alternatives • well suited for event-specific commerce where the outcome is difficult to measure/determine • well suited for standardized commerce contracts due to the high number of necessary decision making 	<ul style="list-style-type: none"> • the market sponsor collects the real world data underlying the security fundamental • consequently, the market sponsor determines the outcome of the event • as the market sponsor may have an interest in a specific event outcome, the objectivity of this design is at least questionable • well suited for event-specific commerce where the outcome is easy to measure/determine • not suited for standardized commerce contracts due to the impractically high number of necessary decision making 	<ul style="list-style-type: none"> • any trader may submit pieces of real world data that document a specific event outcome underlying the security fundamental • a judge or jury then decides whether the submitted documentation is proof enough and decides on the event outcome • this design alternative is expected to provide good objectivity • well suited for event-specific commerce where the outcome is difficult to measure/determine • not suited for standardized commerce contracts due to the impractically high number of necessary decision making

The design options and their corresponding key characteristics are introduced and discussed below.

Data collection & security judging by a third party. In such a design, a trusted third party collects the real world data underlying the security fundamental and eventually

determines the final outcome of the event. This design is suited for event-specific commerce where the outcome is difficult to measure/determine. Furthermore, it is especially well suited for standardized commerce contracts due to the high number of necessary decision making.

An example of an AAM that features such an organizational design is the Economic Derivatives market.³⁸⁵

Data collection & security judging by a market sponsor. In such a design, the market sponsor collects the real world data underlying the security fundamental and eventually determines the final outcome of the event. As the market sponsor typically has an interest in a specific event outcome, such a design is only suited for events, where the outcome can easily be followed through public sources.

Examples of AAMs that feature this organizational design option include the real-money markets IEM, and TradeSports, and the play money markets HSX and Newsfutures.³⁸⁶

Data collection & security judging by traders & a judge or jury. Finally, by the third design option, the real world data underlying the security fundamental is eventually collected and submitted by traders. A judge or jury then decides on the submitted data and eventually determines the final outcome of the event. This design is especially suited for event-specific commerce where the outcome is very difficult to measure/determine. However, it not suited for standardized commerce contracts due to the high number of necessary decision making.

An example of an AAM that features such an organizational design is the Foresight Exchange.³⁸⁷

Application to TF markets

Our evaluation of the application of organizational design alternatives for data collection & security judging to TF markets is summarized in Table 103. Market efficiency is best served by a design employing a widely trusted third party, as traders may place more trust in the objective determination of the eventual event outcome and are therefore likely to generate higher trading activity. A trader & judge/jury-design ranks next in terms of efficiency, if a community has been established that is trusted by

³⁸⁵ see sections 3.5 and 3.6

³⁸⁶ Ibid.

³⁸⁷ Ibid.

other traders. A market sponsor-design may be the design with least market efficiency, if the sponsor is not generally trusted by traders which may, correspondingly, lead to a reduced trading activity.

Table 103: Organizational design for data collection & security judging: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>by third party</i>	<p><i>Higher</i></p> <ul style="list-style-type: none"> • as traders may place more trust in the objective determination of the eventual event outcome, more traders may decide to trade 	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • typically, a third party has to be compensated for their service of establishing the data; thus, this design alternative is associated with a defined cost
<i>by market sponsor</i>	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • as traders may distrust the market sponsor to objectively determine the eventual outcome, e.g. because the sponsor has an interest in a specific outcome, less traders may decide to trade 	<p><i>Contextual</i></p> <ul style="list-style-type: none"> • the cost of collecting the data amounts to the effort the market sponsor needs to spend on acquiring the data; this cost may vary greatly
<i>by traders + jury/judge</i>	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • if a community has been established that is trusted by traders, they may be more willing to participate in trade 	<p><i>Contextual</i></p> <ul style="list-style-type: none"> • the cost of collecting the data is allocated to the traders • the cost of judging is driven by the amount of the submitted data that needs to be reviewed

In terms of financial cost and risk, a third party-design is likely to carry the highest cost, as the third party needs to be compensated for their service of establishing the data and eventually judging the forecasting event. The costs for the other design options may vary greatly, as the cost of collecting the data can amount to the effort the market sponsor needs to spend on acquiring the data, whereas the cost of security judging is driven by the amount of the submitted data that needs to be reviewed.

To conclude, a third party- or a trader & judge- design may be best suited for TF markets, as both options sufficiently address the high level of trust needed in resolving the occurrence of TF events that are typically difficult to measure.

Organizational design for market operation & maintenance

The organizational design of market operation & maintenance offers two principle options, a market operation & maintenance by a market sponsor or by a dedicated platform operator. Table 104 summarizes the characteristics of both alternatives.

Table 104: Organizational design for market operation & maintenance: overview and characterization

Organizational design alternatives for market operation & maintenance	
by market sponsor	by dedicated (platform) operator
<ul style="list-style-type: none"> • a market sponsor operates and maintains the market • by this approach the trader community becomes attached/loyal to the market sponsor (in contrast to the platform operator) • this design is well suited for market sponsors who have a long-term and multiple instances interest in forecasting 	<ul style="list-style-type: none"> • the market is maintained and operated by a dedicated (platform) operator • a dedicated platform provider may provide more expertise at a lower cost, and may provide an established community • this design is well suited for market sponsors who have a short-term or one-time interest in a specific forecast

Subsequently, the design options and their corresponding key characteristics are introduced and discussed.

Market operation & maintenance by the market sponsor. In such a design, the market sponsor operates and maintains the market. This design is suited for market sponsors who have a long-term and multiple instances interest in forecasting.

Examples of AAMs that feature this organizational design option include the real-money markets IEM, TradeSports, and Economic Derivatives, and the play money markets HSX and Foresight Exchange.³⁸⁸

Market operation & maintenance by a dedicated platform operator. In such a design, the market is maintained and operated by a dedicated (platform) operator. Such a design is well suited for market sponsors who have a short-term or one-time interest in a specific forecast. An example of an AAM that features such an organizational design is Newsfutures.³⁸⁹

³⁸⁸ see sections 3.5 and 3.6

³⁸⁹ Ibid.

Application to TF markets

Table 105 summarizes our evaluation of the application of organizational design alternatives for market operation & maintenance to TF markets. The support of market efficiency by both designs will be different in different context. If the forecast is of crucial importance to the market sponsor, operation & maintenance may be internalized to have full control over trade and market efficiency. However, as dedicated platform operators have typically accumulated greater experience, they should be able to produce greater market efficiency through operational measures.

Table 105: Organizational design for market operation & maintenance: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>by market sponsor</i>	<p><i>Contextual</i></p> <ul style="list-style-type: none"> • if the forecast is of crucial importance to the market sponsor, operation & maintenance should be internalized to have full control over trade and market efficiency 	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • A market sponsor operated market is typically less cost efficient due to the relative lack of experience and the limited economies of scale • As operator, the market sponsor is practically exposed to higher legal risk
<i>by dedicated (platform) operator</i>	<p><i>Contextual</i></p> <ul style="list-style-type: none"> • as dedicated platform operators have typically accumulated greater experience, they should be able to produce greater market efficiency through operational measures 	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • Typically, a dedicated platform operator is able to operate more efficiently due to the increased experience and the economies of scale • The outsourcing of market operation typically reduces the exposure to legal risk

Thus, in terms of financial cost and risk, a dedicated platform operator is typically able to operate more efficiently due to the increased experience and the economies of scale. Furthermore, the outsourcing of market operation typically reduces the exposure to legal risk. Correspondingly, a market sponsor operated market is typically less cost efficient due to the relative lack of experience and the limited economies of scale. Additionally, the market sponsor is practically exposed to higher legal risk.

To conclude, an organizational design employing a dedicated platform operator may be better suited for setting up TF markets. As the market sponsor becomes more familiar with TF market operations, the sponsor may decide to internalize market operations & maintenance, if suggested by strategic considerations.

Organizational design for funds management

Two options present themselves for the organizational design of funds management: by a third party, or by a market sponsor. Below, Table 102 summarizes the characteristics of the two alternatives.

Table 106: Organizational design alternatives for funds management: overview and characterization

Organizational design alternatives for funds management	
by third party	by market sponsor
<ul style="list-style-type: none"> • a third party manages the traders' funds; that is, it collects, updates, and releases funds from/to traders • the main point by using such a design is to build trust; traders might be much more comfortable knowing that their funds have been deposited with a large and reputable financial institution • the market sponsor would be restricted from direct control of any of the deposited funds • this design is used for real money markets with considerable amounts of money at stake, e.g. max. account value of €100–€1000 	<ul style="list-style-type: none"> • the market sponsor manages the traders' funds; that is, it collects, updates, and releases funds from/to traders • simple design alternative • this design is used for play money markets or real money markets with relatively small amounts of money at stake, e.g. max. account value of €100

The design options and their corresponding key characteristics are introduced and discussed below.

Funds management by a third party. In such a design, a trusted third party manages the traders' funds; that is, it collects, updates, and releases funds from/to traders. The main point by using such a design is to build trust; traders might be much more comfortable knowing that their funds have been deposited with a large and reputable financial institution. Thus, such a design is typically used for real money markets with considerable amounts of money at stake.

Examples of AAMs that feature this organizational design option include the real-money markets TradeSports, and Economic Derivates.³⁹⁰

Funds management by a market sponsor. In such a design, the market sponsor manages the traders' funds; that is, it collects, updates, and releases funds from/to

³⁹⁰ see sections 3.5 and 3.6

traders. This simple design alternative is typically used for play money markets or real money markets with relatively small amounts of money at stake. Examples of AAMs that feature this organizational design option include the real-money market IEM, and the play money markets HSX, Foresight Exchange, and Newsfutures.³⁹¹

Application to TF markets

Our evaluation of the application of organizational design alternatives for funds management to TF markets is summarized in Table 107. Market efficiency is best served by a design employing a widely trusted third party, as traders may place more trust in a third party with no (financial) interest in the forecast outcome and are therefore likely to generate higher trading activity. Conversely, as traders may distrust the market sponsor to manage their funds properly, e.g. because the sponsor has an interest in a specific outcome, less traders may decide to trade if such a design is employed.

Table 107: Organizational design for funds management: application to TF markets

Design alternative	Market efficiency	Financial cost/risk to operator
<i>by third party</i>	<p><i>Higher</i></p> <ul style="list-style-type: none"> • as traders may place more trust in a third party with no (financial) interest in the forecast outcome, more traders may decide to trade • as traders may place more trust in a third party to preserve trader anonymity, more traders may decide to trade 	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • typically, a third party has to be compensated for their service of funds management; thus, this design alternative is associated with a defined cost • The outsourcing of funds management typically reduces the exposure to legal risk
<i>by market sponsor</i>	<p><i>Contextual / Lower</i></p> <ul style="list-style-type: none"> • as traders may distrust the market sponsor to manage their funds properly, e.g. because the sponsor has an interest in a specific outcome, less traders may decide to trade • as traders may distrust the market sponsor to honor trader anonymity, less traders may decide to trade 	<p><i>Contextual / Higher</i></p> <ul style="list-style-type: none"> • Funds management by a market sponsor is typically less cost efficient due to the relative lack of experience and the limited economies of scale • As operator, the market sponsor is practically exposed to higher legal risk

³⁹¹ see sections 3.5 and 3.6

In terms of financial cost or risk, a third party-design has a reduced exposure to legal risk, as this function is outsourced. Funds management by a market sponsor is typically less cost efficient due to the relative lack of experience and the limited economies of scale. Additionally, as operator, the market sponsor is practically exposed to higher legal risk.

To conclude, of the principle design alternatives a third party-design may be better suited real-money TF markets, as it offers higher market efficiency at a comparable or lower cost.

5.10 Step 6b: Technical system design

A detailed discussion of technical system design of AAM is beyond the scope of this work. However, we give a brief overview of key points. To start, the key features of an AAM technical system design are, for obvious reasons, the use of an electronic exchange platform, ideally an internet-based system, and a user access via PC and internet or intranet connection. Furthermore, there is a very principle choice between an off-the-shelve-solution – where the major part of the system is provided by a third party – and a do-it-yourself-solution in which the technical components have to be developed and tied together by oneself. These key features are also summarized by Table 108.

Table 108: Key features of AAM technical system design

-
- Electronic exchange platform / Internet-based system
 - User access via PC and Internet/Intranet
 - Off-the-shelve (OTS)-solution vs. Do-it-yourself (DIY)-solution
-

Meanwhile, some universities and even commercial vendors offer complete system packages for artificial asset markets.³⁹² Such offerings present the obvious advantage of a reduced effort to construct the technical system from scratch and to build on available experience in designing such systems. Furthermore, they enable the conduct of research to focus on the core research questions without diverting much attention to important, but secondary technical details.

³⁹² Universities include the University of Iowa, California Institute of Technology, Massachusetts Institute of Technology, and the University of Karlsruhe; commercial vendors include Newsfutures and HSX

Table 109: Key elements of an AAM technical system

Key system elements	Details
Graphical User Interface (GUI) / Trading interface	<ul style="list-style-type: none"> the GUI or trading interface is, essentially, a trading screen for financial instruments. Market wide information, trader specific information, and order formation features are provided in a standard format that is reasonably intuitive to anyone with mild exposure to online financial trade account management needs to be customized
Crossing and Pricing algorithms	<ul style="list-style-type: none"> crossing and pricing algorithms facilitate the trade of securities by structuring and matching individual supply and demand according to the specified conditions; depends on security design and trade mechanism design needs to be customized
Database	<ul style="list-style-type: none"> stores all market and user data required to handle envisaged scope of traders needs to be customized
Servers	<ul style="list-style-type: none"> run the applications

To facilitate a superficial understanding of an AAM technical system, we briefly introduce the key system elements and we provide illustrations of example systems. Table 109 gives an overview of the key system elements.

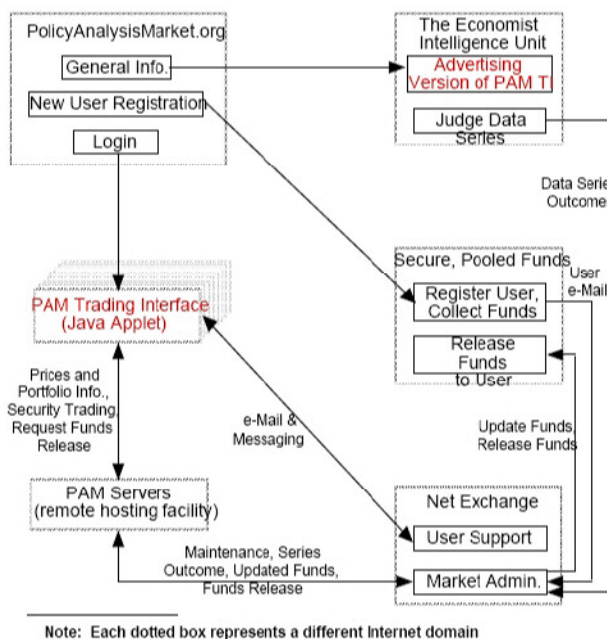


Figure 68: Example for a technical system design (NetExchange 2003c)

Essentially, an AAM technical system consists of a Graphical User Interface (GUI), which represents the trading interface, crossing and pricing algorithms, a database, and servers to host the applications. An example for an AAM technical system design is shown below in Figure 68.

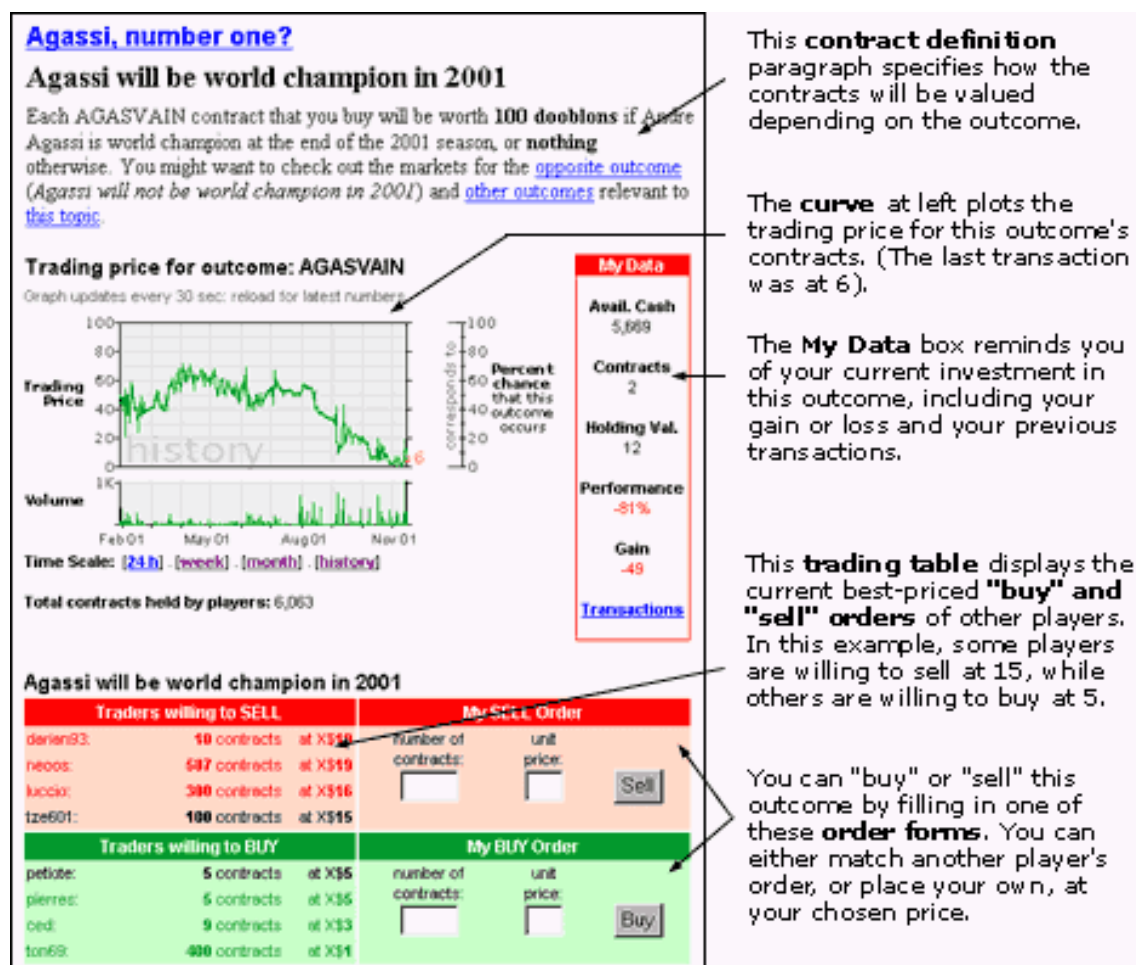


Figure 69: Example for the design of a GUI / trading interface (Newsfutures 2004)

As the most visible key system element, the trading interface is, essentially, a trading screen for financial instruments. Market wide information, trader specific information, and order formation features are provided in a standard format that is reasonably intuitive to anyone with mild exposure to online financial trade account management. An example of such a trading interface is provided below in Figure 69.

5.11 Summary and conclusions

In this chapter we systematically explored the different possible design alternatives for artificial asset markets and we evaluated the different design options for their applicability to the domain of technological forecasting. Below, we summarize more specifically the achievements presented in this chapter:

- We developed a seven-step design process for artificial asset markets
- We established criteria to evaluate the suitability of different design alternatives for artificial asset markets
- We summarized general guidelines for the design of artificial asset markets
- We discussed each step of the design process and established the principle design alternatives
- To be mentioned, we also discussed those aspects of design that are more relevant for implementation, such as the various organizational and technical design options
- We evaluated the design alternatives for their applicability to artificial asset markets for technological forecasting and established, where appropriate, a design recommendation

As we have explored the design of artificial asset markets and discussed which of the many design options are suitable for TF, we move on to apply these findings by implementing an artificial asset market for technological forecasting in the field, that is, in the "real world". This is to be the subject of the next chapter.

6. Implementation of an artificial asset market for technological forecasting

Motivated by application of the design guidelines developed in the previous chapter and the two-stream empirical research proposed in chapter 4, we design an artificial asset market for technological forecasting and document its implementation.

First, we establish the project concept which documents the project goal, resources and scope. We then develop specific technological forecasting questions. Next, we establish the design of the AAM for TF based on the design guidelines developed in the previous chapter and limited by the constraints given by the project concept.

Finally, we document the design of the implemented AAM for TF. We conclude the chapter with a brief summary.

6.1 Project concept

As outlined in chapter 4, this thesis follows a two-stream empirical research effort. The task at hand described in this chapter is to produce new empirical data for further research by design and set-up of new TF markets. The timeframe for the setup is limited to one year by constraints imposed on the author, but operation should last at least three years if not considerably longer.

Table 110: Project concept

Issue	Specification
Goals	1. to produce empirical data for further research 2. by design and set-up of a new TF markets
Timeframe	<ul style="list-style-type: none"> ▪ Setup: <1 year (2005) ▪ Operation: >3 years
Financial Resources	None
Partner	Chair of Information Services and Electronic Markets, University of Karlsruhe (Platform provider)

Another constraint is to undertake this effort without any financial resources. However, such constraints can be circumvented through partnership with the Chair of Information Services and Electronic Markets of the University of Karlsruhe which provide the market platform. The project concept is summarized by Table 110

6.2 Market design

In designing the artificial asset market for technological forecasting we follow the six step-process developed in chapter 5, see also Table 111 below. The design decisions in each step are constrained by the project concept developed in the section above.

Table 111: Design process for AAM – as developed in chapter 5

No.	Process step
1	Establish market purpose & content
2	Characterize information environment
3	Define artificial asset
4	Establish trading mechanism
5	Establish trader access & incentivitation design
6	Establish organizational & technical system design

As the first step, the market purpose and content need to be established. Based on the purpose of this thesis, obvious goals are to produce technological forecasts and, by this, to produce empirical data for research. Furthermore, we would like to engage the academic and professional community to participate in this research. Finally, a further goal is to proscribe all financial interest, as financial cost and risk need to be minimized to near zero to meet the financial constraint outlined in the project concept above. An overview of all goals is presented in Table 49.

Table 112: Market purpose

No.	Purpose statement
1	to produce technological forecasts
2	to proscribe all financial interest
3	to engage the academic and professional community
4	to produce empirical data for further research

Next, the market content needs to be developed. For this purpose, mainly two public sources with broad coverage of technology issues were screened, the M.I.T. Technology Review and the Siemens Research Magazine "Pictures of the future". By this screening several promising technologies of various technological fields were arbitrarily selected. For the selected technologies, specific technological forecasting questions were developed. These forecasting questions are summarized by Table 113.

Table 113: Selected TF questions to be forecasted by TF markets

TF subject	Specific TF question
Biotechnology & Healthcare	
<i>Organ substitutes: artificial kidney</i>	➤ When will five people have survived at least two years after they have been implanted a fully implantable artificial kidney?
<i>Medical nanorobots</i>	➤ When will precisely control led or programmable medical nanomachines for medical purposes have been applied upon 1.000 people (including clinical trials)?
Computers & Electronics	
Radio Frequency Identification (RFID)	➤ When will 5 of the international top 10 retailers (by countries of operation, then by sales) use RFID on a significant scale (>30% in their countries of operation OR >40% of their total stores)?
Keyboard as text-input device	<ul style="list-style-type: none"> ➤ When will keyboards as text-input device be second to some alternative text-input device or method (e.g. voice recognition, Dasher) measured by annual new unit sales in any one of the G8 countries or measured by a representative survey of users in any one of the G8 countries? ➤ Which G8 country will meet these criteria first?
LED performance plateau	➤ At what performance in lm/W will white LEDs reach a performance plateau? (performance after 3 years of CAGR <5% in performance increase)
Energy, Environment, & Agriculture	
<i>Solar battery- or fuel battery-power for notebooks, PDA and mobile phones</i>	<ul style="list-style-type: none"> ➤ When will solar battery- or fuel battery-powered devices account for 25% of new unit sales for either notebooks, PDAs or mobile phones in any one of the G8 countries? ➤ Which G8 country will meet these criteria first?
<i>Hybrid Electric Vehicle (HEV) cars</i>	<ul style="list-style-type: none"> ➤ When will HEV account for >25% of annual new car sales (in units!) in any one of the G8 countries? ➤ Which G8 country will meet these criteria first?
<i>Conventional engine cars</i>	➤ When will today's conventional engine cars be second to some alternative powered car (e.g. hybrid, fuel cell) measured by annual new unit sales in any one of the G8 countries?
Materials excl. electronics	
<i>Changeable photorefractive material</i>	➤ When will photo-refractive material that can reversibly change its photorefractive index by 0.1 or more be commercially available?
Software	
<i>LSI design software</i>	➤ When will a software be commercially available which can completely automatically design high performance LSIs with several hundred kilo gates or more when given the required system-level specifications written in a high-level language such as C?
Telecom & Internet, Media and Entertainment	
<i>Music media format</i>	➤ When will today's conventional hard-format music media (CDs, Music-DVDs, cassettes and LPs) be second to digital format music media measured by annual global sales in USD or EUR?
<i>10 Gbps optical subscriber systems</i>	➤ When will 25% of residential homes be equipped with >10 Gbps optical subscriber systems in any one of the G8 countries?
Transportation	

<i>Self-driving cars</i>	<ul style="list-style-type: none"> ➤ When will self-driving cars account for >25% of annual new car sales (in units!) in any one of the G8 countries? For purpose of this market, a car is regarded as self-driving, if it is able to safely transport without human intervention 2 passengers over 25 km of standard traffic from the drive-up lane to the departure lane of a highway ➤ Which G8 country will meet these criteria first?
<i>Segway</i>	<ul style="list-style-type: none"> ➤ When will the Segway and its clones surpass conventional motorbikes (incl. scooters) in annual unit sales in any one of the G8 countries? ➤ Which G8 country will meet these criteria first?

As we have established the market purpose and content, we proceed to the second design step, the characterization the information environment. In section 5.5 we already discussed and developed the characterization of the information environment for TF markets. Table 114 presents the results of this effort.

Table 114: General characterization of the information environment for TF markets

Criteria	TF info environment	Implications for market design
0 – Random variable		
<i>Outcome solution space</i>	Technology performance or prevalence	➤ Security design to cover continuous variable
<i>Outcome affectability</i>	Low	➤ "Insiders" allowed to trade
<i>Duration</i>	Multi-year horizon	➤ Long-term incentives
I – Information sourcing		
<i>Private / Public information</i>	Public, <u>not</u> widely known	<ul style="list-style-type: none"> ➤ Principle asset value: open ➤ A&I: anonymity of traders!
<i>No. of inputs</i>	Many	➤ Optional: standardized commerce
<i>Frequency of input changes</i>	Infrequent	➤ Annual prize ascertainment
<i>Geographic spread</i>	Global	<ul style="list-style-type: none"> ➤ Global trader base ➤ continuous trade, 24/7
<i>Demographic spread</i>	Small distinct group + "coverage" industry	➤ Peer acknowledgement: rank-order-tournament
II – Information analysis		
<i>Task balance</i>	Opinion formation	➤ Peer acknowledgement: rank-order-tournament
<i>Complexity – effort</i>	High	<ul style="list-style-type: none"> ➤ Principle asset value: open ➤ Access & Incentivation design
<i>Complexity – degree of insight (overall vs. partial insight)</i>	Partial insight	➤ Combinatorial trade mechanism with standardized commerce
III – Information outcome		
<i>Solution space ambiguity</i>	Ambiguous	➤ Detailed, peer-reviewed security definitions
<i>Outcome verifiability</i>	Difficult	➤ Use of judges

Based on the established market purpose & content and the characterization of the information environment, we move on the complete steps 3 to 6 of the market design process. We follow the analysis and recommendations developed in chapter 5 in choosing those design alternatives that, applied to TF markets, are best suited for our market design. However, where our ideal design choice is in conflict with the project concept or the market purpose & content, we limit our decision the best available design that is not in conflict.

A summary of the design choices made in completion of the design steps 3 to 6 is presented in Table 47.

Table 115: AAM design for TF markets

Design feature	Chosen design alternative
Artificial asset design	
Instrument type	<ul style="list-style-type: none"> ➤ Discrete outcome solution space ➤ Discrete security state space ➤ Multiple contract sets
Expiration	➤ Combined event-triggered / Time-sequential expiration
Payoff function	➤ Binary
Asset structure	<ul style="list-style-type: none"> ➤ Event-specific commerce ➤ Serial markets
Trading mechanism design	
Emission mechanism	➤ Unit portfolio emission
Core trading mechanism	➤ Continuous double auction (CDA)
Trading rules	<ul style="list-style-type: none"> ➤ Trading hours: 24 hours / 7 days a week ➤ Order types: Limit orders ➤ No short selling ➤ No caps
Combinatorial trade	➤ Simple (non-combinatorial)
Access and Incentivation design	
Trader identity	➤ Anonymous identity
Trader base shaping	➤ Public access
Asset value and market currency	➤ Artificial asset values / Artificial market currency
Incentivation scope	➤ Cross-market
Trader subsidization	➤ Endowment
Prize ascertainment	➤ Performance-based
Prize constitution	➤ Intangible
Organizational design	
Security creation	➤ by market sponsor
Data collection	➤ by traders
Security judging	➤ by market sponsor

Market operation & maintenance	➤ by dedicated platform operator
Funds management	➤ no funds management required as market currency is play money
Technical system design	
Core	<ul style="list-style-type: none"> ➤ Electronic exchange platform / Internet-based system ➤ User access via PC and Internet/Intranet ➤ <u>Off-the-shelve-solution</u>: Use of the platform supplied by University of Karlsruhe, Chair of Information Services and Electronic Markets (EM)

Next, as we have established the design concept of the TF market, we proceed to market implementation.

6.3 Market implementation

Based on the design defined in the previous section, the "Technology Futures Markets" has been implemented in collaboration with the Chair of Information Services and Electronic Markets, University of Karlsruhe. The market is accessible to the open public via the internet at <http://www.tfmmarkets.com>

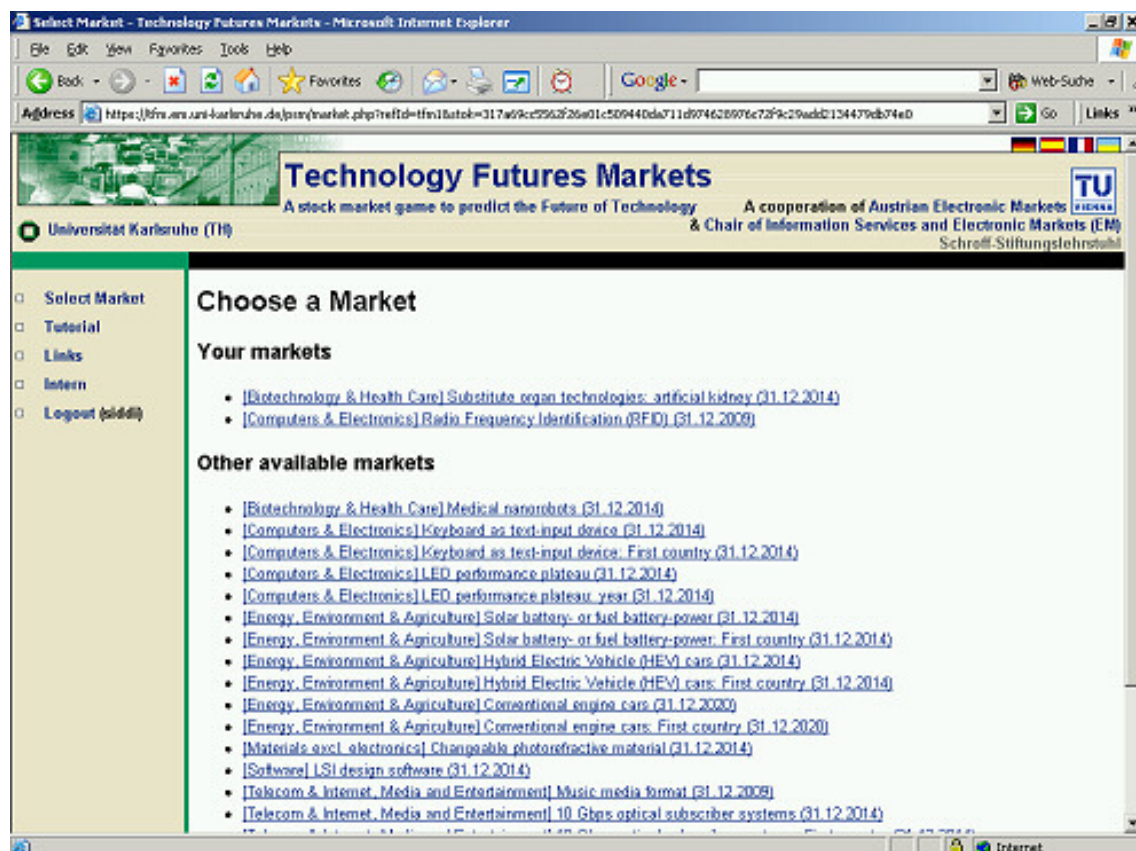


Figure 70: Screenshot TFM – Selecting a TF market

After brief and anonymous registration, the user reaches the market selection screen (see Figure 70). At this point, the user may choose his market of interest – which represents a technological forecast. The choice of markets or technological forecasts is presented in Table 113.

After selecting a market, the user is shown the market screen where he can access a detailed prospectus describing the tradable securities and its terms. See Table 116 for an example of information contained in such a prospectus.

Table 116: Detailed description of the TF market for Hybrid Electric Vehicles (HEV)

Hybrid Electric Vehicle (HEV) cars
<p>When will HEV account for >25% of annual new car sales (in units!) in any one of the G8 countries?</p> <p>➤ contract set: 2005, 2006, 2007, 2008, ..., 2014+ (10 contracts)</p>
<p>Which G8 country will meet these criteria first?</p> <p>➤ contract set: Canada, France, Germany, Italy, Japan, Russia, United Kingdom, United States (8 contracts)</p>
<p>Information links</p> <p>➤ Alternative Fuel Vehicle Group < http://www.altfuels.com/ ></p> <p>➤ U.S. Department of Energy <http://www.fueleconomy.gov/feg/atv.shtml></p> <p>➤ Newsgroups <http://groups.google.at/groups?hl=de&lr=&group=misc.transport>, <http://groups.google.at/groups?hl=de&lr=&group=sci.energy></p> <p>➤ Keywords (e.g. Google): [market] hybrid electric [vehicle, cars]</p> <p>➤ Siemens "Pictures-of-the-Future": english <http://w4.siemens.de/Ful/en/index.html>, deutsch <http://w4.siemens.de/Ful/de/index.html></p> <p>➤ M.I.T. Technology Review: english < http://www.technologyreview.com>, deutsch < http://www.technologyreview.de></p>
<p>Prospectus</p> <p>On Day X, August X, 2004, at 12:00 CET, the Technology Futures Market (TFM) will open trading in a winner-takes-all market based on the year in which Hybrid Electric Vehicle (HEV) technology meets a certain establishment criteria.</p> <p>Initially, ten contracts will trade in this market, each representing one of ten possible unique and exhaustive outcomes. The liquidation value of the contract which represents the actual half-year of establishment according to the specified criteria will be \$100. All other contracts will have a value of zero.</p> <p>This document describes the market and should be viewed as a supplement to the Trader's Manual. Except as specified in this prospectus, trading rules for this market are the same as those specified in the Trader's Manual for the Technology Futures Market (TFM).</p> <p>CONTRACTS</p> <p>The initial pseudo-financial contracts initially traded in this market are:</p> <p>Code Contract Description</p> <p>2005 \$1 if the establishment criteria is met within 01-01-2005 and 31-12-2005, \$0 otherwise</p> <p>2006 \$1 if the establishment criteria is met within 01-01-2006 and 31-12-2006, \$0 otherwise</p> <p>2007 \$1 if the establishment criteria is met within 01-01-2007 and 31-12-2007, \$0 otherwise</p> <p>2008 \$1 if the establishment criteria is met within 01-01-2008 and 31-12-2008, \$0 otherwise</p> <p>2009 \$1 if the establishment criteria is met within 01-01-2009 and 31-12-2009, \$0 otherwise</p> <p>2010 \$1 if the establishment criteria is met within 01-01-2010 and 31-12-2010, \$0 otherwise</p> <p>2011 \$1 if the establishment criteria is met within 01-01-2011 and 31-12-2011, \$0 otherwise</p> <p>2012 \$1 if the establishment criteria is met within 01-01-2012 and 31-12-2012, \$0 otherwise</p>

2013 \$1 if the establishment criteria is met within 01-01-2013 and 31-12-2013, \$0 otherwise
2014+ \$1 if the establishment criteria is met at or after 01-01-2014, \$0 otherwise

DETERMINATION OF LIQUIDATION VALUES (incl. ESTABLISHMENT CRITERIA)

This is a winner-takes-all market. For the purpose of this market, Hybrid Electric Vehicle (HEV) technology is considered as established, if HEV account for >25% of annual new car sales in any one of the G8 countries.

The contract that corresponds to the actual year of establishment according to the specified criteria will have a liquidation value of \$100; all other contracts will have a value of \$0.

Anyone may submit an authoritative source claiming the specified establishment criteria to be satisfied. The source will be reviewed by the TFM Directors and judged on validity.

Authoritative sources include e.g. The Economist, The New York Times, Neue Zürcher Zeitung, or Frankfurter Allgemeine Zeitung. Authoritative sources must be in English or German. Submission must occur through <email address> or <fax number via fax2mail>.

The judgment of the TFM Directors will be final in resolving questions of interpretation and typographical or clerical errors.

CONTRACT SPIN-OFFS

The Directors of the TFM reserve the right to introduce new contracts to the market as spin-offs of existing contracts. When a contract spin-off occurs, an original contract will be replaced by new contracts which divide the payoff range of the original contract into sub-intervals. No holder of the pre-spinoff contracts will be adversely affected. Traders will receive the same number of each of the new contracts as they held in the original, and the sum of the liquidation values of the new contracts will equal the liquidation value of the original.

Outstanding limit orders to buy or sell the contract which is to be spun-off will be canceled just prior to the spin-off.

Decisions to spin-off a contract will be announced at least two days in advance of the spin-off. The new contract names, the specifications regarding liquidation values and the timing of the spin-off will be included in the announcement. This announcement will appear as an Announcement on your login screen.

CONTRACT PORTFOLIOS

Fixed price contract portfolios consisting of one share of each of the contracts in this market can be purchased from or sold to the TFM system at any time. The price of each fixed price contract portfolio is \$100. Because exactly one of the outcomes will result from the market claim, the total payoff from holding a contract portfolio until the market closes is \$100.

To buy or sell fixed price contract bundles from the system, use the "Trade Portfolios" option from the trading console. Select "X" from the Market Orders list to buy portfolios. Select "Y" to sell portfolios.

Portfolio purchases will be charged to your cash account and bundle sales will be credited to your cash account.

MARKET CLOSING

This market will remain open until contract liquidation. Liquidation values will be credited to the cash accounts of market participants.

MARKET ACCESS

Current and newly enrolled TFM traders will automatically be given access rights to the HEV_Est_wta Market. Access to this market is achieved by logging into the TFM and choosing "HEV_Est_wta" from the Navigation Bar.

Funds in a trader's cash account are fungible across TFM markets so new investment deposits are not required.

New traders can open accounts using the Account Registration page (<http://tbd>). There is no account registration fee and new traders receive a one-time endowment of 100.000 \$.

After the user has studied the details of the prospectus he can review the historical price development of the securities offered in the selected market (see Figure 71). The user should see the securities priced at their probable liquidation values.

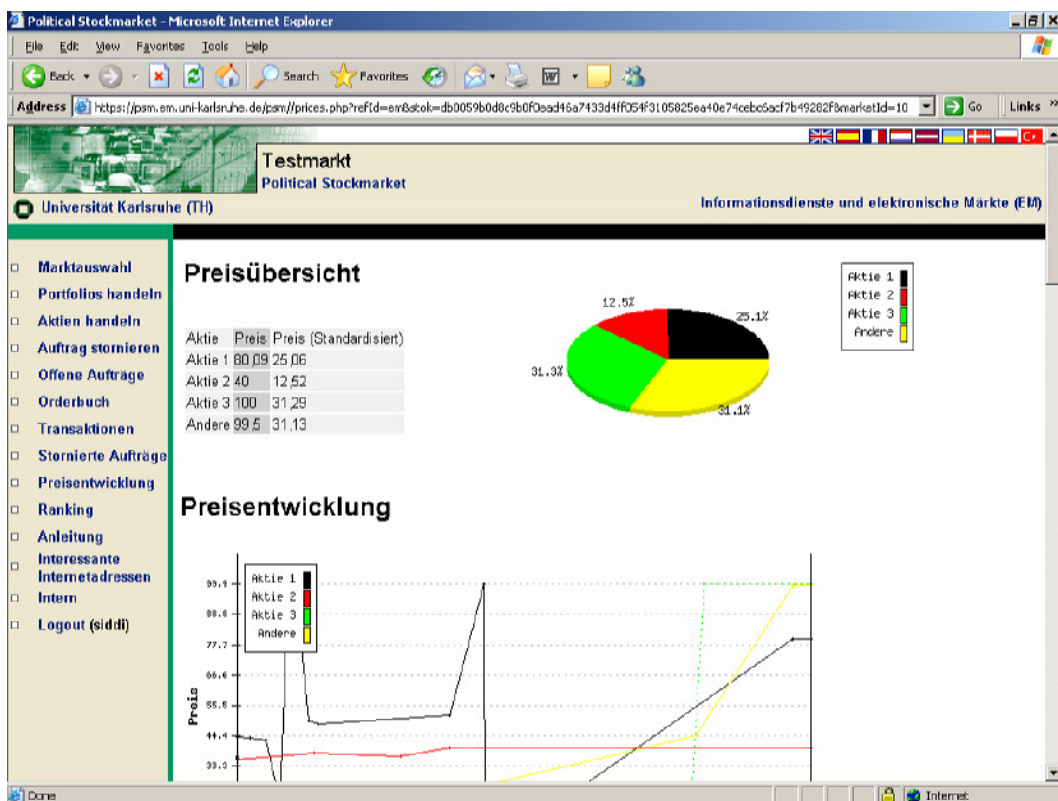


Figure 71: Screenshot TFM – Monitoring price development

As the trader reviews security prices, he needs to interpret their meaning. As prices are normalized to values between 0 and 100, prices translate directly into probabilities. A value of 0 translates into a probability of 0 for the underlying event, that is, the forecast is that the event will not occur. Conversely, a security price of 100 translates into a probability of 100 for the underlying event, that is, the forecast is that the event will definitely happen. See Figure 72 for an illustration of this price interpretation logic.

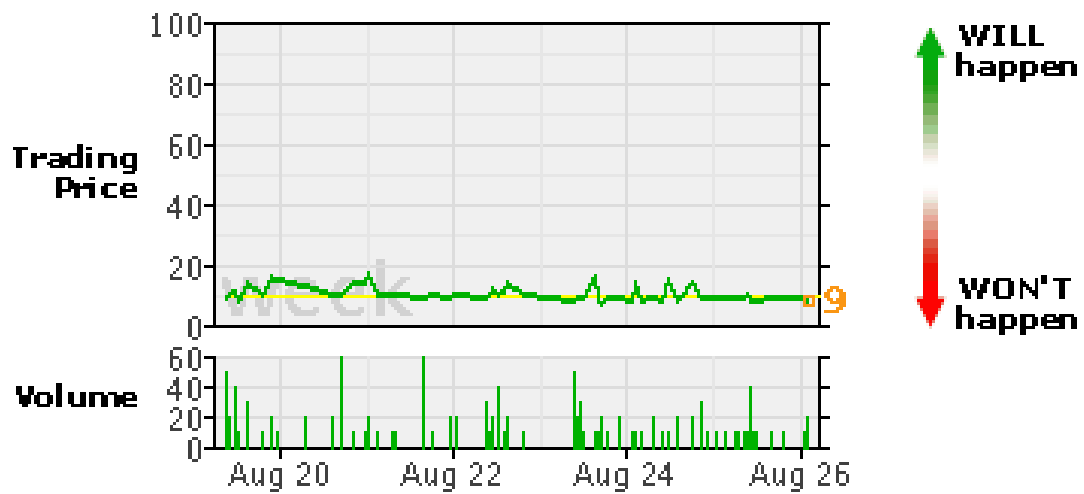


Figure 72: Interpretation of security prices on TFM

If the user decides to trade, he may choose between the primary and the secondary market. By trading in the primary market, he buys a complete set of shares, that is, a unit portfolio containing equal shares of each possible outcome. Buying and selling unit portfolios takes place between traders and the market institution. Buying a unit portfolio allows the trader to trade without waiting for other traders to offer their shares. Furthermore, it allows the trader to keep some the desired portion of shares while selling the unwanted shares at his terms, that is, his desired price.³⁹³ Figure 73 shows the trading screen for the primary market. The trader simply chooses whether he wants to buy or sell, and the respective amount of unit portfolios.

³⁹³ See section 5.7.2 for a description of trade in the core trading mechanism

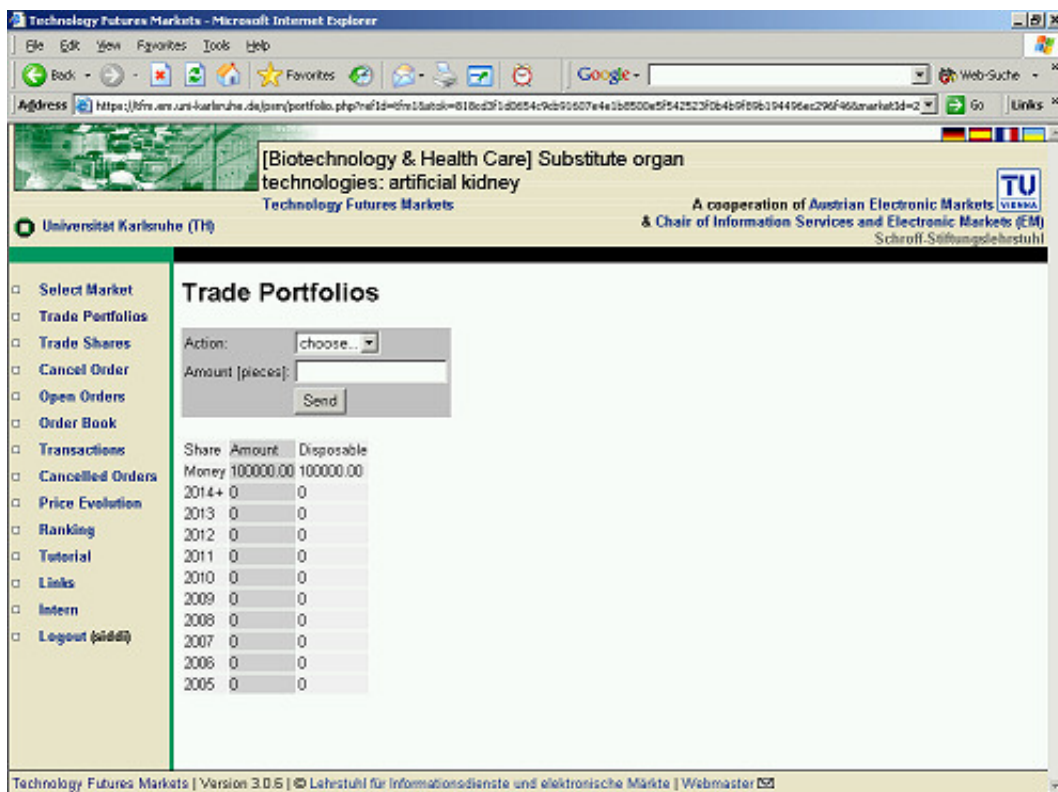


Figure 73: Screenshot TFM – Trading unit portfolios in the primary market

If the user decides to trade in the secondary market, he can trade specific shares instead of complete unit portfolios. As trade takes place between traders only, the buyer needs to find another trader willing to sell at the desired price and vice versa. Figure 74 shows the trading screen for the secondary market. After choosing whether to buy or to sell shares, the trader quotes the amount of shares to trade and at which price he wants to trade. Furthermore, the trader can define a date at which his order expires if no other trader is willing to trade at the given price.

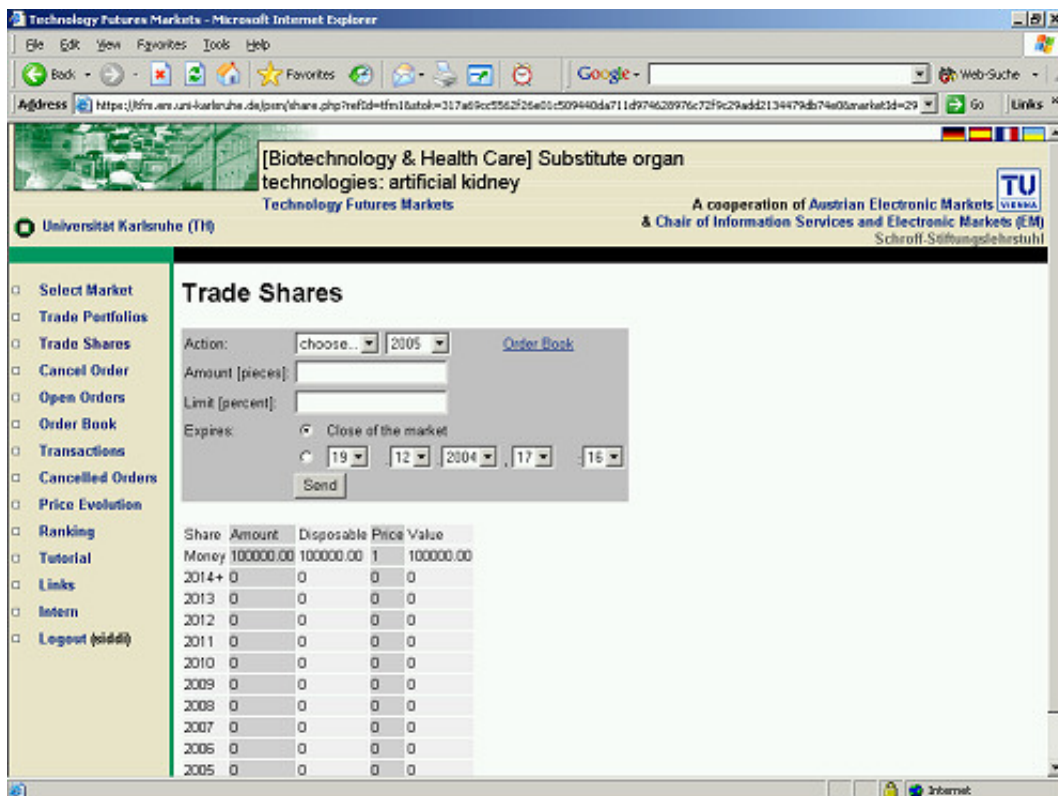


Figure 74: Screenshot TFM – Trading shares in the Secondary market

After trading the user can review his portfolio which contains all the shares owned by the trader. As activity continues in the market, the values of the shares, and of the portfolio in total, changes over time. The traders goal is maximize the value of the portfolio over time by trade in pursuit of profit and at pain of loss.

Since January 2005 registration is open to the public. Attracting a sufficient user base is the most critical milestone of market implementation and is a problem of marketing. Training this user base is a milestone subordinate to marketing.

A user base of between 100 and 1000 traders is sufficient to test the value of TFM as a forecasting tool, so long as this user base contains a substantial percentage of experts in the technology areas relevant to TFM. In addition, TFM would benefit, and may well require, the participation of a number of trading experts whose portfolio and risk analysis skills can discipline the market through arbitrage and speculation.

The first few signed users will be key. These are to be well-established, thus well-networked, members of their demographics. However, from there onwards, attaining

the desired demographic balance will be left to self-selection, the networking effects of the first registrants, and the cost barrier to casual registration (part of the self-selection effect). Academic forums, research conferences, press interviews, and presentations to institutional gatherings offer such venues.

All other proactive marketing should be web-based. Passive and reactive marketing should result from press coverage; thus, a TFM press policy and crafted messaging strategy need to be put in place.

All training need to be on-line – the logistics and cost of in-person training cannot be supported. All user support and help services will likewise be on-line. A market administrator needs to be responsible for monitoring and maintaining all training and user support functions.

6.4 Summary and conclusions

In this chapter, we documented the design and implementation of an artificial asset market for technological forecasting.

After establishing a brief project concept, we followed the seven step-design process developed in the previous chapter. We developed a range of specific technological forecasting questions and established a corresponding market design. Finally, we implemented 19 markets on a market platform provided by the Chair of Information Services and Electronic Markets of the University of Karlsruhe. The purpose of this effort is to produce valuable empirical data that, although not covered by this thesis, will be subject to future research.

7. Conclusion

The research presented in this thesis can be attributed to the disciplines of product development, technological forecasting, and to the discipline of experimental economics alike. Its research approach followed, in general, the theoretical expression and empirical validation of the method of forecasting technologies by artificial asset markets. Specifically, the ability of artificial asset markets to forecast technologies was tested in terms of absolute forecasting performance, accuracy and reliability, and in terms of relative forecasting performance.

Subsequently, we summarize the main findings of the research presented in this thesis, review and evaluate the achievement of the research objectives, and give an outlook of further development and research.

7.1 Summary of findings

Technological advancement can have a major impact on corporate profitability or the well-being of nations. For this reason technological forecasts are produced. The forecast of technologies and technological change along with the required information acquisition and processing is a major challenge for decision makers in both commercial enterprises and government. Many forecasting methods have been developed to assist decision makers in making technological forecasts, however, all of them fail in those phases of a technology's lifecycle, in which there is extreme uncertainty combined with rapid change. Most notably, these circumstances occur in the strategically most crucial technology lifecycle phases, as a technology emerges or is threatened by substitution from another technology.

For these situations there is a need for a technological forecasting (TF) method that is at the same time extremely adaptable (in relating relevant inputs to given dimensions of output) and instant (in delivering the current outlook in quasi-real-time without the requirement of going through a lengthy, time-consuming procedure). Addressing this need is the motivation for this thesis to develop a new TF method, technological forecasting by artificial asset markets (TF by AAM). Additionally, it is the first method to utilize an early established principle in forecasting, that is, forecasts provided by efficient markets are optimal. Thus, the new method holds no less than the prospect of delivering better forecasts in terms of forecast accuracy and reliability than forecasts provided by any alternative TF method.

Achievements. By literature review, we established that theory, empirical, and experimental evidence suggest that asset markets have the capacity to collect information that is dispersed, aggregate it like a statistician, and publish the findings in forms of prices.

In a perfectly efficient market, security prices reflect all information; prices reveal to the ignorant participants any initially private information, that is, participants learn by observing prices. Empirical evidence suggests that, in reality, markets are neither perfectly efficient nor completely inefficient; all markets are efficient to a certain extent, some more so than others. Rather than being an issue of black or white, market efficiency is more a matter of shades of gray.

The results of laboratory experiments suggest that the successful aggregation of information in asset markets depends on the features of these markets—rules, information distribution, common knowledge, experience of traders, number, nature and relationship of assets traded, to mention the most important.

While speculative financial markets have long been used to identify and reallocate risk, only very recently have artificial asset markets been created primarily to make forecasts. For example, the Iowa Political Stock Market seems to predict election outcomes better than opinion polls. Several play-money markets have been found to aggregate information well, although they also seem to have problems with biases and limited participation. A few internal corporate real-money markets have also shown promising results.

By empirical research using secondary statistics methodology, we establish that, on average, artificial asset markets for technological forecasting (AAM for TF) predict the eventual outcome of technological developments with a probability of >75% for approximately two years, or 59% of market duration, in advance of market maturation, that is, in advance of the technological event outcome.

Thus, the empirical evidence established by this research supports the hypothesis H1, that is, AAM for TF can forecast technological developments (in principle).

Furthermore, by indirect performance comparison, we were able to establish empirical evidence to support AAM for TF as superior to alternative forecasting methods. As TF markets show better forecasting performance on average than the IEM markets, the longest running set of prediction markets known to us and well documented for their on

average better performance than alternative forecasting methods, we concluded that TF markets perform better than alternative forecasting methods as well.

A direct performance comparison was not possible due to the lack of comparable data of methods used in the same application context.

Thus, the empirical evidence established by this research supports the hypothesis H2, that is, AAM for TF can forecast technological developments better than alternative forecasting methods used in the same application context.

Although we established by empirical research that artificial asset markets for TF work in principle and even perform well in terms of accuracy and reliability, we learned during the literature review that many potential pitfalls lie *in the way of realizing* good TF-relevant information aggregation through speculative markets.

Consequently, we systematically explored the design alternatives for artificial asset markets for TF and we evaluated the different design options for their applicability to the domain of technological forecasting. In the course of this investigation, we developed a six-step design process for artificial asset markets, established criteria to evaluate the suitability of different design alternatives for artificial asset markets, summarized general guidelines for the design of artificial asset markets, and discussed each step of the design process and established the principle design alternatives.

With a possible implementation in mind, we also discussed various organizational and technical design options. As we evaluated the design alternatives for their applicability to artificial asset markets for technological forecasting, we established, where appropriate, a design recommendation.

Finally, motivated by the application of the developed design process and design guidelines, and the purpose of producing valuable empirical data for later research, we designed and implemented an artificial asset market for technological forecasting.

Operating principles of AAM. Drawing on the presented evidence on artificial asset markets, we suggested some generalizations about the operating principles of AAM. Essentially, artificial asset markets perform three tasks:

1. Artificial asset markets provide incentives to seek information
2. Artificial asset markets provide incentives for truthful information revelation
3. Artificial asset markets provide an algorithm for aggregating diverse opinions

More specifically, artificial asset markets provide the following opportunities:

- Artificial asset markets are good information aggregators
 - absolutely
 - relative to the best alternative method
- Artificial asset markets react quickly/instantly to new information
- Artificial asset markets are good forecasting tools
- Artificial asset markets can even convey what might have been (conditional forecasts)

The opportunities presented by artificial asset markets also require categorical attention of the following matters:

- Incentives and market structure have great influence on market success, e.g.
 - Play-money markets can perform as well as real-money markets
 - Price bubbles can be prevented by a low initial liquidity level, deferred dividends, and a bid–ask book that is open to traders
- The subject pool is important
 - Markets can only aggregate what is known
- Traders make mistakes and display biases
 - Large, "thick" markets show no bias as few very rational traders seize such opportunities for arbitrage
 - Small, "thin" markets may reflect bias
- Price manipulation by trade is difficult, but possible
 - Large, "thick" markets quickly compensate such manipulation attempts
 - Small, "thin" markets compensate such manipulation attempts only if sufficient traders recognize the manipulation attempt, and if they are able and willing to profit by the given arbitrage opportunity

Furthermore, the implementation of artificial asset markets raises some considerations:

- Implementable as fully automated, electronic market mechanism
- Off-the-shelf software is available
- Moderate costs for set-up and maintenance, advertising, searching, and transacting
- Worldwide audience potential by placement on internet
- Regulation depends on the design choice of market currency

- Play-money markets require no permission from government authorities or regulatory bodies and inherit negligible legal risk
- Real-money markets are subject to extensive regulation which incurs very significant technical, regulatory, and fiduciary costs

Speculative, artificial asset markets appear to offer several apparent advantages over other prediction institutions, such as surveys, or reports by expert committees or by assigned specialists. Market estimates should be cheap to create, can be frequently updated, are numerically precise, and should offer contributors strong reasons to be careful and honest. Market estimates are also more immune to challenge, as dissenters can always be invited to trade and attempt to profit by correcting the errors they think they see.

Suggested application context. Whereas the state of the art in TF methods cope well with the operating environment of established technologies, AAM for TF appear to be particularly suited for the unserved need for a TF method that is able to cope with the operating environment in the **emerging** technology maturity phase or in **disruptive** maturity phases, and that supplies the management with an **instant** marginal forecast availability.

7.2 Evaluation of thesis research goals

At the onset of the research presented in this thesis we set research goals by formulating research questions and expressing research objectives. As we conclude our research, we review these research questions and objectives and evaluate whether they have been addressed, answered and met. Table 117 and Table 118 summarize this effort.

Table 117: Evaluation of research questions answered by this thesis

Research question	Answered by this thesis	Reference
Does the method TF by artificial asset markets work in principle?	✓	chapter 3, chapter 4
How does the method TF by artificial asset markets perform in terms of accuracy and reliability?	✓	chapter 4

How does the method TF by artificial asset markets perform in comparison to existing TF methods?	(✓) ¹⁾	chapter 4
What is the theoretical, empirical and experimental foundation of artificial asset markets?	✓	chapter 3
How should artificial asset markets for TF be designed?	✓	chapter 5
Can artificial asset markets forecast technological developments?	✓	--

1) by indirect comparison

By our judgment, essentially all research questions have been addressed and answered. Most essentially, we have established that artificial asset markets forecast technological developments with good accuracy and reliability. By indirect comparison, we have established that TF by AAM performs better than alternative methods. A direct performance comparison of TF by AAM to alternative TF methods was not possible due to the lack of comparable data and, thus, remains to be established.

Table 118: Evaluation of research objectives completed by this thesis

Research objective	Completed by thesis	Reference
Primary objectives		
to validate artificial asset markets as a tool for TF	✓	chapter 4
to design and implement an artificial asset market for TF	✓	chapter 6
Secondary objectives		
to produce a description and analysis of artificial asset markets as instrument of TF	✓	chapter 3
to produce a set of design guidelines of artificial asset markets for TF	✓	chapter 5
to establish absolute and comparative performance data on artificial asset markets for TF	✓	chapter 4
to perform an experimental investigation of artificial asset markets as instrument of TF	✓	chapter 4, chapter 6

A review of the research objectives shows that all objectives have been met. Most importantly, we have validated artificial asset markets as a tool for technological forecasting and we designed and implemented an AAM for TF.

7.3 Outlook and further research

Artificial asset markets for technological forecasting present an exciting opportunity for application and further research. We start by discussing the academic outlook that contains suggestions for further research and continue with a discussion of the application of AAM by TF in the commercial world.

Academic outlook. By the research presented in this thesis we have established evidence that artificial asset markets can be used as new method of technological forecasting. However, we are just beginning to understand the use of artificial asset markets for technological forecasting. Based on detailed discussions in chapters 3, 4, and 5, several issues present themselves for further research:

- Which performance can be achieved in direct comparison to alternative technological forecasting methods (especially Delphi and expert forecasts) used in the same application context?
- How to secure incentivitation for long-term markets?
- How to design non-monetary incentivitation schemes?
- How to design market mechanism and trading rules for thin market conditions?

Although we established evidence that AAM by TF perform better than alternative TF methods, this should be supported by further evidence based on a direct performance comparison to alternative TF forecasting methods, such as the Delphi method or expert forecasts. Such a comparison needs to be specifically designed and conducted over a sufficiently long period of time, that is, at least five years or more to sufficiently cover a range of technological developments.

How to achieve long-term engagement of traders as well as the design of non-monetary incentivitation schemes are further opportunities for research. As the forecasting horizon of technologies can typically take several years, traders need to wait as long to eventually receive the payoff of contract liquidation. As this waiting period may be too long to entertain traders for the complete trading period, other sources of motivation should be identified to maintain trader interest. Because monetary incentivitation schemes come with considerable burdens, as discussed in chapter 5, research needs to direct further attention to the development of non-monetary incentivitation schemes. A promising approach appears to build on reputation-enhancing und –building properties.

In chapter 5 we also discussed the problem of "thin" market conditions, which characterizes trading periods with very little trading activity, either because there are only few traders or traders have no interest in (further) trade. Beside the attempt to induce more trading activity, an alternative approach is to design trading mechanisms that can appropriately deal with such situations. As introduced in chapter 5, such mechanisms have been proposed but they still lack empirical validation.

Application and commercial outlook. The science of artificial asset markets is still evolving, as is the debate about their relevance to public and corporate life. However, artificial asset markets have received a lot of coverage in the media in the recent months due to the recent Nobel prize award to Vernon Smith, who developed experimental economics in the 60's and 70's, and the Pentagon's ill-fated plan to launch so called "Terrorism Futures" in 2003.³⁹⁴ Meanwhile, even standard software for artificial asset markets is available from several vendors. Thus, we can envisage AAM for TF as corporate solution in the near future, including approaches such as:

- a public market to reflect technological development in a specific technological field of interest – with a focus on timing (leading indicator)
- an internal market to identify the most promising technological development projects as a guide for resource allocation

The primary purpose of application of TF by AAM, as discussed throughout this piece of research, meets the need of commercial corporations to forecast the technological development in a specific technological field with an eye on the timing of the development, that is, at what time a given performance is reached. However, an alternative application may be to use TF by AAM to guide the funding of development projects on several competing technologies. By such an application, the technology with the most promising prospects would emerge from the AAM as the winning technology and would therefore receive the funding.

With these positions we conclude the outlook of TF by AAM that presents many exciting opportunities for further development. We hope that the contribution by this thesis will add to the growing interest in the subject and will support further research efforts.

³⁹⁴ see also sections 3.6 and 5.7.4

8. References

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Appendix

Appendix

A. Empirical data

Market ID: ADED

Claim Commodore Business Machines International was recently purchased by Escom GmbH to form two new companies.

This claim deals with Amiga Technologies GmbH.

It has been a year since any serious development on the Amiga platform. It is because of this the Amiga is quite way behind technologically.

If Amiga Technologies does not play their cards right, the Amiga will not have a chance in the current market of IBM clones and Apple computers.

The claim: The Amiga will die (manufacturing will have ceased, no further development will occur and no more product will be available) by 01/01/97. This will be a result of the amount of power the IBM compatibles have in the market place today.

Start 11.07.1995

End 01.01.1997

Outcome JUDGED at 0

Transaction data

Quant	Price	Date	GMT	Pairs	People	Buyer	Seller											
14	5	1996/12/01	15:06:07	88	8	116	583	5	18	1995/11/20	09:50:59	543	27	0	0			
2	5	1996/11/28	02:01:41	74	7	116	97	10	22	1995/11/17	23:19:39	533	27	0	0			
2	5	1996/11/20	21:24:43	72	6	373	97	10	20	1995/11/17	23:15:46	523	27	0	0			
10	14	1996/10/09	01:43:39	70	5	464	239	15	18	1995/11/16	08:43:39	520	27	0	0			
5	12	1996/10/09	01:43:19	60	5	464	239	8	18	1995/11/13	03:23:57	512	26	0	0			
5	12	1996/10/09	01:42:50	55	5	464	239	1	50	1995/11/06	23:33:47	511	26	0	0			
10	10	1996/08/19	16:40:21	50	3	278	97	1	50	1995/11/06	23:30:16	510	26	0	0			
40	10	1996/07/25	00:34:51	40	2	176	97	1	51	1995/11/05	13:15:04	510	27	0	0			
10	4	1996/07/03	16:57:13	1414	41	0	0	1	51	1995/10/30	20:03:32	511	28	0	0			
12	1	1996/07/02	14:05:20	1402	40	0	0	1	50	1995/10/26	00:14:11	510	27	0	0			
1	2	1996/06/20	10:59:32	1401	39	0	0	50	10	1995/10/11	14:29:52	510	28	0	0			
20	5	1996/05/29	20:49:28	1381	38	0	0	1	12	1995/10/09	12:42:28	511	28	0	0			
100	8	1996/05/14	05:16:30	1281	38	0	0	20	28	1995/10/05	21:53:29	491	28	0	0			
50	8	1996/05/04	00:55:30	1231	38	0	0	20	27	1995/10/05	21:51:44	471	28	0	0			
51	6	1996/05/02	00:01:44	1180	38	0	0	10	25	1995/10/05	21:44:31	461	28	0	0			
10	4	1996/04/25	23:36:14	1180	38	0	0	10	23	1995/10/05	21:42:52	461	29	0	0			
50	6	1996/03/25	12:24:50	1130	37	0	0	20	15	1995/10/05	21:41:27	441	29	0	0			
79	10	1996/03/20	00:42:18	1051	37	0	0	1	14	1995/10/05	21:39:55	440	28	0	0			
200	10	1996/03/20	00:37:25	851	37	0	0	1	13	1995/10/05	07:41:25	440	28	0	0			
100	10	1996/03/20	00:33:57	751	37	0	0	30	15	1995/10/02	07:07:27	410	28	0	0			
50	10	1996/03/20	00:26:23	701	37	0	0	10	15	1995/09/29	00:31:27	400	28	0	0			
20	12	1996/03/20	00:11:53	681	36	0	0	10	15	1995/09/29	00:29:32	390	28	0	0			
50	14	1996/03/10	12:09:56	701	36	0	0	10	17	1995/09/28	05:11:08	390	27	0	0			
20	12	1996/03/09	21:12:53	681	35	0	0	10	17	1995/09/26	14:52:41	390	28	0	0			
1	10	1996/02/27	10:27:52	709	37	0	0	10	36	1995/09/18	14:30:49	390	29	0	0			
10	10	1996/02/06	17:02:13	699	37	0	0	10	10	1995/09/18	09:33:53	390	29	0	0			
10	10	1996/02/06	17:02:13	689	36	0	0	10	10	1995/09/18	09:11:48	400	30	0	0			
50	10	1996/02/06	17:02:13	688	35	0	0	14	29	1995/09/18	04:22:51	400	30	0	0			
10	3	1996/02/06	15:29:35	678	33	0	0	10	37	1995/09/18	03:34:35	390	29	0	0			
1	10	1996/02/06	12:19:51	678	32	0	0	1	38	1995/09/14	18:59:21	389	28	0	0			
20	4	1996/01/17	08:04:22	658	31	0	0	10	38	1995/09/14	15:06:42	379	27	0	0			
30	4	1996/01/05	20:19:05	628	29	0	0	36	30	1995/09/12	07:13:18	379	27	0	0			
14	3	1996/01/04	03:39:43	614	29	0	0	22	37	1995/09/12	07:07:32	379	28	0	0			
14	3	1996/01/04	03:38:19	600	29	0	0	20	38	1995/09/12	07:02:09	379	28	0	0			
14	3	1996/01/04	03:30:46	586	29	0	0	10	44	1995/09/08	03:32:56	369	27	0	0			
14	3	1996/01/04	03:25:03	572	29	0	0	10	43	1995/09/07	18:24:59	359	26	0	0			

Market ID: X400

Claim	<p>X.400, the mail standard, will be irrelevant by the year 2000.</p> <p>The claim will be judged NO if one of the following is true:</p> <p>A major retail software distributor reports that sales of X.400 end-user UAs are significant (more than 10% of its category) Gateways don't count here.</p> <p>A believable survey shows at least 10% of E-mail traffic in some category with X.400/Internet competition is carried by X.400. Gateways count; politically chosen networks (like EC offices) don't.</p> <p>The claim will be judged YES if one of the following is true:</p> <p>ITU or ISO deletes X.400 from its list of standards/Recommendations in force</p> <p>No major trade association (like EMA or EEMA) advocates the use of X.400</p> <p>None of the 5 biggest network operators in the US offer an X.400 service to new customers (legacy systems don't count)</p> <p>If none of the claims above are decidable, decision will be made by a poll announced to relevant newsgroups.</p> <p>If claims both in the YES and NO category are true, the return will be divided equally between the YES and NO holders.</p>
Start	24.08.1995
End	01.01.2000
Outcome	JUDGED at 100

Transaction data

Quant	Price	Date	GMT	Pairs	People	Buyer	Seller								
1		88	1999/01/07	05:44:13	727	17	987	73							
1		94	1998/12/23	23:48:44	727	16	346	483							
10		93	1998/12/17	14:54:38	727	16	346	483							
20		92	1998/12/17	05:24:45	727	16	346	483							
10		92	1998/12/13	14:12:54	727	16	346	483							
160		88	1998/12/08	01:53:24	727	16	987	483							
10		88	1998/11/25	19:14:23	732	16	987	2341							
41		94	1998/08/05	22:50:52	732	15	1902	483							
1		93	1998/08/05	22:49:59	809	16	1902	617							
1		92	1998/08/05	22:49:58	809	16	1902	483							
5		91	1998/08/05	22:49:56	849	16	1902	617							
2		90	1998/08/05	13:43:31	853	16	1902	617							
1		90	1998/08/05	13:43:31	863	16	1902	14							
1		89	1998/08/02	12:35:00	863	16	1902	14							
5		90	1998/08/01	13:56:10	863	16	1902	483							
1		89	1998/08/01	13:56:09	893	16	1902	617							
1		88	1998/08/01	13:56:08	903	16	1902	14							
1		87	1998/07/12	15:45:10	903	16	1902	14							
35		85	1998/07/05	13:43:18	903	16	1902	14							
10		84	1998/07/04	14:38:34	903	16	1902	14							
12		82	1998/06/29	12:52:20	903	16	1902	14							
30		80	1998/06/22	08:41:16	903	16	617	14							
105		80	1998/06/22	00:12:22	879	16	483	14							
100		80	1998/06/21	19:55:08	860	16	483	1902							
200		95	1998/06/15	12:59:16	859	16	346	62							
50		94	1998/06/15	10:25:35	859	15	62	617							
5		94	1998/06/15	10:23:17	854	15	62	1690							
30		93	1998/06/15	10:18:40	854	15	62	617							
30		93	1998/06/15	09:54:28	849	15	62	617							
10		93	1998/06/15	09:54:28	844	15	62	483							
1		91	1998/06/15	09:49:59	844	15	62	346							
10		90	1998/06/15	09:49:58	844	16	62	483							
1		87	1998/06/15	09:49:57	844	16	62	617							
1		85	1998/06/15	09:47:56	844	16	62	483							
1		83	1998/06/15	09:47:56	844	16	62	1094							

20	16	1995/06/30	15:52:40	378	23	0	0	25	14	1995/04/12	05:40:02	270	13	0	0
1	15	1995/06/30	15:49:01	377	23	0	0	25	14	1995/04/11	12:30:12	245	12	0	0
23	13	1995/06/30	15:45:47	354	23	0	0	3	20	1995/04/08	07:23:36	245	13	0	0
20	11	1995/06/29	10:38:55	354	22	0	0	20	20	1995/04/08	00:20:21	245	13	0	0
62	13	1995/06/28	15:39:30	292	22	0	0	21	20	1995/04/08	00:20:21	245	12	0	0
15	13	1995/06/28	05:06:24	277	20	0	0	22	20	1995/04/08	00:20:21	245	12	0	0
1	11	1995/06/24	17:33:32	277	19	0	0	34	19	1995/04/07	22:04:35	245	11	0	0
26	18	1995/05/30	14:28:08	327	20	0	0	65	14	1995/04/07	22:01:25	180	11	0	0
2	15	1995/05/30	12:48:05	325	20	0	0	35	15	1995/04/07	21:58:16	180	11	0	0
8	15	1995/05/30	12:48:05	317	20	0	0	30	19	1995/04/05	06:34:56	150	11	0	0
2	15	1995/05/25	16:17:04	315	18	0	0	10	17	1995/04/04	06:55:42	150	11	0	0
10	14	1995/05/25	07:39:23	325	19	0	0	20	17	1995/04/04	06:52:49	150	10	0	0
20	15	1995/05/23	07:40:57	325	18	0	0	10	13	1995/04/02	13:07:40	140	9	0	0
15	13	1995/05/20	15:20:25	325	17	0	0	30	13	1995/04/02	05:53:13	170	10	0	0
1	13	1995/05/18	16:06:56	324	17	0	0	20	10	1995/03/29	13:50:57	170	9	0	0
10	13	1995/05/18	16:06:56	324	18	0	0	45	15	1995/03/28	21:02:10	170	10	0	0
10	14	1995/05/18	16:04:33	314	16	0	0	25	20	1995/03/28	20:24:37	145	8	0	0
9	13	1995/05/07	11:47:17	305	16	0	0	10	25	1995/03/28	16:15:40	145	9	0	0
11	13	1995/05/07	11:47:17	305	16	0	0	9	25	1995/03/28	16:15:40	136	9	0	0
20	18	1995/05/05	07:57:43	325	17	0	0	30	26	1995/03/28	16:02:19	106	8	0	0
15	13	1995/05/01	10:06:47	330	17	0	0	20	35	1995/03/28	13:50:00	86	8	0	0
10	22	1995/04/27	06:29:50	320	16	0	0	10	35	1995/03/28	11:57:53	76	7	0	0
10	13	1995/04/26	16:22:12	320	15	0	0	20	40	1995/03/28	11:46:52	56	5	0	0
15	20	1995/04/18	09:34:22	305	15	0	0	1	25	1995/03/28	06:57:30	55	4	0	0
30	20	1995/04/18	09:30:17	275	15	0	0	10	45	1995/03/28	05:54:36	55	3	0	0
5	20	1995/04/18	01:05:41	270	14	0	0	5	55	1995/03/28	01:34:40	50	2	0	0
25	19	1995/04/13	10:35:31	270	13	0	0	50	60	1995/03/28	01:32:22	0	0	0	0

Market ID: UNIX

Claim According to DataQuest's analyses, sales of the UNIX operating system will peak in 1996 and decline thereafter to a level of 1.8M/year by 2000.

A YES claim states that DataQuest's market estimates for the year 2000 will report that UNIX unit-sales have peaked and have declined to a level of 1.8M/year. Whether they peak in 1996 is irrelevant to the claim.

Background:

From: Wendell Craig Baker (wbaker@splat.baker.com), Date: March 14, 1995

Yesterday's Wall Street Journal (3-13-95) had a very interesting article entitled "Sellers of Unix Systems Adopt Standard against Microsoft" (page B6) on the planned announcement today of the so-called Common Desktop Environment by HP, IBM, Novell and Sun.

The article was extremely interesting by virtue of how this information was presented by the reporter. "I think its too late," Robert Enderie of Dataquest is quoted as saying. There was a telling little table in the corner:

Unix Falls Behind	
Shipments, in thousands	
1994	1998
actual	projected
Unix	1,855 2,195
Windows NT	555 12,552
Windows 3.1, 95	23,833 75,901

Note: Table assumes that NT eventually becomes an operating system for server computers linking desktop machines while future versions of Windows 95 become desktop systems linked to NT

Source: DataQuest

That projection of 75M copies of Windows 3.1/95 being sold in 1998 is interesting. It most likely comes from DataQuest's analysis of Intel's production capacity.

On March 8, Martin Reynolds, who is Director of Technology Assessment at DataQuest gave a talk at Stanford entitled ``Processors in the Real World." Most of the talk was on how DataQuest goes about generating estimates of what Intel is planning to do. The direction of Intel being what controls the destiny of the processor industry at this point.

Significant here though was his analysis of Intel's current in-place fab capability. He had two slides full of Intel plants that are either blowing glass today or will be online in the next 18 months. AMD by contrast has just the one plant. Based on the analysis Reynolds stated that Intel's plan is to have ship 70 million P6 chips by Q1 1997. This will roughly double the installed base of the x86 architecture -- and almost half of them will be the 6th generation.

This makes claims that the Microsoft marketplace in '98 will be 37 times bigger than the whole Unix marketplace a bit more credible.

But the WSJ article was on standards and how the Unix has used them and how CDE is going to change that. I was amused that finally the reporters had identified the cartel behavior in the Unix marketplace (lack of standards, attempts on the part of vendors to differentiate themselves from their competitors by making their software unique, a strategy of selling computer systems by locking customers into their proprietary brand of software, etc.).

Enderle's predictions for DataQuest go on that HP, SGI and DEC are expected to ``rapidly adopt" Windows NT and that Unix sales will peak in 1996 and decline thereafter to a level of 1.8M/year by 2000. Microsoft at that point is predicted to be selling 22M units of NT and 99M units of the Windows client OSes.

But what about the extra performance that you get with the RISC processors on which Unix runs? Isn't that worth paying something for? Yes, Reynolds said it is -- the market will absorb a 2X to 3X price jump for that extra 50 to 100% in performance that you get in RISC-based systems. But while the RISC architectures currently hold the high ground in terms of performance some of them have only fair-to-poor ratings in terms of price/performance.

Start	14.03.1995
End	01.01.2001
Outcome	JUDGED at 0

Transaction data

Quant	Price	Date	GMT	Pairs	People	Buyer	Seller								
								25	3	2000/11/10	07:23:22	8644	83	1664	2766
								1	4	2000/10/21	02:59:03	8644	82	97	17
1		2001/01/08	18:29:12	9445	86	1908	3299	60	4	2000/10/21	02:58:14	8644	82	387	17
1		2001/01/08	18:29:12	9444	86	97	3299	20	5	2000/10/19	18:39:24	8704	83	2559	387
19		2001/01/08	18:29:12	9444	86	1239	3299	40	5	2000/10/19	18:39:24	8704	83	10	387
1		2001/01/06	13:27:21	9425	84	97	73	50	5	2000/10/11	07:18:04	8704	82	45	3233
7		2001/01/06	13:27:21	9426	84	62	73	50	5	2000/09/11	04:50:04	8704	82	45	3233
99		2001/01/06	13:27:21	9433	85	1664	73	100	5	2000/09/04	06:17:33	8704	82	10	3233
889		2001/01/06	02:51:50	9532	85	73	3314	110	5	2000/08/08	22:54:56	8704	81	45	251
1		2001/01/04	05:24:32	8643	83	97	286	40	6	2000/08/03	20:25:12	8704	81	3226	251
5		2001/01/04	05:24:32	8643	83	10	286	40	5	2000/07/31	17:34:37	8704	82	45	3226
7		2000/12/28	22:11:08	8643	84	10	251	45	5	2000/07/11	20:15:09	8704	81	45	251
1		2000/12/11	16:21:20	8643	84	10	97	1	5	2000/06/19	20:38:51	8704	81	45	97
1		2000/12/11	03:43:15	8643	84	97	3475	1	5	2000/06/19	20:38:49	8705	82	45	97
10		2000/12/11	03:43:15	8643	84	3477	3475	1	5	2000/06/19	20:38:46	8706	82	45	97
33		2000/12/11	03:43:15	8643	85	1664	3475	1	5	2000/06/19	20:38:44	8707	82	45	97
5		2000/12/11	03:41:48	8643	85	1664	3475	1	5	2000/06/19	20:38:41	8708	82	45	97
1		2000/12/09	23:46:50	8643	84	1664	97	60	7	2000/04/07	04:58:10	8709	82	45	280
1		2000/12/09	23:46:47	8643	84	1664	97	5	5	2000/01/20	19:43:55	8709	82	10	251
1		2000/12/09	23:46:43	8643	84	1664	97	120	5	2000/01/15	21:19:41	8709	82	10	1664
21		2000/12/09	23:46:36	8643	84	10	251	50	6	2000/01/15	21:19:41	8709	82	2568	1664
1		2000/12/09	23:46:35	8643	84	10	97	20	7	2000/01/14	15:07:58	8659	82	2568	280
1		2000/12/09	23:45:36	8643	84	10	97	25	6	2000/01/06	10:14:07	8639	82	187	2857
50		2000/12/09	23:45:36	8643	83	10	251	10	5	1999/12/30	14:05:24	8639	83	10	732
1		2000/12/09	23:44:34	8643	83	10	97	25	5	1999/12/14	13:32:12	8649	84	10	187
10		2000/12/09	19:04:42	8644	84	1664	3477	1	6	1999/12/04	07:27:52	8649	83	97	286
160		2000/12/05	19:56:17	8644	83	1664	3226	20	7	1999/11/19	18:52:31	8648	82	132	280
36		2000/11/30	17:41:32	8644	83	2559	2766	10	6	1999/10/15	09:01:04	8648	82	17	2857
25		2000/11/27	06:20:38	8644	84	1664	2766	1	7	1999/10/12	17:13:14	8638	81	97	2568
15		2000/11/14	17:11:55	8644	84	1664	3226	10	7	1999/10/12	17:13:14	8638	81	2559	2568
25		2000/11/13	13:18:16	8644	84	1664	3226	1	8	1999/10/12	17:12:22	8648	81	97	2568

10	27	1995/05/06	11:20:47	542	23	0	0	10	35	1995/04/07	11:24:13	325	16	0	0
6	26	1995/05/02	11:37:26	561	23	0	0	4	35	1995/04/02	21:35:28	321	15	0	0
5	26	1995/05/02	08:44:29	556	22	0	0	15	35	1995/03/31	14:06:49	321	15	0	0
10	26	1995/05/02	03:18:33	546	21	0	0	5	34	1995/03/30	01:24:02	316	14	0	0
17	25	1995/04/27	12:45:41	535	21	0	0	6	35	1995/03/29	23:21:14	311	13	0	0
3	25	1995/04/27	04:42:28	535	21	0	0	90	40	1995/03/29	18:23:07	221	13	0	0
25	25	1995/04/23	16:55:08	510	20	0	0	100	40	1995/03/29	18:18:29	121	12	0	0
25	25	1995/04/23	16:09:12	510	21	0	0	10	40	1995/03/29	17:11:17	111	10	0	0
10	25	1995/04/23	15:14:21	510	20	0	0	5	35	1995/03/29	07:09:12	116	11	0	0
2	50	1995/04/23	14:16:58	508	19	0	0	4	35	1995/03/27	17:11:12	116	11	0	0
25	45	1995/04/23	14:10:51	483	18	0	0	6	35	1995/03/27	12:51:28	116	11	0	0
3	41	1995/04/23	14:02:36	480	18	0	0	10	35	1995/03/27	09:42:04	116	11	0	0
70	36	1995/04/23	13:58:25	410	17	0	0	10	42	1995/03/20	09:52:37	106	9	0	0
5	35	1995/04/17	09:17:08	410	19	0	0	1	42	1995/03/17	14:16:47	105	8	0	0
6	36	1995/04/17	09:15:03	410	19	0	0	20	43	1995/03/17	14:11:01	85	7	0	0
30	39	1995/04/14	17:08:42	380	18	0	0	5	20	1995/03/17	08:13:42	85	7	0	0
19	39	1995/04/14	14:22:08	380	19	0	0	20	40	1995/03/16	07:18:30	85	6	0	0
1	40	1995/04/14	14:06:10	380	19	0	0	5	35	1995/03/15	16:33:50	80	5	0	0
20	39	1995/04/12	09:25:02	360	18	0	0	50	30	1995/03/15	09:14:33	30	4	0	0
15	39	1995/04/11	17:42:40	345	17	0	0	25	30	1995/03/14	22:52:50	5	2	0	0
10	39	1995/04/11	15:27:54	345	18	0	0	5	90	1995/03/14	14:33:44	0	0	0	0
10	40	1995/04/08	19:14:41	335	17	0	0								

Market ID: PlsCom

Claim Wireless "Pulse" Techology is a method of transmitting digital data over radio waves by using carefully timed pulses of radio energy. Sending data over radio today is done by modulating a carrier wave, but Pulse equipment has greater range, longer lifespan on batteries, far higher bandwidth capabilities, and can even be used to tell the distance between two communicators.

For examples, see <http://www.time-domain.com>

The claim is that this technology will be used in devices sold to the public and that it will supplant or take over 'niches' currently using standard radio transmission methods.

Start 10.05.1999

End 01.01.2002

Outcome JUDGED at 0

Transaction data

Quant	Price	Date	GMT	Pairs	People	Buyer	Seller								
2	6	2001/10/23	15:33:11	680	18	3465	97								
1	5	2001/10/23	15:32:31	678	18	3465	97								
6	1	2002/04/11	15:21:57	1958	24	3601	3465	2	4	2001/09/16	17:30:59	677	17	97	303
1	1	2002/04/02	23:31:34	1964	25	4270	4007	20	4	2001/09/16	17:30:59	677	17	3749	303
13	1	2002/04/02	23:31:34	1963	24	4119	4007	2	5	2001/09/16	17:30:46	657	17	97	303
1	1	2002/03/17	19:57:18	1950	24	4119	4007	2	6	2001/09/16	17:30:46	657	17	97	303
6	1	2002/03/11	22:53:12	1949	23	4119	3465	1	7	2001/09/16	17:30:46	657	17	97	303
1	1	2001/12/14	21:59:38	1949	22	97	3465	2	7	2001/07/21	04:08:51	657	17	97	129
1	1	2001/12/13	23:49:47	1950	22	97	3295	1	8	2001/07/21	04:08:51	657	17	97	129
1000	1	2001/12/13	23:49:47	1950	22	2986	3295	2	10	2001/07/09	19:23:35	657	17	3749	97
2	2	2001/10/30	00:29:59	950	21	97	3314	2	9	2001/07/09	19:23:35	655	17	3749	97
250	2	2001/10/30	00:29:59	950	21	2986	3314	2	8	2001/07/09	19:23:35	653	17	3749	97
2	3	2001/10/30	00:29:59	700	21	97	3314	2	7	2001/07/09	19:22:45	651	17	3749	97
1	4	2001/10/30	00:29:59	700	21	97	3314	1	6	2001/07/09	19:22:44	649	17	3749	97
10	3	2001/10/28	00:37:56	700	20	3825	3465	14	15	2001/07/01	16:37:27	648	16	3763	3167
2	4	2001/10/28	00:37:36	700	19	97	3465	19	15	2001/07/01	16:37:03	634	16	3763	157
2	5	2001/10/28	00:37:36	702	19	97	3465	1	14	2001/07/01	16:37:03	615	15	3763	97
1	6	2001/10/28	00:37:36	704	19	97	3465	1	13	2001/07/01	16:37:02	614	15	3763	97
1	7	2001/10/24	17:06:54	705	19	97	3465	1	12	2001/07/01	16:36:22	613	15	3763	97
2	8	2001/10/23	15:33:12	706	19	3465	97	1	11	2001/07/01	16:36:22	612	15	3763	97
22	8	2001/10/23	15:33:12	704	19	3465	3601	1	10	2001/07/01	16:36:22	611	15	3763	97
2	7	2001/10/23	15:33:12	682	18	3465	97	1	9	2001/07/01	16:36:00	610	15	3763	97

1	8	2001/07/01	16:35:59	609	15	3763	97	10	10	2001/01/02	03:56:49	386	13	2671	97
1	7	2001/07/01	16:35:59	608	15	3763	157	20	10	2001/01/02	03:56:49	376	12	2012	97
1	7	2001/07/01	16:35:32	608	16	3763	97	100	10	2001/01/02	03:56:49	356	12	2986	97
1	6	2001/07/01	16:35:32	607	16	3763	97	2	12	2001/01/02	03:56:49	256	12	3167	97
1	5	2001/07/01	16:35:32	606	16	3763	97	2	14	2001/01/02	03:56:48	256	12	3167	97
1	4	2001/06/19	00:21:22	605	15	3729	97	2	16	2001/01/02	03:56:16	256	12	3167	97
2	3	2001/05/31	16:43:16	604	14	157	303	54	17	2001/01/02	03:56:16	256	12	2559	97
7	3	2001/05/23	03:06:25	603	13	3167	97	10	20	2001/01/02	03:56:16	256	12	2559	97
167	3	2001/05/23	03:06:25	603	13	2986	97	10	20	2000/12/26	22:41:57	256	11	2012	2559
6	4	2001/05/23	03:06:10	436	13	3167	97	50	20	2000/12/26	22:41:57	246	11	2986	2559
3	5	2001/05/23	03:06:10	436	13	157	97	3	25	2000/12/26	22:41:57	196	11	2012	2559
5	5	2001/05/23	03:06:10	436	13	3167	97	1	31	2000/12/22	17:58:28	193	11	3167	2559
4	6	2001/05/23	03:06:10	436	13	3167	97	1	41	2000/12/22	17:58:13	193	11	3167	2559
3	7	2001/05/23	03:05:52	436	13	3167	97	20	47	2000/11/02	23:34:35	193	10	3272	617
2	8	2001/05/23	03:05:51	436	13	3167	97	2	25	2000/10/31	18:25:28	193	9	2012	3167
1	9	2001/05/23	03:05:51	436	13	3167	97	5	28	2000/10/31	18:25:28	191	8	2986	3167
1	10	2001/05/14	19:05:16	436	13	97	157	50	30	2000/09/06	10:14:32	186	8	617	3299
1	11	2001/04/12	20:50:34	436	13	97	157	5	35	2000/08/18	17:47:45	136	7	2986	3167
1	12	2001/04/12	20:50:34	436	13	97	157	4	40	2000/08/18	17:47:44	131	7	2986	3167
1	13	2001/04/12	20:50:33	436	13	97	157	15	45	2000/08/11	16:43:46	127	7	2974	3167
36	15	2001/01/30	13:06:20	436	12	3299	3167	2	46	2000/08/11	16:43:45	112	6	2986	3167
1	14	2001/01/30	13:06:20	436	13	3299	97	1	47	2000/08/11	16:43:04	110	6	2986	3167
4	14	2001/01/30	13:06:20	436	13	3299	3167	10	50	2000/07/18	20:00:48	109	6	2714	129
1	13	2001/01/30	13:05:26	436	13	3299	97	50	50	2000/07/18	20:00:48	99	6	617	129
3	13	2001/01/30	13:05:26	436	13	3299	3167	20	51	2000/07/18	20:00:48	49	5	2986	129
1	12	2001/01/30	13:05:25	436	13	3299	97	25	55	2000/07/18	20:00:48	29	5	2696	129
2	12	2001/01/30	13:05:25	436	13	3299	3167	1	60	2000/06/15	17:26:50	5	4	2714	3167
1	11	2001/01/30	13:05:25	436	13	3299	3167	1	61	2000/06/15	17:26:07	4	4	2986	3167
1	11	2001/01/30	13:05:25	436	13	3299	97	1	62	2000/06/15	17:26:06	3	4	2986	3167
1	10	2001/01/22	20:33:29	436	13	97	3167	1	63	2000/06/15	17:26:06	2	4	2986	3167
50	10	2001/01/22	20:33:29	436	13	617	3167	1	70	2000/02/26	08:55:29	1	2	2714	2986
1	11	2001/01/10	14:03:06	386	13	3167	97	1	90	2000/02/10	08:07:35	1	2	2986	2696
2	10	2001/01/02	03:56:49	386	13	3167	97								

Market ID: GrWv

Claim YES coupons pay \$1 if Gravitational waves are detected at a gravitational wave observatory before 1/1/2003 GMT. Detection must be certain at the 95% confidence level according to physicists and astronomers in the year 2003 or before. This will be judged on the basis of preprints and papers published in the year 2003 or before. Indirect detection by, for example, observation of effects gravitational waves have on the cosmic microwave background or interstellar gas does not count as a YES.

Information: Gravitational waves are waves in space-time geometry predicted by Einstein's General Theory of Relativity. Possible sources of detectable gravitational waves include supernova, neutron star collisions, black hole collisions and the big bang. A Gravitational Wave observatory with prospects for detection of gravitational waves before 2003 is the American LIGO: The Laser Interferometer Gravitational-Wave Observatory. LIGO is being built in two parts. Construction of the Washington LIGO began in 1992 and it is scheduled to begin gravitational wave searches in 1998. Construction of the second LIGO in Louisiana began in June 1995. GEO and VIRGO are other planned gravitational wave observatories in Europe. There are a number of others some of which have been operational for years.

Start 22.08.1995

End 01.01.2004

Outcome JUDGED at 0

Transaction data

Quant	Price	Date	GMT	Pairs	People	Buyer	Seller								
79	2	2003/11/07	00:53:20	3512	65	6116	3329								
10	1	2003/08/17	18:10:32	3512	65	17	4465								
90	1	2003/11/22	05:31:31	3612	66	17	5542								
10	2	2003/11/07	00:53:20	3522	65	6116	3191	100	1	2003/08/11	21:00:32	3523	66	73	260
10	2	2003/11/07	00:53:20	3512	65	6116	17	10	1	2003/08/05	05:44:09	3423	65	73	4465

B. Forecast verification: measurement and comparison of forecast accuracy

Forecast verification is the process of assessing the quality of a forecast as a prediction of the future state.³⁹⁵ The forecast is compared, or verified, against a corresponding observation of what actually occurred, or some good estimate of the true outcome.³⁹⁶ The verification can be qualitative or quantitative, in either case it provides information about the nature of the forecast errors.³⁹⁷

If the interest in forecast verification is limited to the average magnitude of the difference between the forecast and observations, a single statistic that would give the accuracy of the forecast, such as the mean absolute error (MAE), would be sufficient.³⁹⁸ However, there are at least nine "attributes" that contribute to the quality of a forecast³⁹⁹. Traditionally, forecast verification has emphasized accuracy and skill⁴⁰⁰. But which of these attributes is most important to the scientist, administrator or end-user will determine which verification scheme addressing the different attributes in different ways is preferred.⁴⁰¹

For example, for daily maximum and minimum temperatures forecasts it is important to get the magnitude right, and avoid large errors.⁴⁰² Statistics that would be useful in this case would be the mean difference (to measure bias), mean absolute (or RMS) error, and perhaps a binary accuracy score based on a temperature error threshold.⁴⁰³

Furthermore, the many different forecasting applications suggest the use of different forecast types that adequately match the purpose.⁴⁰⁴ For example, rather than forecasting if hybrid-electric vehicles (HEV) will establish in Austria by reaching a market share of 15% before the year 2010 or not (binary, dichotomous forecast: yes/no), the forecast may ask in which year this will happen (multi-category or continuous forecast: 2006, 2007, ..., 2020+).

³⁹⁵ see (Ebert, Brown et al. 2004), p.2

³⁹⁶ Ibid.

³⁹⁷ Ibid.

³⁹⁸ see (Ebert 2003), p.1

³⁹⁹ see (Murphy 1993)

⁴⁰⁰ see (Ebert, Brown et al. 2004), p.2

⁴⁰¹ see (Jolliffe and Stephenson 2003), p.7

⁴⁰² see (Ebert, Brown et al. 2004), p.1

⁴⁰³ Ibid.

⁴⁰⁴ see (Ebert 2003), p.1

Thus, there are many types of forecasts addressing different forecasting needs, each of which calls for different methods of verification.⁴⁰⁵ See Table 119 for an overview of forecast types and the corresponding verification methods.⁴⁰⁶

Table 119: Forecast quality attributes: overview and brief description (Murphy 1993; Ebert, Brown et al. 2004)

Attributes	Description
Bias	the correspondence between the mean forecast and mean observation
Association	the strength of the linear relationship between the forecasts and observations (for example, the correlation coefficient measures this linear relationship)
Accuracy	the level of agreement between the forecast and the truth (as represented by observations). The difference between the forecast and the observation is the error. The lower the errors, the greater the accuracy
Skill	the relative accuracy of the forecast over some reference forecast. The reference forecast is generally an unskilled forecast such as random chance or persistence (defined as the most recent set of observations, "persistence" implies no change in condition). Skill refers to the increase in accuracy due purely to the "smarts" of the forecast system. For example, weather forecasts may be more accurate simply because the weather is easier to forecast – skill takes this into account.
Reliability	the average agreement between the forecast values and the observed values. If all forecasts are considered together, then the overall reliability is the same as the bias. If the forecasts are stratified into different ranges or categories, then the reliability is the same as the conditional bias, i.e., it has a different value for each category.
Resolution	the ability of the forecast to sort or resolve the set of events into subsets with different frequency distributions. This means that the distribution of outcomes when "A" was forecast is different from the distribution of outcomes when "B" is forecast. Even if the forecasts are wrong, the forecast system has resolution if it can successfully separate one type of outcome from another.
Sharpness	the tendency of the forecast to predict extreme values. To use a counter-example, a forecast of "climatology" has no sharpness. Sharpness is a property of the forecast only, and like resolution, a forecast can have this attribute even if it's wrong (in this case it would have poor reliability).
Discrimination	ability of the forecast to discriminate among observations, that is, to have a higher prediction frequency for an outcome whenever that outcome occurs.
Uncertainty	the variability of the observations. The greater the uncertainty, the more difficult the forecast will tend to be.

The forecast need of artificial asset markets is typically expressed as a parameter of a mean, median, or probability.⁴⁰⁷ In addition, the asset structure can also be designed in a way that it reveals the market's uncertainty about these parameters.⁴⁰⁸ For example,

⁴⁰⁵ see (Ebert, Brown et al. 2004), p.1

⁴⁰⁶ It is often possible to convert from one type of forecast to another simply by rearranging, categorizing, or thresholding the data; see (Ebert, Brown et al. 2004), p.1

⁴⁰⁷ see also section 5.6.1

⁴⁰⁸ see also section 5.6.4

a set of state-contingent winner-takes-all contracts covering the entire solution space will produce the entire probability distribution reflecting the market's expectations.

Thus, artificial asset markets can produce deterministic as well as probabilistic forecasts.⁴⁰⁹

Deterministic forecast. A deterministic forecast is certain about the event it forecasts; there is no remaining uncertainty about the event it forecasts.⁴¹⁰ In general, it is relatively easy to verify a single deterministic forecast.⁴¹¹

Probabilistic forecast. A probabilistic forecast gives a probability of an event occurring, with a value between 0 and 1 (or 0 and 100%).⁴¹² Typically, as soon as a forecast is expressed probabilistically, all possible outcomes are forecast – the result is a probability distribution over the entire solution space.⁴¹³ In general, it is difficult to verify a single probabilistic forecast – instead, a set of probabilistic forecasts, p_i , is verified using observations that those events either occurred ($o_i=1$) or did not occur ($o_i=0$).⁴¹⁴

It is possible to convert probabilistic forecasts to deterministic forecasts by recognizing a different discrete state if the probability exceeds a threshold minimum.⁴¹⁵ By raising the threshold, less recognitions are likely to happen – reducing the potential of issuing a false alarm, but increasing the potential of a miss. Conversely, by lowering the threshold, more recognitions are likely to happen – reducing the potential of a miss, but increasing the potential of a false alarm.

An accurate probability forecast system has reliability (agreement between forecast probability and mean observed frequency), sharpness (tendency to forecast probabilities near 0 or 1, as opposed to values clustered around the mean), and resolution (ability of the forecast to resolve the set of sample events into subsets with characteristically different outcomes).⁴¹⁶

Subsequently, we review the most important verification methods and discuss their application to technological forecasts by artificial asset markets.

⁴⁰⁹ see also section 5.6.1

⁴¹⁰ see (Ebert, Brown et al. 2004), p.20

⁴¹¹ Ibid.

⁴¹² Ibid.

⁴¹³ Ibid.

⁴¹⁴ Ibid.

⁴¹⁵ see (Ebert, Brown et al. 2004), p.20

Table 120: Forecast types and corresponding verification methods (Ebert, Brown et al. 2004)

Dimension	Type	Illustrative use	Standard verification methods
Nature of forecast	Qualitative	quantitative rainfall forecast	see type <dichotomous, Multi-category>
	Deterministic	quantitative rainfall forecast	see dimension <specificity>
	Probabilistic	probability of rainfall, ensemble forecast	For (R)eliability, (S)harpness, Resol(u)tion: <ul style="list-style-type: none"> ▪ reliability diagram (R, U) ▪ histogram (S) ▪ Relative operating characteristic (U) ▪ brier score (R,S,U), logarithmic score (R) ▪ Ranked probability score (R)
Specificity of forecast	Dichotomous	tornado or no tornado	Categorical statistics based on a 2x2 contingency table showing the frequency of forecasts and observations <ul style="list-style-type: none"> ▪ fraction correct, bias score, probability of detection (POD), false alarm ratio (FAR), probability of false detection (POFD), threat score, odds ratio
	Multi-category	cold, normal, or warm conditions (>2 conditions)	Categorical statistics based on a NxN category contingency table showing the frequency of forecasts and observations <ul style="list-style-type: none"> ▪ distributions approach ▪ histogram ▪ accuracy, Heidke skill score, Hanssen and Kuipers discriminant based on probabilistic forecast: <ul style="list-style-type: none"> ▪ Ranked probability score
	Continuous	maximum temperature	measures how the values of the forecasts differ from the values of the observations <ul style="list-style-type: none"> ▪ Visual: scatter plot, Box plot ▪ Mean error, multiplicative bias, MAE, RMSE, MSE ▪ correlation coefficient, anomaly correlation, S1 score, skill score
	Object- or event-oriented	tropical cyclone motion and intensity	see type <spatial distribution>
Space-time domain	time series	daily maximum temperature forecasts for a city	
	spatial distribution	map of geopotential height, rainfall chart	<ul style="list-style-type: none"> ▪ <u>Scale decomposition methods</u>: Wavelet decomposition, Multi-scale statistical organization, discrete cosine transform. ▪ <u>Object oriented methods</u>: CRA verification, Object-based diagnostic approach, Event verification using composites
	pooled space and time	monthly average global temperature anomaly	

⁴¹⁶ see (Ebert, Brown et al. 2004), p.20

Table 121: Common error measures based on the dichotomous contingency table; adapted from (Ebert, Brown et al. 2004)

Error measure	Definition	Description
Accuracy [fraction correct]	$\frac{H + CN}{Total}$ Range: 0 to 1 Perfect score: 1	<ul style="list-style-type: none"> H: hits; CN: correct negatives Measures what fraction of the forecasts were correct Can be misleading since it is heavily influenced by the most common category, usually "no event" in the case of rare occurrences
Bias score [frequency bias]	$\frac{H + FA}{H + M}$ Range: 0 to ∞ Perfect score: 1	<ul style="list-style-type: none"> H: hits; FA: false alarms; M: misses Measures the ratio of the frequency of forecast events to the frequency of observed events Indicates whether the forecast system has a tendency to underforecast (BIAS<1) or overforecast (BIAS>1) events Does not measure how well the forecast corresponds to the observations, only measures relative freq.
Probability of detection (POD) [hit rate]	$\frac{H}{H + M}$ Range: 0 to 1 Perfect score: 1	<ul style="list-style-type: none"> H: hits; M: misses Measures what fraction of the observed "yes" events were correctly forecast Sensitive to hits, but ignores false alarms; very sensitive to the basic frequency of the event; thus, good for rare events Can be artificially improved by issuing more "yes" forecasts to increase the number of hits Should be used in conjunction with false alarm ratio
False alarm ratio (FAR)	$\frac{FA}{H + FA}$ Range: 0 to 1 Perfect score: 0	<ul style="list-style-type: none"> H: hits; FA: false alarms Measures what fraction of the predicted "yes" events actually did not occur Sensitive to false alarms, but ignores misses. Very sensitive to the basic frequency of the event Should be used in conjunction with POD
Threat score (TS) [critical success index – CSI]	$\frac{H}{H + M + FA}$ Range: 0 to 1 0 indicates "no skill" Perfect score: 1	<ul style="list-style-type: none"> H: hits; FA: false alarms; M: misses Measures the fraction of observed and/or forecast events that were correctly predicted Sensitive to hits, penalizes both misses and false alarms, does not distinguish source of forecast error Depends on basic frequency of events (poorer scores for rarer events) since some hits can occur purely due to random chance
Hanssen and Kuipers discriminant (HK) [true skill statistic, Peirces's skill score]	$\frac{H}{H + M} - \frac{FA}{FA + CN}$ Range: -1 to 1 0 indicates "no skill" Perfect score: 1	<ul style="list-style-type: none"> H:hits; FA:false alarms; M:misses; CN:Correct negat. Measures how well the forecast separated the "yes" events from the "no" events Does not depend on a basic event frequency For rare events HK is unduly weighted toward the first term (same as POD), so this score may be more useful for more frequent events
Odds ratio	$\frac{H \cdot CN}{M \cdot FA}$ Range: 0 to ∞ 1 indicates "no skill" Perfect score: ∞	<ul style="list-style-type: none"> Measures the ratio of the odds of a "yes" forecast being correct to the odds of a "yes" forecast being wrong The logarithm of the odds ratio is often used instead of the original value, as it allows to take prior probabilities into account and gives better scores for rarer events

Contingency tables and attached categorical statistics

The standard methods for verifying dichotomous and multi-category forecasts are based on a contingency table showing the frequency of forecasts and observations for the different categories.⁴¹⁷ Table 122 shows such a contingency table for dichotomous forecasts.

Table 122: Contingency table for dichotomous forecasts; (Ebert, Brown et al. 2004), p.7

		Observed	
		YES	NO
Forecast	YES	hits (H)	false alarms (FA)
	NO	misses (M)	correct negatives (CR)

The four combinations of forecasts and observations, called the joint distribution, are hits, misses, false alarms, and correct negatives. A perfect forecast system would produce only hits and correct negatives, and no misses or false alarms.⁴¹⁸ Thus, the contingency table is a useful way to see what types of errors are being made.⁴¹⁹

A large variety of categorical statistics can be computed from the elements in the contingency table to describe particular aspects of forecast performance. Some of them are briefly described in Table 121.

As noted above, the verification methods for multi-category forecasts are also based on a contingency table showing the frequency of forecasts and observations for the different categories. The general contingency table for multi-category forecasts is displayed in Table 123.

Table 123: Contingency table for multi-category forecasts (Ebert, Brown et al. 2004), p.12

		Observed category				Total
		1	2	...	K	
Forecast category	i,j			...		
	1	$n(F_1, O_1)$	$n(F_1, O_2)$...	$n(F_1, O_K)$	$N(F_1)$
	2	$n(F_2, O_1)$	$n(F_2, O_2)$...	$n(F_2, O_K)$	$N(F_2)$

	K	$n(F_K, O_1)$	$n(F_K, O_2)$...	$n(F_K, O_K)$	$N(F_K)$
Total	$N(O_1)$	$N(O_2)$...	$N(O_K)$	N	

⁴¹⁷ see (Ebert, Brown et al. 2004), p.7

⁴¹⁸ Ibid.

⁴¹⁹ Ibid.

In Table 123, $n(F_i, O_j)$ denotes the number of forecasts in category i that had observations in category j ; $N(F_i)$ denotes the total number of forecasts in category i ; $N(O_j)$ denotes the total number of observations in category j ; and N is the total number of forecasts.

A perfect forecast system would have values of non-zero elements only along the diagonal, and values of 0 for all entries off the diagonal.⁴²⁰ The off-diagonal elements give information about the specific nature of the forecast errors. The marginal distributions (N's at right and bottom of table) show whether the forecast produces the correct distribution of categorical values when compared to the observations.⁴²¹

A forecast verification method that examines the relationship among the elements in the multi-category contingency table is known as the distributions approach.⁴²² The advantage of such an approach is that the nature of the forecast errors can more easily be diagnosed, the disadvantage is that it is more difficult to condense the results into a single number.⁴²³ There are fewer statistics that summarize the performance of multi-category forecasts, see Table 124.

Table 124: Common error measures based on the multi-category contingency table; adapted from (Ebert, Brown et al. 2004)

Error measure	Definition	Description
Accuracy [fraction correct]	$\frac{1}{N} \sum_{i=1}^K n(F_i, O_i)$ <p>Range: 0 to 1 Perfect score: 1</p>	<ul style="list-style-type: none"> ▪ Measures what fraction of the forecasts were in the correct category ▪ Can be misleading since it is heavily influenced by the most common category, usually "no event" in the case of rare occurrences
Hansen and Kuipers discriminant [true skill statistic, Peirce's skill score]	$\frac{\frac{1}{N} \sum_{i=1}^K n(F_i, O_i) - \frac{1}{N^2} \sum_{i=1}^K [N(F_i) \cdot N(O_i)]}{1 - \frac{1}{N^2} \sum_{i=1}^K [N(F_i)]^2}$ <p>Range: -1 to 1 0 indicates "no skill" Perfect score: 1</p>	<ul style="list-style-type: none"> ▪ Measures the fraction of correct forecasts after eliminating those forecasts which would be correct due purely to random chance ▪ This is one form of a generalized skill score, where the score in the numerator is the number of correct forecasts, and the reference forecast in this case is random chance

⁴²⁰ see (Ebert, Brown et al. 2004), p.13

⁴²¹ Ibid.

⁴²² The distributions approach is developed in detail by (Murphy and Winkler 1987), (Murphy, Brown et al. 1989) and (Brooks and Doswell 1996)

⁴²³ see (Ebert, Brown et al. 2004), p.13

However, any multi-category forecast verification can be converted to a series of $K-1$ yes/no-type verifications by defining "yes" to be "in category i " or "in category i or higher", and "no" to be "not in category i " or "below category i ".⁴²⁴

Methods for continuous variable forecasts

The verification of forecasts of continuous variables measures how the values of the forecasts differ from the values of the observations. Table 125 presents an overview with a rating for the most common error measures in forecasting.

Reliability refers to insensitivity towards the used scale, whereas construct validity refers to the measure's ability to produce findings that agree with other measures of accuracy.⁴²⁵ Outlier protection refers to an error measure's insensitivity towards outliers and control for difficulty refers to the sensitivity towards time series that are more difficult to forecast than others.⁴²⁶

Table 125: Overview and ratings of common error measures in forecasting (Armstrong 2001a)

Error measure	Reliability	Construct validity	Outlier protection	Control for difficulty?
Root Mean Square Error (RMSE)	poor	fair	poor	no
Percent better	good	fair	good	yes
Mean Absolute Percentage Error (MAPE)	fair	good	poor	no
Median APE (MdAPE)	fair	good	good	no
Geometric Mean of RAE* (GMRAE)	fair	good	fair	yes
Median RAE* (MdRAE)	fair	good	good	yes

*) RAE: Relative Absolute Error

Most notably, research suggests that the RMSE should not be used for comparisons across series, as it is unreliable, especially if the data might contain mistakes or outliers.⁴²⁷ Furthermore, R^2 should also be avoided for measuring and comparing errors as it is misleading.⁴²⁸

⁴²⁴ see (Ebert, Brown et al. 2004), p.13

⁴²⁵ see (Armstrong 2001a), p.455-460

⁴²⁶ Ibid.

⁴²⁷ Ibid.

Reliability diagram

The reliability diagram is a method to evaluate probabilistic forecasts.⁴²⁹ It gauges how well the predicted probabilities of an event correspond to their observed frequencies. The observed frequency is plotted against the forecast probability, where the range of forecast probabilities is divided into K bins (for example, 0-5%, 5-15%, 15-25%, etc.). The sample size in each bin is often included as a histogram or values beside the data points.

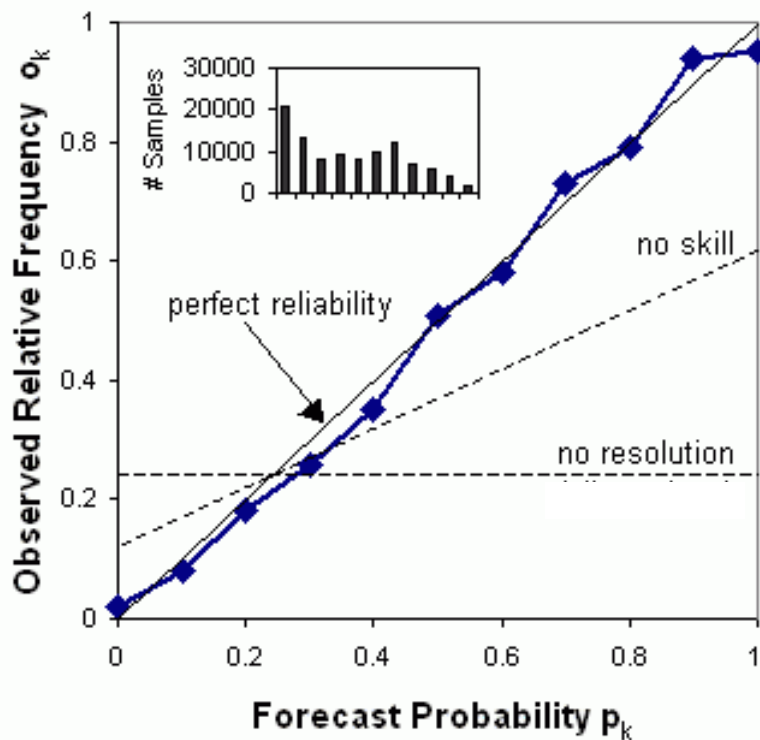


Figure 75: Forecast accuracy: Reliability diagram (or "Attributes diagram" when the no-resolution and no-skill lines are included); (Ebert, Brown et al. 2004)

Reliability is indicated by the proximity of the plotted curve to the diagonal; the deviation from the diagonal gives the conditional bias.⁴³⁰ If the curve lies below the line, this indicates "overforecasting" (probabilities too high); points above the line indicate "underforecasting" (probabilities too low).⁴³¹

⁴²⁸ Ibid.

⁴²⁹ see (Ebert, Brown et al. 2004), p.20-21

⁴³⁰ Ibid.

⁴³¹ Ibid.

The flatter the curve in the reliability diagram, the less resolution it has.⁴³² A no skill-forecast of persistence ("no change") does not discriminate at all between events and non-events, and, thus, has no resolution.⁴³³ The frequency of forecasts in each probability bin (shown in the histogram) shows the sharpness of the forecast.⁴³⁴

The reliability diagram is conditioned on the forecasts (i.e., given that X was predicted, what was the outcome?), and can be expected to give information on the real meaning of the forecast. It is a good partner to the Relative Operating Characteristic (ROC), which is conditioned on the observations.⁴³⁵

Scoring rules and the Average Logarithmic Score (ALS)

The "goodness" of a forecast can be defined as a constitution of three types of goodness, value (utility), quality (also known as accuracy or skill), and consistency.⁴³⁶ Value is concerned with the economic worth to the user, whereas quality is the correspondence between forecast and observations.^{437,438}

Consistency is achieved when the forecaster's best judgment and the forecast actually issued coincide.⁴³⁹ The choice of verification scheme can influence whether or not this happens.⁴⁴⁰ Scoring rules are inspired by the idea that the resulting device should oblige those who make probability evaluations to be as accurate as they can, and, in case they have to compete with others, to be honest.⁴⁴¹ A rule of this kind, working as a measure of the success of predictions, is apt to improve probability evaluations.

Thus, if forecasters are rewarded according to a "proper" score, they can maximize their expected return by reporting their probability estimates truthfully. Additionally,

⁴³² Ibid.

⁴³³ Ibid.

⁴³⁴ Ibid.

⁴³⁵ see (Ebert, Brown et al. 2004), p.20-21

⁴³⁶ see (Murphy 1993), p.281

⁴³⁷ see (Jolliffe and Stephenson 2003), p.8

⁴³⁸ see also the nine attributes of quality described at the beginning of this section

⁴³⁹ see (Murphy 1993), p.281

⁴⁴⁰ Ibid.

⁴⁴¹ see (de Finetti 1962), p.361

more accurate forecasters can expect to earn a higher score than less competent forecasters.⁴⁴²

Some schemes have scores for which a forecaster knows that he or she will score better on average if the forecast made differs (e.g. closer to the long-term average of the quantity being forecast) than his or her best judgment of what will occur.⁴⁴³ Such scoring systems are called improper and should be avoided.⁴⁴⁴ In particular, administrators should avoid measuring or rewarding forecasters' performance on the basis of improper scoring schemes, as this is likely to lead to biases in the forecasts.⁴⁴⁵

Examples of proper scoring rules include:⁴⁴⁶

$$\begin{aligned} \text{Quadratic} \quad s_i &= a_i + br_i - b \sum_j r_j^2/2, \\ \text{Spherical} \quad s_i &= a_i + br_i/(\sum_j r_j^2)^{1/2}, \\ \text{Logarithmic} \quad s_i &= a_i + b \log(r_i), \\ \text{Power Law} \quad s_i &= a_i + b\alpha \int_0^{r_i} \rho_i^{\alpha-2} d\rho_i - b \sum_j r_j^\alpha \end{aligned}$$

Power law rules are proper scoring rules for $\alpha \geq 1$ (Selten 1998), and both the quadratic (Brier 1950) and logarithmic rules (Good 1952) are special cases of this, for α of 2 and 1 respectively. The quadratic rule satisfies a number of desirable properties.⁴⁴⁷ The logarithmic rule also satisfies desirable properties⁴⁴⁸, and, most notably, it is the only rule satisfying that an agent's payoff depends only on the probability he assigned to the actual event.⁴⁴⁹ Thus, the logarithmic rule is the only one that can simultaneously reward agents and evaluate them via standard likelihood methods.⁴⁵⁰

⁴⁴² see (Pennock, Lawrence et al. 2001), p.5

⁴⁴³ see (Jolliffe and Stephenson 2003), p.8

⁴⁴⁴ Ibid.

⁴⁴⁵ see (Jolliffe and Stephenson 2003), p.8

⁴⁴⁶ see, e.g. (Hanson 2002), p.4

⁴⁴⁷ (Hanson 2002), p.4 cites (Selten 1998)

⁴⁴⁸ (Hanson 2002), p.4 cites (von Holstein 1970)

⁴⁴⁹ (Hanson 2002), p.4 cites (Savage 1971)

⁴⁵⁰ (Hanson 2002), p.4 cites (Winkler 1969)

For the logarithmic rule the score for a compound event is the sum of the scores for the component events, for probabilities that are multiplied the corresponding penalty scores add.

Table 126: Logarithmic score for different forecast probabilities and outcomes

forecast (p)	0.00	0.01	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
event occurs	$-\infty$	-200	-100	-70	-52	-40	-30	-22	-15	-10	-5	0
no event	0	-5	-10	-15	-22	-30	-40	-52	-70	-100	-200	$-\infty$

Values for the logarithmic score range from $-\infty$ to 0, the latter being the maximum score. Table 126 shows the logarithmic score for different forecast probabilities and outcomes. For example, a forecaster may judge an 80% chance of rain for tomorrow and therefore a 20% chance of none. If it does rain, his score is -10, but if it doesn't rain his score will be -100.

The objective for the forecaster, over many probability assessments, is to achieve an average score as close to zero as possible.⁴⁵¹ One way to do this is to be very knowledgeable. If the forecaster judges the probability to be high and this turns out to be correct, then he is given a low penalty score.⁴⁵²

But whatever the forecaster's state of uncertainty, he can also minimize the penalty score by expressing his uncertainty accurately when reporting it as a probability.⁴⁵³

For example, suppose the forecaster from the earlier example decides to cheat and reports he is 90% sure, hoping for a score of only -5. Of course if it doesn't rain, he will get a score of -200. Since his true belief is 80%, he must think there is an 80% chance of earning that score of -5, and a 20% chance of receiving -200. That gives an expected score of:

$$0.80 \times (-5) + 0.20 \times (-200) = -44$$

But the expected score would be closer to zero if he would to report accurately:

$$0.80 \times (-10) + 0.20 \times (-100) = -28$$

The expected score associated with an inaccurate report of the forecaster's uncertainty is always worse than the expected score for his real belief. This statement is always

⁴⁵¹ see, e.g. (Potts 2003) pp.13

⁴⁵² Ibid.

⁴⁵³ Ibid.

true whatever the forecaster's real belief. Consequently, in the long run the forecast's score will be minimized by reporting accurately.⁴⁵⁴

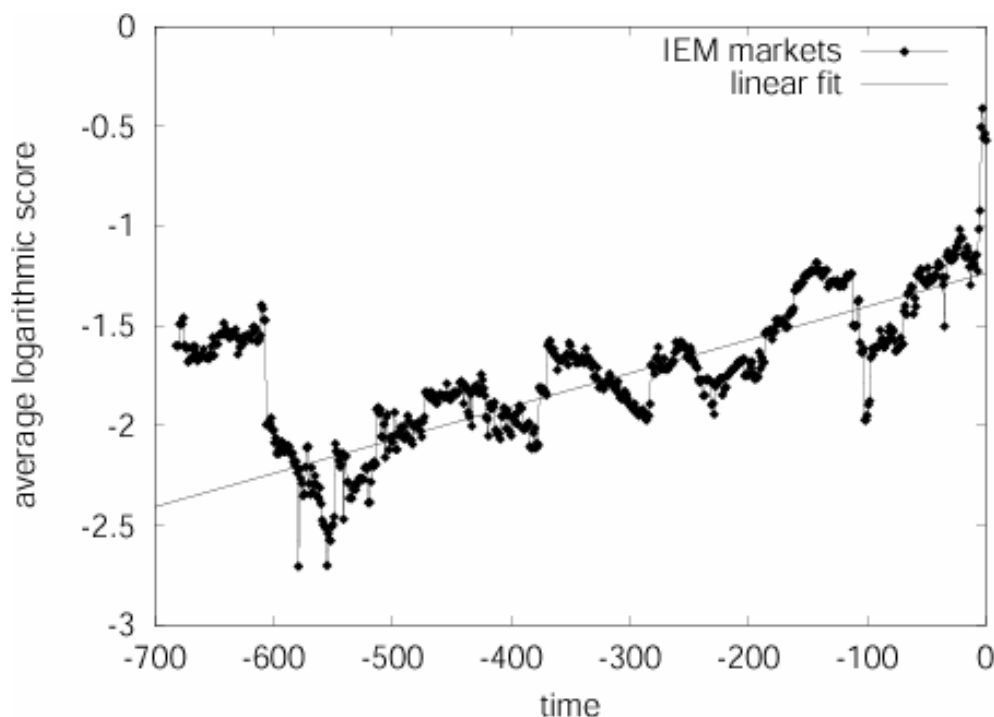


Figure 76: Forecast accuracy: Average logarithmic score (ALS) for 22 IEM markets over market duration; (Pennock, Debnath et al. 2002)

The logarithmic score is a powerful measure of forecast performance by evaluating forecast consistency and forecast accuracy. It has recently been used by researchers in the field of artificial asset markets to evaluate different field-deployed markets such as the IEM, HSX, and FX⁴⁵⁵, see also section 3.6. These researchers advocate the logarithmic score as to evaluate the market in same way as to evaluate experts providing forecasts.⁴⁵⁶

Conclusion

There are many types of forecasts addressing different forecasting needs, each of which calls for different methods of verification. Furthermore, a forecast has at least nine quality attributes and features a consistency as a dimension of "goodness" which again is subject to different interests of different uses. Consequently, it does not appear

⁴⁵⁴ Ibid.

⁴⁵⁵ see, e.g. (Pennock, Lawrence et al. 2000; Pennock, Lawrence et al. 2001; Pennock, Debnath et al. 2002; Debnath, Pennock et al. 2003b)

⁴⁵⁶ see (Pennock and Wellman 2004), p.104

sensible to construct or use a single measure that attempts to reflect overall forecast accuracy.

Instead, only after a specific forecasting purpose and a respective interest in selected quality or "goodness" attributes have been established, should one or rather several forecast verification methods of the range presented be selected.

For artificial asset markets for technological forecasting the described approach is performed in section 4.3.

Biography / Lebenslauf

Siddhartha Sampathkumar was born 1975 in Bombay, India. From 1995 to 2000 he studied Aeronautical Engineering at Technische Universität München from where he graduated as Diplomingenieur. In his final term he visited the Massachusetts Institute of Technology where he wrote his Diplomingenieur-thesis under the supervision of Prof. Don Clausing at the Center for Innovation in Product Development. The thesis produced research on technology development and commercialization strategies for new technologies. In 2001 S. Sampathkumar joined Roland Berger – Strategy Consultants, a top-management consultancy, where he still maintains his professional career. In 2003 he started a Doktorat study at the Vienna University of Technology where he is writing his Dissertation-thesis – the work presented here – under the supervision of Prof. Wolfgang Katzenberger of the Institute for Management Science. The thesis develops a new method of technological forecasting by artificial asset markets. Since 2005 S. Sampathkumar continues his career as a consultant at Roland Berger – Strategy Consultants. He can be contacted via e-mail at ssa@gmx.at

Siddhartha Sampathkumar wurde 1975 in Bombay, Indien, geboren. Er studierte von 1995 bis 2000 an der Technischen Universität München das Studium der Luft- und Raumfahrttechnik, das er als Diplomingenieur abschloss. Im letzten Studienjahr des Diplomstudiums besuchte er als Visiting Research Associate das Massachusetts Institute of Technology, wo er am Center for Innovation in Product Development unter Anleitung von Prof. Don Clausing seine Diplomarbeit verfasste. Inhalt der Diplomarbeit waren Technologieentwicklungs- und -kommerzialisierungs-Strategien für neue Technologien. Seit 2001 arbeitet S. Sampathkumar als Berater bei der Top-Management-Unternehmensberatung Roland Berger – Strategy Consultants. In 2003 nahm er im Rahmen eines Sabbaticals ein Doktoratsstudium an der Technischen Universität Wien auf, wo unter der Betreuung von Prof. Wolfgang Katzenberger vom Institut für Managementwissenschaften seine Dissertation – die vorliegende Arbeit – anfertigt. Inhalt der Dissertation ist die Entwicklung einer neuen Methode der Technologieprognose mittels experimenteller Aktienmärkte. Seit 2005 arbeitet S. Sampathkumar wieder als Berater bei Roland Berger – Strategy Consultants. Er kann via E-Mail unter ssa@gmx.at erreicht werden.