Professional MBA
Automotive Industry

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# The Effect of the COVID-19 Pandemic on New Passenger Car Registrations in Western Europe

A Master's Thesis submitted for the degree of
"Master of Business Administration"

supervised by
Prof. Dale Lehman, BA, MA, PhD

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00448075

Vienna, 17.03.2022

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# Affidavit

I, **MAG. ROBIN DAVID KILLIAN**, hereby declare

1. that I am the sole author of the present Master's Thesis, "THE EFFECT OF THE COVID-19 PANDEMIC ON NEW PASSENGER CAR REGISTRATIONS IN WESTERN EUROPE", 130 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted the topic of this Master's Thesis or parts of it in any form for assessment as an examination paper, either in Austria or abroad.

Vienna, 17.03.2022

Signature

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# List of Abbreviations

| | |
|---|---|
| abs. | absolute |
| ACEA | European Automobile Manufacturers' Association |
| ACF | Autocorrelation Function |
| AIC | Akaike's Information Criterion |
| AICc | biased-corrected Akaike's Information Criterion |
| AR model | Autoregressive model |
| ARCH model | Autoregressive Conditional Heteroskedasticity model |
| ARIMA model | Autoregressive Integrated Moving Average model |
| ARMA model | Autoregressive Moving Average model |
| AT | Austria |
| BE | Belgium |
| BIC | Bayesian Information Criterion |
| Brexit | Exit of the United Kingdom form the European Union on January 01, 2021 |
| CAGR | Compound Annual Growth Rate |
| $CO_2$ | Carbon Dioxide |
| DE | Germany |
| EFTA | European Free Trade Association: Iceland, Liechtenstein, Norway, Switzerland (EFTA 2022) |
| EMDE | Emerging Markets and Developing Economies |
| ES | Spain |
| ETS model | Exponential Smoothing model |
| EU | European Union |

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| | |
|---|---|
| EU14 | Originally 15 member states at the time of the enlargement of the European Union (EU) in 1995. After the exit of the United Kingdom on January 01, 2021 (Brexit), only 14 remaining member countries in reference to the year 1995: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden (EU 2022) |
| EU27 | 27 member countries of the European Union (2022): EU14 + Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia (EU 2022) |
| FR | France |
| GARCH model | Generalized Autoregressive Conditional Heteroskedasticity model |
| GBM model | Geometric Brownian Motion model |
| GDP | Gross Domestic Product |
| GLVS | Global Light Vehicle Sales |
| IMF | International Monetary Fund |
| IT | Italy |
| KPPS Test | Kwiatkowski-Phillips-Schmidt-Shin Test |
| LVS | Light Vehicle Sales |
| MA model | Moving Average model |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| MLE | Maximum Likelihood Estimation |
| NAFTA | North American Free Trade Agreement |
| NL | Netherlands |
| $NO_X$ | Nitrogen Oxide |
| NPCR | New Passenger Car Registrations |
| NPCR obs. | New Passenger Car Registrations observed / observations |

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| | |
|---|---|
| obs. | observed / observations |
| OECD | Organisation for Economic Co-operation and Development |
| OEM | Original Equipment Manufacturer |
| PACF | Partial Autocorrelation Function |
| per. | percentage |
| PI | Prediction Interval |
| PL | Poland |
| RMSE | Root Mean Squared Error |
| SARIMA | Seasonal Autoregressive Integrated Moving Average model |
| SE | Sweden |
| SEATS | Seasonal Extraction in ARIMA Time Series |
| STL | Seasonal and Trend decomposition using Loess |
| UK | United Kingdom |
| US | United States |
| USMCA | United States–Mexico–Canada Agreement |
| VAR model | Vector Autoregression model |
| VARIMA model | Vector Autoregressive Integrated Moving Average model |
| VARMA model | Vector Autoregressive Moving Average model |

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# 1 Introduction

The Covid-19 pandemic accompanied by social distancing, lockdowns, and partial business closures led to a global recession in the year 2020 which extent was exceeded only by the two World Wars and the Great Depression, considering the current and the last century (World Bank 2021a, p.3). In particular, the automotive industry is one of the sectors, which has been hit hard by the Covid-19 pandemic. Although the global automotive industry was even before Covid-19 in a general downward cycle which started in 2018 (ACEA 2020, p.14), the impact of the pandemic changed the prevailing market conditions completely and with an unexpectedly rapid pace. The spread of the virus and related containment measures led to a resulting strong decline from 89,9 million light vehicles[1] sold in 2019 to 77,2 million in 2020 - a global light vehicle sales contraction of 14,2%. From the three biggest automotive markets (China, North America, Europe[2]), Europe suffered the largest decline of 19,7% in the year 2020 (IHS Markit 2021). By considering the aggregate new passenger car[3] registrations in the EU14[4], the EFTA[5], and the United Kingdom (UK), Covid-19's impact in the year 2020 was even more severe, with a decline of about 3,5 million new passenger cars registrations or a respective drop of 24,5% in comparison to 2019. This contraction, demonstrated the deepest yearly decline in car demand ever measured (ACEA 2021a, p.6).

However, in the third quarter of 2020, a strong recovery started. Consumers returned earlier to the markets than expected, reflected by high levels of consumer spending, accelerated by savings accumulated during the first lockdown periods (ACEA 2021b, p.2). As a result, OEMs around the world have experienced a surge in demand, which led some OEMs to produce on record levels from the third quarter of 2020 through the first quarter of 2021 (Hensley et al. 2021, p.1). Yet, starting in the second quarter of 2021, supply bottlenecks arose which drastically intensified during 2021. The fast recovery in demand and the slower

[1] Light vehicle are vehicles with a maximum mass not exceeding 6 tons (IHS Markit 2022a).
[2] The designation Europe encompasses the informal geographical areas Central-, Eastern-, and Western-Europe, as by definition of IHS Markit (IHS Markit 2021).
[3] Passenger cars are vehicles with a maximum mass not exceeding 3,5 tons (ACEA 2022c).
[4] The member states of the EU14 are defined in the List of Abbreviations.
[5] The member states of the EFTA are defined in the List of Abbreviations.

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recovery of production capacities have created significant supply-demand mismatches. Shortages of commodities and key inputs, especially semiconductors, a resulting sharp increase in delivery times and shipping bottlenecks, heavily constrained production in the automotive industry. The resulting reduced availability of new cars and low inventory levels heavily affected car sales on a global basis, particularly in the second half of 2021 (OECD 2021a, pp. 17-20).

Especially, the global semiconductor shortage put again strong downward pressure on an already struggling automotive industry. As a result, global light vehicle sales are still far below their pre-pandemic level at the end of the year 2021. Nevertheless, global light vehicle sales increased at a moderate rate of 2,9% in 2021, however in comparison to a very low 2020 level. Light vehicle sales in Europe (Central, East, West) were more or less at par with the level of 2020, with an increase of just 0,1% in 2021(IHS Markit 2021). However, new passenger car registrations in the EU14, the EFTA, and the UK further declined by 1,9% in 2021 in comparison to 2020, basically due to the drastic semiconductor shortages in the second half of 2021 (ACEA 2022a).

## 1.1 Methodical Framework

The previous introductory section gave some information on the impact of Covid-19 and resulting after-effects on European new passenger car registrations in reference to a year-to-year comparison. However, to evaluate the effects of the pandemic and the resulting after-effects on new passenger car registrations (NPCR) in an adequate way, the establishment of a clear baseline is required. To establish this baseline, suitable time series models (SARIMA-models) will be fitted in R to datasets of the ACEA - for NPCR by country (ACEA 2021e) and by manufacturer (ACEA 2021f) in Europe - for a specified pre-Covid time-frame (Jan/2003-Dec/2018 for countries, Jan/2001-Dec/2018 for manufacturers). Additionally, the best fitting stochastic processes will be verified by a comparison of the forecasts with the actual observed values in a specified pre-Covid verification time frame (Jan/2019-Dec/2019). After the verification of the best-fitting time series models, the models will be used to forecast stochastic events of new passenger car registrations in Europe for different OEMs and countries for a specified post-Covid-19 time frame (Jan/2020-Dec/2021). Hence the forecasted events can be considered as realizations of new passenger car registration, which are neglecting the disruptive Covid-19 effects, and consider time-series variability only. This approach allows for an adequate evaluation of the quantitative Covid-19 impact through the calculation of the difference between the observed new passenger

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car registrations and the forecasted realization in the specified post-Covid time frame.

## 1.2 Research Questions

In reference to the topic of the thesis, the following research questions will be defined:

**1. Research Question - Facts:**

What was the quantitative impact of Covid-19 on new passenger car registrations in Europe . . .

(a) by country,

(b) and by manufacturer (OEM)

. . . measured against the pre-Covid time series variability exhibited in the automotive industry?

**2. Research Question - Interpretation:**

(a) Did certain countries perform better and recover faster in terms of new passenger car registrations than other ones so far during the Covid-19 pandemic?

(b) Did certain OEMs perform better and recover faster in terms of new passenger car registrations than other ones so far during the Covid-19 pandemic?

(c) Speculations on potential causes for differences in the results suggested by the analysis based on: specific car types (fuel-based, electric, hybrid, etc.), supply chain resilience, innovative retail strategies, governmental automotive policies, and governmental responses to the pandemic, etc.

## 1.3 Structure

The remainder of this thesis is structured as follows. Chapter 2 introduces the general effects of Covid-19 on the automotive industry. However, before the effects of the Covid-19 pandemic on the automotive industry will be discussed, an analysis of the automotive industry from a pre-Covid-19 perspective will be presented in the first section 2.1 to get a better understanding of the baseline. Section 2.2 discusses the impact of Covid-19 on the global economy and serves

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as a macroeconomic starting point for an analysis of the automotive sector. Subsequently, in section 2.3 Covid-19's impact on the global automotive industry will be discussed, while the impact on global light vehicle sales, prevailing disruptive mega-trends, automotive supply chains, and the car sales process will be elaborated in detail. Finally, section 2.4 discusses the effects of Covid-19 on the European automotive industry with a focus on the year to year impact on new passenger car registrations by countries and by OEMs and states some information on how these effects will be evaluated more adequately in the numerical studies presented in chapter 4.

Chapter 3 is dedicated to time series analysis and forecasting and sets the theoretical framework for the numerical studies presented in chapter 4. The first section 3.1 gives a general overview of forecasting methods and provides related basic terminology, with a focus on quantitative forecasting methods, and especially on stochastic time series models. Following this, section 3.2 states a definition of the quantitative forecasting process in reference to this thesis. Section 3.3 is dedicated to preliminary time series analysis and covers topics like general time series pattern, stationarity, autocorrelation, transformations, and trend and seasonal adjustments. Based on that, the theory of ARIMA models, which are used for forecasting in chapter 4, will be discussed in section 3.4. Finally, section 3.5 is dedicated to the ARIMA modeling approach, where order selection, parameter estimation, information criteria, residual analysis, and forecast accuracy evaluation will be discussed in detail. Beyond that, practical examples related to the topic of the thesis and the numerical studies presented in chapter 4 will be stated.

Chapter 4 is concerned with the evaluation of the quantitative impact of Covid-19 and resulting after-effects on European new passenger car registrations in relation to the research questions, stated in section 1.2. The first section 4.1 gives a summary of the approach which was used for the evaluation, in connection with the theory of time series analysis and forecasting, presented in chapter 3. Following this, sections 4.2 and 4.3 are dedicated to the quantitative evaluation of Covid-19's impact on European new passenger car registrations by countries and by OEMs respectively, which will be measured against the pre-Covid-19 time series variability exhibited in the automotive industry.

Finally, chapter 5 states concluding remarks, summarizes the findings of this thesis, and provides an outlook for possible future research.

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# 2 The Impact of COVID-19 on the Automotive Industry

The following chapter provides an introduction to the general effects of Covid-19 on the automotive industry. However, before the effects of the Covid-19 pandemic on the automotive industry will be discussed, an analysis of the automotive industry from a pre-Covid-19 perspective will be presented in the first section 2.1 of this chapter, to get a better understanding of the baseline. Section 2.2 discusses the impact of Covid-19 on the global economy and serves as a macroeconomic starting point for an analysis of the automotive sector. Subsequently, in section 2.3 Covid-19's impact on the global automotive industry will be discussed, while the impact on global light vehicle sales, prevailing disruptive mega-trends, automotive supply chains, and the car sales process will be elaborated in detail. Finally, section **??** discusses the effects of Covid-19 on the European automotive industry with a focus on the year to year impact on new passenger car registrations by countries and by OEMs and states some information on how these effects will be evaluated in a more adequate way in the numerical studies presented in chapter 4.

## 2.1 Pre-Covid Analysis of the Automotive Industry

In 2018, OEMs and automotive suppliers reached the peak of the longest growth phase in the history of the automotive industry since the 1950s. After the recovery of the global financial crisis (2007-2009) and the following European sovereign debt crisis (2009-2013), the automotive market had strong momentum. Hence the US automotive market grew by a CAGR of approximately 5% between 2010 and 2018, and the European automotive market experienced a 5-year growth period with a CAGR of approximately 4% between 2014 and 2018 (Collie et al. 2019, pp.1-3). However, after this upward cycle, global GDP forecasts showed signs of softening before even the Covid-19 pandemic started, in an environment of global trade uncertainty and increasing trade restrictions (World Bank 2019, p.1). In 2019, a general risk of a broad retreat from globalization was prevailing. Trade tensions, especially between the US and China, but also between the US and the EU, the transformation of the NAFTA (North American Free Trade Agreement) to the more restrictive USMCA (United States - Mexico - Canada Agreement) or the forthcoming exit of Great Britain from the European Union (Brexit), were probably the most prominent examples from a 2019 perspective (IHS Markit 2019, p.2).

In addition, there were signs of saturated automotive markets, especially in the US and the EU, as higher incentives did not generate higher car sales anymore. In reference to a pre-Covid study of the Boston Consulting Group, which was published in 2019, it was forecasted that car sales would drop in the EU by approximately 5% - 10% and in the US by approximately 9% - 15% from 2019 to 2021. At that time, it was expected that markets would recover in 2023 (Collie et al. 2019, pp.2-3). Beyond that, the strong upswing in China which created huge demand in the past was gradually slowing down and Chinas industry policy was striving to dominate the local market (KPMG 2019, pp.2-3). From a 2019 pre-Covid perspective, which is still valid today at the beginning of 2022, there was limited potential for growth in mature markets (United States, Euro Zone, Canada, Japan, South Korea, Australia, New Zealand), while emerging markets were considered key for future growth in the automotive industry (IHS Markit 2019, p.5).

### 2.1.1 Disruptive Mega-Trends in the Automotive Industry

Furthermore, it was expected, that the forthcoming downturn would be different from downturns in the past because the automotive industry was facing four major disruptive mega-trends - *vehicle electrification, connectivity, autonomous driving and shared mobility* - which would massively transform the automotive industry over the next decades (Cornet et al. 2019, p.14). On one hand, traditional carmakers were forced by government regulations regarding $CO_2$-emission targets (e.g. the Average Fleet Consumption in the EU[1]) and $NO_x$-emissions targets, to change from fuel-based to alternative engine technologies (European Commission 2022a). On the other hand, they were forced to a massive transformation by

[1]The Average Fleet Consumption is an EU regulation which sets $CO_2$-emission thresholds on the average EU-emissions of an OEMs fleet (cars and vans). On January 1, 2020, the targets have been tightened to 95 g $CO_2$/km for cars and 147 g $CO_2$/km for vans, thresholds which cannot be reached with only fuel-based engines on average over an OEMs fleet, at least from today's perspective. In addition, these targets will be set stricter again in the years 2025 and 2030. An OEM must pay high penalties for not reaching the target, which is incentivizing OEMs in developing zero- and low emission vehicles (European Commission 2022a). Similar mechanisms to reduce $CO_2$-emissions but also $NO_x$-emissions are in place in other regions of the world, like the US or China.

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uprising innovative start-ups with a focus on cars with electric or fuel-cell engines, autonomous driving, and new data-based business models, like Tesla. The British mathematician and entrepreneur Clive Humby once said in 2006 that *"data is the new oil"* in the future, which the more than ever true in an age of digital transformation and related new business models. Consequently, tech companies like Google, Apple, Amazon, and Huawei were interested more and more in the automotive sector, with a focus on monetizable services, in mind that a car is generating a huge amount of valuable customer data. A resulting highly competitive and disruptive environment evolved, where classical automotive OEMs, innovative start-ups, and tech companies were, and still are, fighting for the dominant market position at the end of the supply chain close to the customer (KPMG 2019, pp.30-41).

Another important factor from a pre-Covid perspective was the ongoing change in mobility behavior. Where it was, and still is, a symbol of status to poses one or more cars, a change of this behavior was taking place accompanied by shared mobility concepts and service innovations. According to McKinsey's Urban Mobility 2030 Berlin case study (Cornet et al. 2019, p.14), which was published in pre-Covid 2019, one of ten cars sold in 2030 was expected to be a shared car. In addition, it was stated that services like autonomous *"robotaxis"* would become a cheaper mobility option than private vehicles until 2030, especially in urban areas. Another McKinsey study (Kaas et al. 2016, p.8) stated that, while consumers today use their cars for all kinds of purposes, consumers in the future will choose an optimal solution based on mobility services for each specific purpose.

### 2.1.2 Pre-Covid Forecast of Global Light Vehicle Sales

While most of the previously mentioned trends are even more present today, the 2019 baseline scenario was characterized by a general economic downward cycle, a retreat from globalization, saturated car markets in advanced economies, a change of mobility behavior, and a highly disruptive environment in the automotive industry - partly induced by government regulations and partly by a high degree of competition and innovation. On the other hand, customer demand, especially for electric vehicles, was still subdued because of relatively high initial costs, the availability of charging stations, and hesitancy based on habits and technology readiness. Taking all factors into account, in 2019 it was prospected that growth rates of global light vehicle[2] sales would stay subdued over the next decade, as illustrated in figure 2.1 (IHS Markit 2019, pp.2-4).

[2]Light vehicle are vehicles with a maximum mass not exceeding 6 tons (IHS Markit 2022a).

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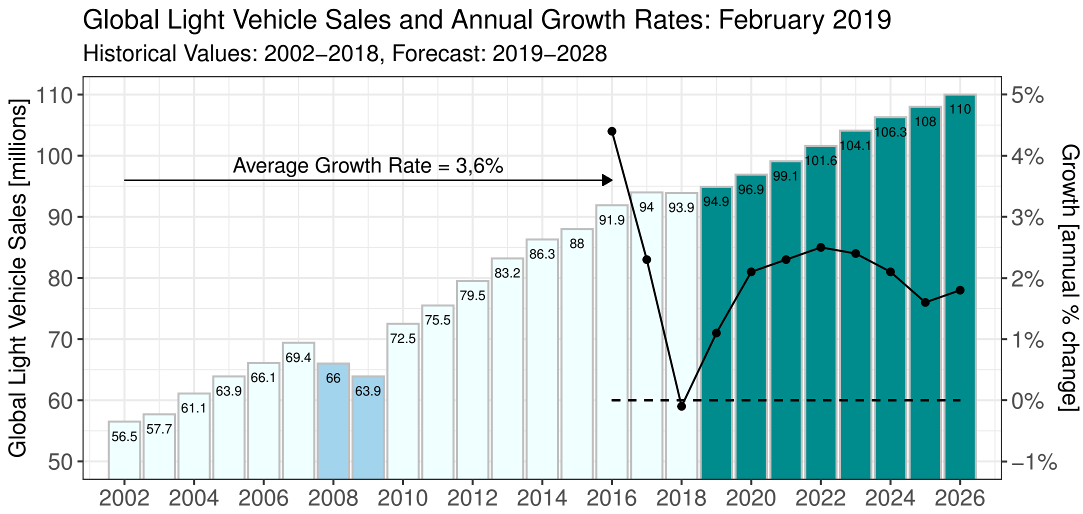


Figure 2.1: Global Light Vehicle Sales and Annual Growth Rates: Feb. 2019
Data Source: (IHS Markit 2019)

In the next section, the impact of Covid-19 on the global economy will be elaborated to present some general macroeconomic background information for a detailed analysis of the global and the European automotive sector in sections 2.3 and 2.4.

## 2.2 Covid-19's Impact on the Global Economy

The Covid-19 pandemic accompanied by social distancing, lockdowns, and partial business closures led to a global recession in the year 2020 which extent was exceeded only by the two World Wars and the Great Depression, considering the current and the last century (World Bank 2021a, p.3). As a result of the Covid-19 induced economic shock in China at the end of 2019, which spread to a global macroeconomic crisis in the following months, the worldwide economy has contracted in total by 3,4% in 2020. Subdivided into regions, the Euro Area has contracted by 6,4%, the US market by 3,4%, and of the BRICS countries (Brazil, Russia, India, China, South Africa) only China's economy has grown at a moderate rate of 2,2%, as illustrated in figure 2.2 below (World Bank 2022, p.4).

Following the heavy contraction of the economy in the first half of 2020, the global economy had significant momentum. Demand was boosted by relaxations of pandemic-related lockdowns and containment measures, business reopenings, and spendings of retained household savings (OECD 2020, p.4). Due to this acceleration, the global economy grew at an estimated rate of 5,5%, the Euro Area by 5,2%, the US market by 5,6% and the Chinese market by 8% in 2021,

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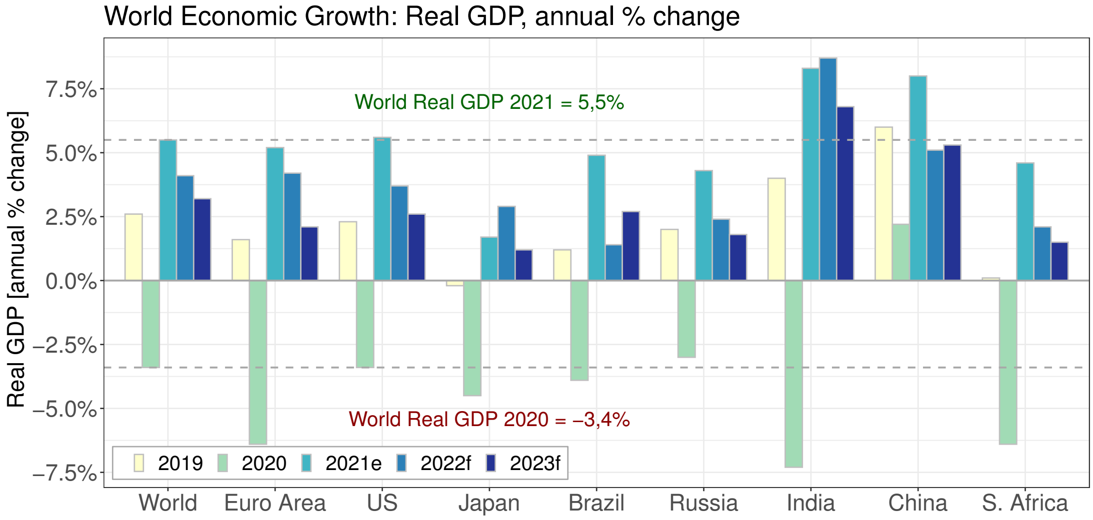


Figure 2.2: World Economic Growth, annual percentage change
Data Source: (World Bank 2022, p.4)

which demonstrates the strongest recovery pace from a recession for 80 years (World Bank 2021b, p.3). However, in 2021, momentum has begun to slow down. The appearance of the more infectious and harmful Delta-variant, persisting supply bottlenecks because of the recurring pandemic-induced factory and port shutdowns, and extreme weather events, significantly contributed to a slowdown of global growth. Beyond that, shortages in labor, commodity, and key inputs, like the continuing semiconductor scarcity in the automotive industry, heavily constrained production in some industries and played a major role in slowing merchandise trade growth, especially in the second half of 2021 (World Bank 2022, p.5). Significant supply-side problems arose and faced unexpectedly rapid increases in demand. Following these supply-demand mismatches, commodity prices in 2021 have risen sharply in comparison to their low levels in 2020 (IMF 2021, p.1). Additionally, food and energy prices have increased significantly as well as prices for durable goods, like for cars, where supply bottlenecks were and still are most present (OECD 2021a, p.12).

### 2.2.1 Global Macroeconomic Prospects

Under the assumption of continuing Covid-19 outbreaks in the year 2022, persisting supply bottlenecks, and reduced policy support, it is forecasted that global economic growth will decrease from 5,5% in 2021 to 4,1% in 2022. Beyond that, it is expected that global growth is decreasing further in 2023 to 3,2%, because of a continuing reduction in economic policy support and satisfied pent-up demand (World Bank 2022, p.5). Despite the easing growth pace, global output reached its pre-pandemic level at the end of 2020. However, the recovery is incomplete, as

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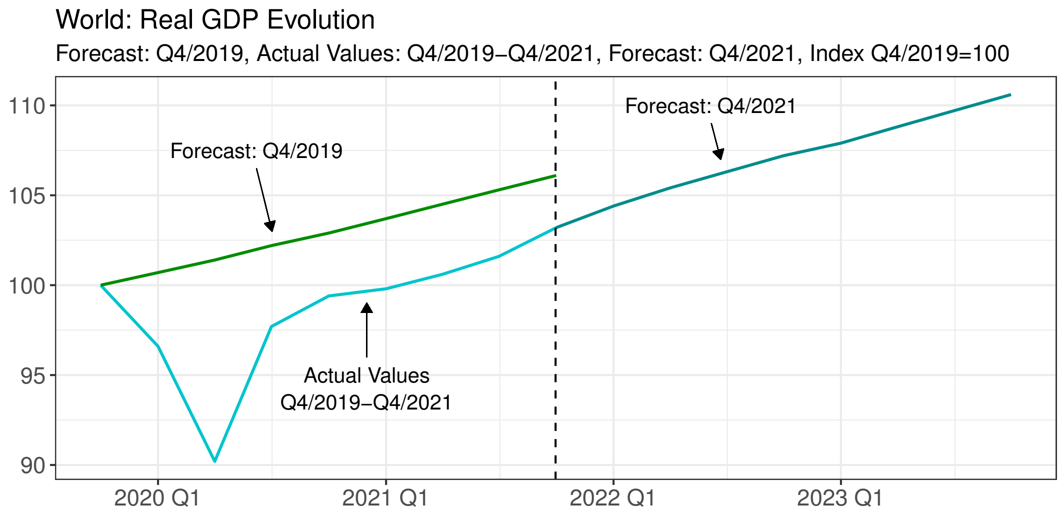


Figure 2.3: World: Real GDP Evolution
Data Source: (OECD 2021b)

can be seen from figure 2.3.[3] Global growth from 2020 has been lost and global real GDP was still about 3,5% below its pre-pandemic forecast in mid of 2021. Furthermore, the economic loss was distributed unequally. Especially for emerging markets and developing economies (EMDEs), with limited access to vaccines and restricted policy support, the impact was proportionally greater and the recovery slower (OECD 2021a, p.14). In advanced economies, it is expected that the development of economic growth will be adequate to reach its pre-pandemic projection between the end of 2022 and the first half of 2023, as depicted for the

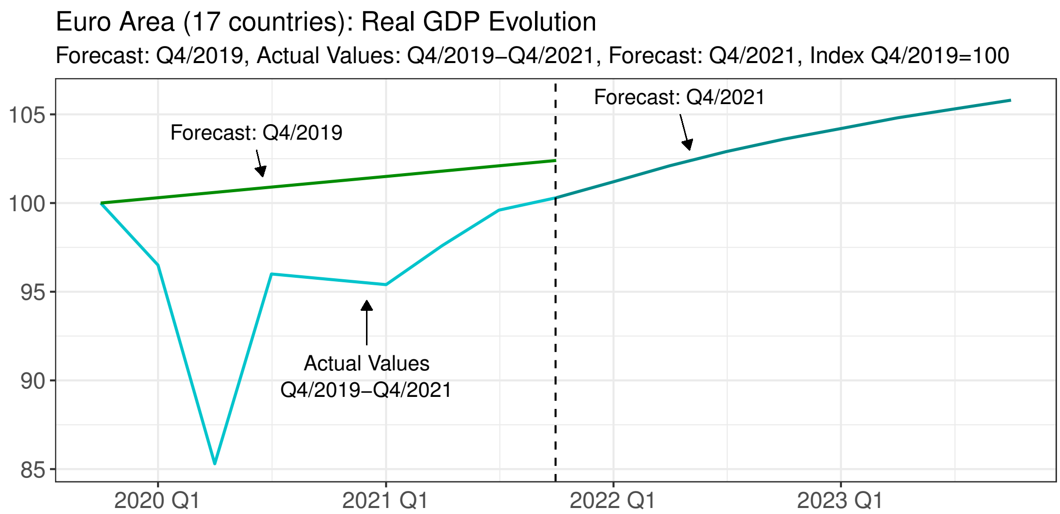


Figure 2.4: Euro Area: Real GDP Evolution
Data Source: (OECD 2021b)

[3] It can be observed that the general trend of the Q4/2021 global real GDP forecast of the OECD (OECD 2021b) has not changed compared to the Q4/2019 forecast, except for the downward shift due to the error in the Q4/2019 forecast.

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Euro Area in figure 2.4 below. In contrast, however, it is projected that most EMDEs (excluding China), will take mid- to long-term economic damage from the impact of the pandemic. From today's perspective, the average EMDEs recovery pace is by far not strong enough to reach its pre-Covid projection soon, with an estimated 4% below its pre-Covid growth trend in 2023 and about 6% below, without considering China (World Bank 2022, p.6).

Generally, it is expected, that continuing Covid-19 outbreaks will take place around the world, yet with steadily decreasing health and economic consequences. In addition, it is assumed, that consumer price inflation will reach its peak in the first half of 2022 and will gradually wane through 2023 (World Bank 2022, pp.26-27). Furthermore, supply-side constraints, shortages of commodities, key inputs, and related price pressure are estimated to gradually decrease through 2022-23, as a result of expanding production capacities, the return of more people to the labor force, and stabilizing demand patterns (OECD 2021a, p.12). On the other hand, current global economic prospects, such as those of the World Bank (World Bank 2022), the IMF (IMF 2021) or the OECD (OECD 2021a) are clouded by various downside risks. A stronger than expected resurge of pandemic outbreaks by more harmful virus variants, vaccination hesitancy and unequal vaccine distribution around the world, worsening and longer than expected supply shortages, related de-anchored inflation pressure, financial stress as a result of record-high debt levels, especially in EMDEs, climate-change-induced extreme weather events, rising political tensions between the US and Russia and the EU and Russia, increasing political trade restrictions between major economies, and a rise of social tensions due to intensifying within- and between-country inequalities, make currently released economic forecasts highly uncertain (World Bank 2022, pp.27-31). This uncertainty makes it even more important to have a good baseline forecast for comparison in order to evaluate the quantitative impacts of future changes. How to establish an adequate baseline forecast for the evaluation of the quantitative impact of Covid-19 and resulting after-effects on new passenger car registrations (NPCR) will be explained in sections 2.4.1 and 4.1 of this thesis.

## 2.3 Covid-19's Impact on the Automotive Industry

The automotive industry is one of the sectors, which has been particularly hit hard by the Covid-19 pandemic. However, as mentioned in section 2.1 and depicted in figure 2.5, the automotive industry was on a general downward cycle in 2018, even before Covid-19 started. Global light vehicle sales dropped by 4,2% in pre-Covid

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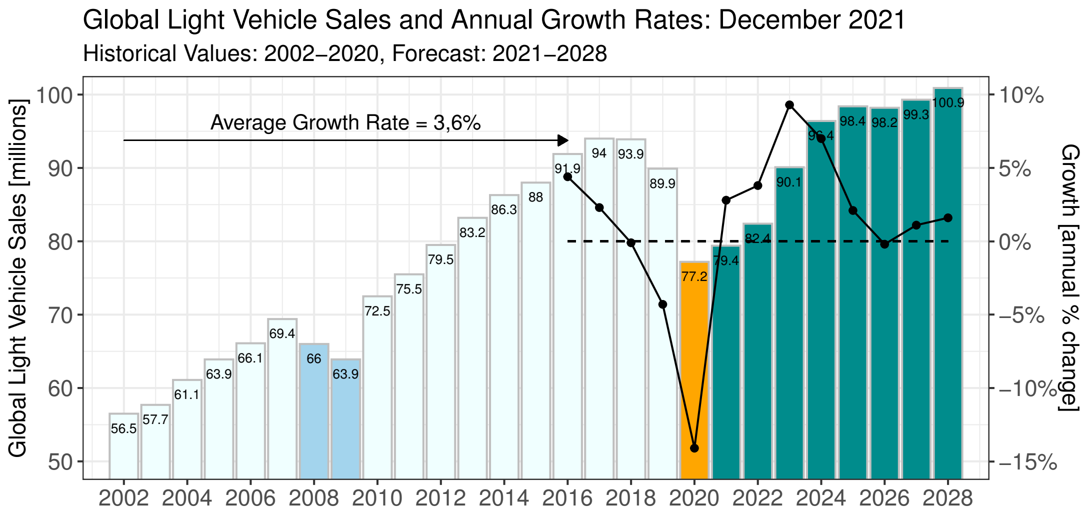


Figure 2.5: Global Light Vehicle Sales and Annual Growth Rates: Dec. 2021
Data Source: (IHS Markit 2021)

2019, with sales in North America dropping by 2,0% and in China[4] by 8,2%, after almost three decades of continuing Chinese growth (ACEA 2020, p.14). Beyond that, light vehicle sales in Japan/Korea, South America, India[5] and the Middle East/Africa declined as well, while only Europes[6] light vehicle market grew at a moderate rate of 0,7% in the year 2019 (IHS Markit 2021), as depicted in figure 2.6.

Yet, the impact of the pandemic changed the prevailing market conditions completely and at an unexpectedly rapid pace. The spread of the virus and related lockdowns and containment measures led to a deep recession and a resulting strong decline from 89,9 million light vehicles sold in 2019 to 77,2 million in 2020 - a global light vehicle sales contraction of 14,2% - as can be seen from figure 2.5 (IHS Markit 2021). Light vehicle sales by regions are stated in figure 2.6. From the three biggest automotive markets (China, North America, Europe), Europe suffered the largest decline of 19,7% in the year 2020. Furthermore, light vehicle sales in North America dropped by 15,9%, at a comparable moderate rate of 4,5% in China and by 6,9% in Japan/Korea. From the EMDEs, South America was hit hardest with a decline of 27,8%, followed by India with a drop of 20,7% and the Middle East/Africa with a contraction of 18,1% (IHS Markit 2021).

In the third quarter of 2020, a strong recovery started. Consumers returned to

[4]The designation China in figure 2.5 comprises the countries of the informal geographical area Greater China, as by definition of IHS Markit (IHS Markit 2021).
[5]The designation India in figure 2.5 comprises the countries of the Indian Subcontinent, as by definition of IHS Markit (IHS Markit 2021).
[6]The designation Europe in figure 2.5 encompasses the informal geographical areas Central-, Eastern-, and Western-Europe, as by definition of IHS Markit (IHS Markit 2021).

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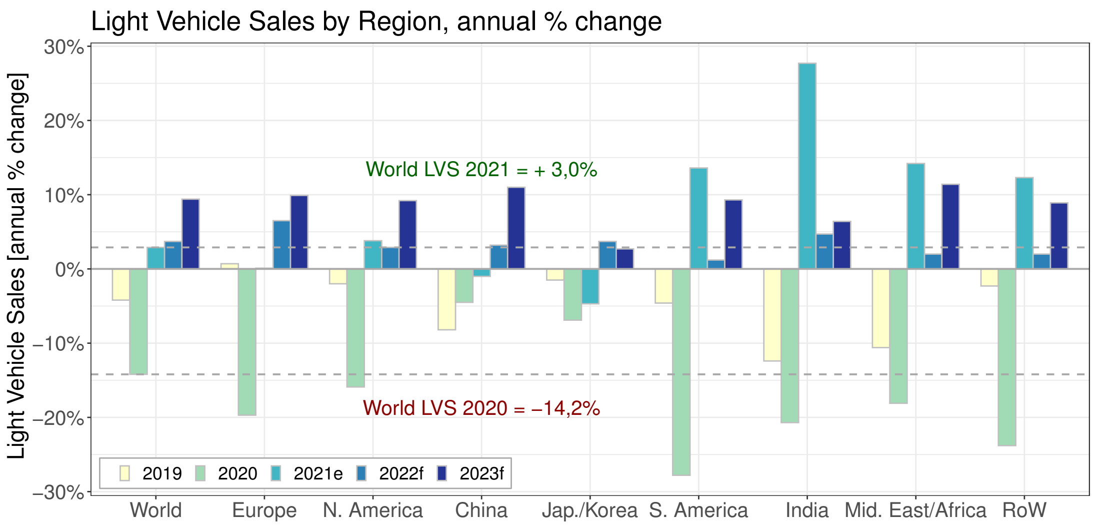


Figure 2.6: Light Vehicle Sales by Region, annual percentage change
Data Source: (IHS Markit 2021)

the markets earlier than expected, reflected by high levels of consumer spending, accelerated by savings accumulated during the first lockdowns (ACEA 2021b, p.2). As a result, OEMs around the world have experienced a surge in demand, which led some OEMs to produce on record levels from the third quarter of 2020 through the first quarter of 2021 (Hensley et al. 2021, p.1). However, starting in the second quarter of 2021, supply bottlenecks arose which drastically intensified during 2021. The fast recovery in demand and the slower recovery of production capacities have created significant supply-demand mismatches. Shortages of commodities and key inputs, especially semiconductors, a resulting sharp increase in delivery times and shipping bottlenecks, heavily constrained production in the automotive industry. The resulting reduced availability of new cars and low inventory levels heavily affected car sales on a global basis, particularly in the second half of 2021 (OECD 2021a, pp.17-20).

Especially the global semiconductor shortage put severe downward pressure again on the automotive industry. As a result, global light vehicle sales (GLVS) are still far below their pre-pandemic level at the end of 2021, as illustrated in figure 2.5. Nevertheless, GLVS increased at a moderate rate of 2,9% in 2021, however in comparison to a very low 2020 level. Light vehicle sales in Europe are more or less at par with the level of 2020, with an increase of just 0,1%. Beyond that, light vehicle sales in North America went up by 3,8%, while the Chinese and the Japanese/Korean markets contracted again in 2021 by 1% and 4,7% respectively. Furthermore, light vehicle sales in South America increased by 13,6%, in India by 27,7% and in the Middle East/Africa by 14,2% in 2021, however all from a low 2020 basis (IHS Markit 2021), as depicted in figure 2.6.

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### 2.3.1 Comparison of Pre- and Post-Covid Forecast of GLVS

A comparison of the pre-Covid global light vehicle sales forecast from February 2019 (IHS Markit 2019) stated in figure 2.1, and the post-Covid global light vehicle sales forecast from December 2021 (IHS Markit 2021), depicted in figure 2.5 is also interesting. As can be seen from the comparison of the forecasts in table 2.1, it is expected, that global light vehicle sales will reach their pre-pandemic level of about 90 million cars sold (baseline December 2021 forecast) in 2023.

| **GLVS Forecast** [millions] | Baseline 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | Total 20-26 |
|---|---|---|---|---|---|---|---|---|---|
| Feb. 2019, fig. 2.1 | 94.9 | 96.9 | 99.1 | 101.6 | 104.1 | 106.3 | 108.0 | 110.0 | 726.0 |
| Dec. 2021, fig. 2.5 | 89.9 | 77.2 | 79.4 | 82.4 | 90.1 | 96.4 | 98.4 | 98.2 | 622,1 |
| Δ 2019 - 2021 [abs.] | 5.0 | 19.7 | 19.7 | 19.2 | 14.0 | 9.9 | 9.6 | 11.8 | 103,9 |
| Δ 2019 - 2021 [%] | -5.3% | -20.3% | -19.9% | -18.9% | -13.4% | -9.3% | -8.9% | -10.7% | -14.3% |

Table 2.1: Comparison of Pre- and Post-Covid Forecast of GLVS
Data Source: (IHS Markit 2019), (IHS Markit 2021)

However, from today's perspective, the forecasted recovery pace of global light vehicle sales is by far not strong enough to reach its pre-Covid projection from February 2019, with a delta of still 11,8 million cars in 2026 and a total projected loss of 103,9 million cars or -14,3% from 2020 through 2026. Yet, it is hard to say, whether this projected gap is just a result of the Covid-19 pandemic and its related after-effects. It might be possible that a part of this gap is a result of the prevailing highly disruptive environment in the automotive industry, increasing political tensions and trade restrictions, saturating major automotive markets, a change in mobility behavior, or one of the various challenges which the automotive industry is facing today and over the next decades. Such an analysis could be part of future research. What can be assumed, however, is that the Covid-19 pandemic and the related after-effects most likely contributed to a great part of this gap.

### 2.3.2 Post-Covid Forecast, Growth and Market Share by Region

Historical and forecasted light vehicle sales were stated before on a global aggregate basis in figure 2.5. Table 2.2 below illustrates historical and forecasted light vehicles sales by region. Additionally, absolute annual growth, the growth rate, and the development of the corresponding market shares are illustrated until 2028.

The impact of the Covid-19 pandemic is clearly visible in the years 2020 and

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2021, as was already explained in more detail in section 2.3. Beyond that, a moderate recovery of 3,7% of global light vehicle sales is expected for 2022 as well as relatively high growth rates of 9,4% and 7,0% in the following two years 2023 and 2024. This seems to be reasonable under the assumption that supply-side constraints, shortages of commodities, and key inputs, like semiconductors, are expected to gradually diminish through 2022-23 (OECD 2021a, p.12). Beyond 2024 however, growth of global light vehicle sales is forecasted to slow down again to quite low levels, at least in comparison to an average growth rate of 3,6% between 2002 and 2016 (IHS Markit 2019, p.4). The modest levels of global light vehicle sales growth in 2025 through 2028, can be traced back to the minor growth rates in advanced economies (Europe, North America, and Japan/Korea). In reference to the forecast presented in table 2.2, it is even expected that the light vehicle sales market in Europe will contract in 2026, between 2026 to 2028, in North America and in Japan/Korea between 2025 to 2028, which contributes

| **LVS** [millions] | | **Past** | | **Fore.** 12/21 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Region / Year | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 |
| China | 27.5 | 25.3 | 24.1 | 23.9 | 24.7 | 27.4 | 29.5 | 30.3 | 30.6 | 31.2 | 31.9 |
| Europe | 20.7 | 20.8 | 16.7 | 16.8 | 17.8 | 19.6 | 21.2 | 21.2 | 20.7 | 20.8 | 20.9 |
| N. America | 20.7 | 20.3 | 17.1 | 17.7 | 18.2 | 19.9 | 20.9 | 20.9 | 20.6 | 20.5 | 20.3 |
| Jap./Kor. | 6.9 | 6.8 | 6.4 | 6.1 | 6.3 | 6.5 | 6.7 | 6.6 | 6.4 | 6.2 | 6.1 |
| India | 4.3 | 3.7 | 3.0 | 3.8 | 4.0 | 4.2 | 4.4 | 4.7 | 4.9 | 5.1 | 5.5 |
| M. East/Afr. | 4.3 | 3.9 | 3.2 | 3.6 | 3.7 | 4.1 | 4.5 | 4.8 | 4.8 | 4.9 | 5.1 |
| S. America | 4.7 | 4.5 | 3.2 | 3.7 | 3.7 | 4.1 | 4.5 | 4.8 | 5.1 | 5.3 | 5.6 |
| RoW | 4.7 | 4.6 | 3.5 | 3.9 | 4.0 | 4.3 | 4.8 | 5.1 | 5.2 | 5.3 | 5.5 |
| World | 93.9 | 89.9 | 77.2 | 79.4 | 82.4 | 90.1 | 96.4 | 98.4 | 98.2 | 99.3 | 100.9 |

| **LVS** [millions] abs. change y/y | | **Past** | | **Forec.** 12/21 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Region / Year | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 |
| China | - | -2.3 | -1.1 | -0.2 | 0.8 | 2.7 | 2.1 | 0.9 | 0.2 | 0.6 | 0.7 |
| Europe | - | 0.1 | -4.1 | 0.1 | 1.1 | 1.8 | 1.5 | 0.1 | -0.5 | 0.1 | 0.2 |
| N. America | - | -0.4 | -3.2 | 0.6 | 0.5 | 1.7 | 1.0 | 0.1 | -0.4 | -0.1 | -0.2 |
| Jap./Kor. | - | -0.1 | -0.5 | -0.3 | 0.2 | 0.2 | 0.2 | -0.1 | -0.2 | -0.1 | -0.1 |
| India | - | -0.5 | -0.8 | 0.8 | 0.2 | 0.3 | 0.2 | 0.3 | 0.2 | 0.2 | 0.4 |
| M. East/Afr. | - | -0.5 | -0.7 | 0.5 | 0.1 | 0.4 | 0.4 | 0.3 | 0.1 | 0.1 | 0.1 |
| S. America | - | -0.2 | -1.2 | 0.4 | 0.1 | 0.3 | 0.4 | 0.4 | 0.3 | 0.2 | 0.2 |
| RoW | - | -0.1 | -1.1 | 0.4 | 0.1 | 0.4 | 0.5 | 0.3 | 0.1 | 0.2 | 0.1 |
| World | - | -3.9 | -12.7 | 2.2 | 3.0 | 7.7 | 6.3 | 2.0 | -0.3 | 1.2 | 1.6 |

| **LVS** [%] perc. change y/y | | **Past** | | **Forec.** 12/21 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Region / Year | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 |
| China | - | -8.2% | -4.5% | -1.0% | 3.2% | 11.0% | 7.6% | 3.0% | 0.8% | 1.9% | 2.3% |
| Europe | - | 0.7% | -19.7% | 0.1% | 6.5% | 9.9% | 7.9% | 0.1% | -2.3% | 0.3% | 0.9% |
| N. America | - | -2.0% | -15.9% | 3.8% | 2.9% | 9.2% | 4.8% | 0.2% | -1.7% | -0.4% | -0.8% |
| Jap./Kor. | - | -1.5% | -6.9% | -4.7% | 3.7% | 2.7% | 3.4% | -1.5% | -3.4% | -2.3% | -1.9% |
| India | - | -12.4% | -20.7% | 27.7% | 4.7% | 6.4% | 4.6% | 7.5% | 3.9% | 4.0% | 7.9% |
| M. East/Afr. | - | -10.6% | -18.1% | 14.2% | 2.0% | 11.4% | 9.6% | 5.8% | 0.5% | 2.4% | 2.9% |
| S. America | - | -4.6% | -27.8% | 13.6% | 1.2% | 9.3% | 10.4% | 8.0% | 5.4% | 4.8% | 4.3% |
| RoW | - | -2.3% | -23.8% | 12.3% | 2.0% | 8.9% | 10.4% | 5.3% | 2.0% | 3.6% | 2.8% |
| World | - | -4.2% | -14.2% | 2.9% | 3.7% | 9.4% | 7.0% | 2.1% | -0.3% | 1.2% | 1.6% |

| **m. share** [%] | | **Past** | | **Forec.** 12/21 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Region / Year | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 |
| China | 29.3% | 28.1% | 31.3% | 30.1% | 29.9% | 30.4% | 30.6% | 30.8% | 31.1% | 31.4% | 31.6% |
| Europe | 22.1% | 23.2% | 21.7% | 21.1% | 21.7% | 21.8% | 22.0% | 21.5% | 21.1% | 20.9% | 20.8% |
| N. America | 22.1% | 22.6% | 22.1% | 22.3% | 22.1% | 22.1% | 21.7% | 21.3% | 20.9% | 20.6% | 20.1% |
| Jap./Kor. | 7.4% | 7.6% | 8.3% | 7.6% | 7.6% | 7.2% | 6.9% | 6.7% | 6.5% | 6.3% | 6.0% |
| India | 4.5% | 4.1% | 3.8% | 4.8% | 4.8% | 4.7% | 4.6% | 4.8% | 5.0% | 5.2% | 5.5% |
| M. East/Afr. | 4.6% | 4.3% | 4.1% | 4.6% | 4.5% | 4.6% | 4.7% | 4.8% | 4.9% | 4.9% | 5.0% |
| S. America | 5.0% | 5.0% | 4.2% | 4.6% | 4.5% | 4.5% | 4.6% | 4.9% | 5.2% | 5.4% | 5.5% |
| RoW | 5 | 5.1% | 4.5% | 4.9% | 4.8% | 4.8% | 5.0% | 5.1% | 5.3% | 5.4% | 5.4% |
| World | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% |

Table 2.2: LVS-Forecast, Abs. Change, Per. Change and M. Shares by Region
Data Source: (IHS Markit 2021)

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to a forecasted contraction of 0,3% on a global basis in the year 2026. As stated in section 2.1, it was already expected from a pre- Covid 2019 perspective, that light vehicle markets in advance economies are saturated, growth in China is slowing down in comparison to past record levels, and that future growth will take place in EMDEs, like India, the Middle East/Africa, and South America (IHS Markit 2019, p.5). This development is also clearly visible in table 2.2 from 2025 to 2028, after almost all regions (except for Japan/Korea) reached their pre-Covid 2019 level. In reference to China, it must be mentioned that light vehicle sales growth in absolute values is still approximately at par with the aggregated absolute values of India, the Middle East/Africa, and South America in the year 2028.

The following market shifts result from the forecasted light vehicle sales by region. China will increase its market share of global light vehicle sales by 1,5% from 2021 to 2028 and will still rank at first place in comparison to 2021. The market share of Europe will decrease by 0,3% and by 2,2% in North America in the same time frame, which leads to a change with Europe in second place and North America in third place. Although the light vehicle sales market share of Japan/Korea will contract by 1,6% from 2021 to 2028, these markets will still rank at fourth place on an aggregate basis. Additionally, India will increase its market by 0,7%, the Middle East/Africa by 0,4% and South America by 0,9% in the same time frame.

### 2.3.3 Covid-19's Impact on Disruptive Mega-Trends

The Covid-19 pandemic had different effects on the prevailing disruptive mega-trends in the automotive industry - *vehicle electrification, connectivity, autonomous driving, and shared mobility* - at least in the short run. Investments in shared and smart mobility (e-hailing, micro-mobility, car-sharing) dropped remarkably during the peak of the pandemic in 2020, while investments in autonomous driving contracted even more. Yet, investments in connectivity (infotainment and cybersecurity) were increasing and investments in vehicle electrification initially dropped slightly, before increasing significantly towards the end of 2020 (Hensley et al. 2021, p.2).

Beyond that, the impact of the pandemic on electric vehicles sold is not as strong as for the automotive industry at large. From 2019 to the first half of 2020, the average share of electric vehicle registrations over total car registrations in the EU rose from 3,4% to 7,8%. In addition, the share of electrified vehicles sold, which includes pure electric vehicles as well as plug-in hybrid vehi-

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cles, increased to 26,8% in November 2020 and surpassed thereby diesel vehicle sales in the EU for the second consecutive month (European Parliament 2021, p.19). As a result, the total share of new electrified vehicles registered in the EU increased from 3,2% in 2019 to 10,5% in 2020 (Statista 2022b, p.19). It can be noticed, therefore, that the Covid-19 pandemic influences consumer behavior and amplifies vehicle electrification, primarily for two reasons. The first one reflects the shift from public to more private mobility, mainly because of Covid-19 infection risk protection. This shift in consumer behavior also slows down the trend towards shared mobility, at least in the short to medium term. The second main reason for a boost of electrification is that government regulations regarding CO2 targets, like the average fleet consumption in the EU, are incentivizing climate protection. Additionally, Covid-19 recovery measures are linked to climate protection targets as well (European Parliament 2021, p.19). However, in the long run, it is expected, that all prevailing disruptive mega-trends in the automotive industry - *vehicle electrification, connectivity, autonomous driving, and shared mobility* - will continue to accelerate on a global basis (Hensley et al. 2021, p.1).

### 2.3.4 Covid-19's Impact on the Automotive Supply Chain

After the macroeconomic shock of the Covid19 pandemic in the first half of 2020, demand has recovered at an unprecedentedly rapid pace. Shifts in consumer preferences caused by social distancing and closed contact-intensive service industries lead to an unprecedented increase in demand for goods in general and as well for cars. (European Commission 2021, p.41). OEMs around the world have experienced a resulting surge in demand, which led some OEMs to produce at record levels from the third quarter of 2020 through the first quarter of 2021 (Hensley et al. 2021, p.1). At the same time, this strong rebound in demand was facing a global production and logistics sector whose output was constrained by pandemic containment measures. Recurring pandemic outbreaks, related local lockdowns, arising shortages of labor, and extreme weather events added additional disruption at various points in the global supply- and value chains in the second half of 2020 and in 2021. As a result, a variety of supply bottlenecks arose which contributed to worldwide inflation pressure and serious impediments for final goods production, as in the automotive industry (World Bank 2022, pp.28-29). The most severe impact on global supply chains continues to be raw material shortages (e.g., metals, plastics), the shortage of semiconductors, and massive disruptions in the logistics sector, especially in container shipping (European Commission 2021, p.41).

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Significant shortages of semiconductors and other key-inputs are reflecting synchronized problems on a global scale, which extent is unique in the history of the modern automotive industry. It has never happened before that the automotive sector operates in a supply-led setting in that globally, customers aren't able to buy cars because the production of OEMs is constrained by manufacturing inputs (IHS Markit 2022b, p.7). While the automotive industry is affected by various kinds of shortages and logistical disruptions, the prevailing semiconductor shortfalls are weighing most heavily on the automotive sector (European Commission 2021, p.19). Lead times for semiconductors which are about 12 weeks under normal conditions have significantly increased to 26 weeks or more (IHS Markit 2022b, p.7). In reference to IHS Markit, it is expected that the semiconductor shortages will persist at least until the end of 2022, while for some more advanced chips the shortfalls will range into 2023 (European Commission 2021, p.43). Beyond that, modern cars are developing to *"supercomputers on wheels"*, which leads to a massive increase of semiconductors used to build a car (KPMG 2021a, p.4). Considering this, the persisting semiconductor crisis in the automotive industry must be reflected even more critically.

#### 2.3.4.1 The Semiconductor Crisis in the Automotive Industry

There is no single reason for the semiconductor crisis in the automotive industry, but rather a variety of causes that interact. As a result of the switch to remote work during the pandemic, the demand for electronic devices for work as well as for private use increased. Hence the already strongly growing demand for semiconductors due to the roll-out of new technologies such as 5G or the Internet of Things (IoT), was pushed further (European Commission 2021, p.41). Since the automotive industry experienced a drastic drop in demand in the first half of the year 2020, OEMs reduced their semiconductor orders in 2020. However, other booming sectors seized this opportunity and ordered the contingents that have become available. Hence, ss demand in the automotive sector surged at an unexpectedly rapid pace in the third quarter of 2020, most OEMs had only limited access to semiconductors (European Commission 2021, p.41). Even though the semiconductor industry was expanding its capacities by 180% since 2000, their utilization in 2020 was close to 90%, which can be considered as full utilization in most industries. As a result, there was also very little room for negotiations about extra contingents for a higher price. Additionally, even before Covid-19, many producers for consumer electronics had already significantly increased their inventory levels of semiconductors to prevent upcoming shortages due to rising

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worldwide political and trade tensions. In contrast to the automotive industry, where it's common to keep inventory levels low with just-in-time and just-in-sequence delivery processes (Burkacky et al. 2021, p.3). Beyond that, contract terms for sourcing parts in the automotive industry are more short-term (some weeks to months) in comparison to other industries, which rely on long-term binding contracts (beyond six to twelve months), like take-or-pay agreements. Because OEMs were cutting orders in 2020, semiconductor producers now have already commitments to other industries with long-term contracts (Burkacky et al. 2021, pp.3-4).

#### 2.3.4.2 Short- and Long-Term Solutions for Semiconductor Shortages

The unprecedented supply chain disruptions in the automotive industry caused by Covid-19, force OEMs to review long-established concepts such as just-in-time production and lean inventory (IHS Markit 2022b, p.7). In the short-term there is little room to resolve the current supply and demand mismatches in semiconductor production. Lead times for semiconductor production of variants that are already well established in production lines can go beyond four months. Capacity expansions, by a relocation of the production to other manufacturing plants, take at least additional six months, while switching production to another supplier usually adds more than a year. That's because typically chip designs have to be adjusted to specific production processes of new suppliers, intellectual property rights have to be considered, and new suppliers have to prove their capabilities in complex and long qualification processes required by OEMs (Burkacky et al. 2021, p.5).

As a short-term measure, however, many OEMs tried to significantly improve their supply chain transparency, especially for critical parts such as semiconductors. Special task-forces were established in which supply and demand intelligence tools were combined to create more supply chain transparency (Burkacky et al. 2021, p.5). Yet, the strive for more supply chain transparency started well before Covid-19, because of shortages induced by the earthquake and the tsunami in Japan in 2011 (Hensley et al. 2021, p.2). While this natural disaster had some global impact on automotive supply chains, Japanese OEMs, like Toyota, Honda, and Nissan were hit hard by shortfalls of critical components (Collie et al. 2020, p.2). Especially Toyota improved its supply chain transparency drastically at that time as a reaction to this disruptive event. However, Covid-19 significantly accelerated the strive for more supply chain transparency on a global scale. While most OEMs and tier-1 suppliers only had a limited understanding of processes

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and inventory levels of lower tier-suppliers until recently, parts and raw materials are now tracked more extensively. In some cases also with supply chain monitoring methods which incorporate various OEMs, to split batches of critical components as required and to prevent stockpiling (Hensley et al. 2021, p.2).

In the long run, however, OEMs must reconsider long-established concepts which proved themselves before Covid-19. Contracts for sourcing parts should be settled more binding and long-term, and concepts like just-in-time and lean inventory have to be reviewed, at least for critical components (Burkacky et al. 2021, p.7). Not only because of Covid-19 but also induced by increasing trade tensions and global dependencies on distant countries regarding critical resources, OEMs need to consider a partial return to local sourcing concepts. Additionally, OEMs should strive for an increase in supply chain resilience through the establishment of multi-sourcing concepts, especially for critical parts such as semiconductors (Burkacky et al. 2021, p.7).

### 2.3.5 Covid-19's Impact on the Car Sales Process

The pandemic also had an impact on how customers are buying cars. OEMs already provided digital tools for car configuration, price comparison, and virtual views of vehicles in most countries even before the pandemic has begun. In some countries, it was also possible to settle the complete purchasing process of a car and related services, like financing and insurance, online. However, in most cases, the actual sales process took place at the dealership, because a great part of the customers still prefers to see, feel and test-drive a car before buying it. During the pandemic when meeting in person was not possible because of contact restrictions, digital sales processes got an upswing (Hensley et al. 2021, p.1). As contact restrictions eased many customers returned to the traditional sales process at the dealership, but the pandemic still contributed to an acceleration of innovative sales methods. Different new digital platforms and physical concepts are co-existing, complementing each other as well as competing after two pandemic years. Especially Tesla, but also Porsche, Volkswagen, and Volvo are first movers in the field of innovative sales methods other than classical dealership-concepts (Hensley et al. 2021, p.2). It is interesting to notice that according to KPMG's Global Automotive Executive Survey 2021, 78% of the interviewed executives believe that most car sales will be settled completely online in the year 2030 (KPMG 2021b, p.11).

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## 2.4 Covid-19's year-to-year Impact on NPCR in Europe

The automotive industry is a very important sector in Europe, with a contribution of over 7% to the EU's GDP (European Commission 2022b) and accounting for about 33% of total EU-spendings on innovation (ACEA 2021g, p.-4). Beyond that, the automotive sector is providing work for 12,6 million Europeans (6,6% of all jobs in the EU), while almost a quarter of all cars (23%) and 18% of all commercial vehicles of the world production are manufactured in Europe (ACEA 2021g, pp.8-14).

Figure 2.7 depicts the annual new passenger car registrations from 2002 through 2021 in the EU14[7], the EFTA[8] and the United Kingdom (UK), which can be considered as the most advanced markets in Europe. As can be seen from figure 2.7, these markets are quite saturated, at least on an aggregate basis. Growth from 2002 to 2007 was quite moderate with a CAGR of approximately 0,55 %. From 2008 through 2013, the impact of the Financial Crisis (2008-2009) and the resulting European Debt Crisis (2010-2013) is clearly visible, as well as the following recovery phase from 2014 through 2017. It is interesting to see, that the pre-Financial Crisis level in 2007 of about 14,8 million registered new passenger cars has never been reached again. Beyond that, a beginning downward cycle in pre-Covid 2018 is observable, as noted earlier in this chapter.

However, the impact of the pandemic in 2020, change the situation completely. As mentioned in section 2.3, out of the 3 biggest automotive markets (China, North America, Europe), light vehicle sales[9] in Europe (West, Central, East) were hit hardest by the Covid-19 impact in 2020, with a contraction of 19,7% (IHS Markit 2021). By considering the aggregate new passenger car[10] registrations in the EU14, the EFTA, and UK in figure 2.7, Covid-19's impact in the year 2020 was even more severe, with a decline of about 3,5 million new passenger cars registrations or a respective drop of 24,5% in comparison to 2019. This contraction demonstrated the deepest yearly decline in car demand ever measured (ACEA 2021a, p.6). Additionally, it can be noticed from figure 2.7, that new passenger car registrations in 2021 declined further by 1,9% in comparison to 2020, mainly due to the drastic semiconductor shortages in the second half of 2021.

Covid-19's disruptive impact on the ten biggest car sales markets[11] of the

[7]The member states of the EU14 are defined in the List of Abbreviations.
[8]The member states of the EFTA are defined in the List of Abbreviations.
[9]Light vehicle are vehicles with a maximum mass not exceeding 6 tons (IHS Markit 2022a).
[10]Passenger cars are vehicles with a maximum mass not exceeding 3,5 tons (ACEA 2022c).
[11]The ten biggest car sales markets depicted in figure 2.8 covered a market share of 84,14%

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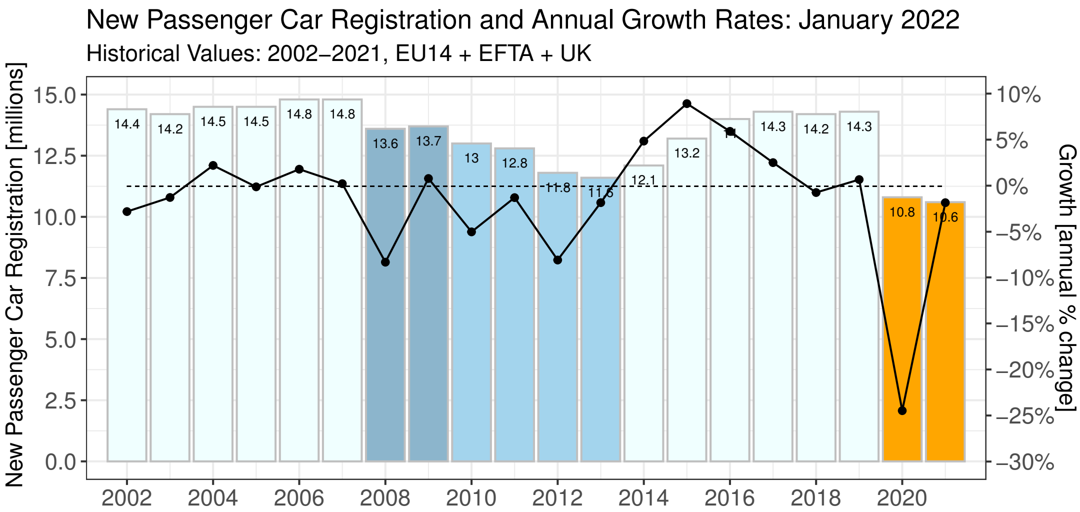


Figure 2.7: NPCR and Annual Growth Rates, EU14+EFTA+UK
Data Source: (ACEA 2021e), (ACEA 2022a)

EU27[12], the EFTA and the UK, is illustrated in figure 2.8. All depicted markets suffered losses in the range of -15% to -35% in comparison to 2019, because of the pandemic containment measures in 2020. Spain suffered the biggest decline of 32,3%, followed by the UK with a contraction of 29,4%, Italy (-27,9%), and France (-25,5%). The car registrations in Austria (-24,5%), Poland (-22,6%), Belgium (-21,5%) and the Netherlands (-20,1%) declined in a range of -20% to -25%, while Germany and Sweden were settled at the lower end of the impact range of the ten biggest markets, with drops of 19,1% and 18,0% respectively.

After months of remarkable gains in the first half of 2021 (in comparison to low 2020 levels), the situation deteriorated drastically again due to restricted vehicle supply caused by the intensifying semiconductor scarcity in the automotive industry (ACEA 2021b, p.8). The semiconductor shortages led to a severe drop of new passenger car registrations in the EU27 in all months of the second half of 2021, ranging from -19,1% in August 2021 to -30,3% in October 2021 (ACEA 2021c, p.1). Beyond that, the October 2021 contraction led even to the lowest October registrations in volume terms since the records of the ACEA had begun in 1990 (ACEA 2021d, p.1). Nevertheless, six out of the 10 biggest markets - Italy (5,4 %), Poland (4,5 %), Sweden (3,1 %), Spain (1 %), the United Kingdom (1,0 %) and France (0,5 %) could close the year with a plus, while Austria (-3,6 %), the Netherlands (-8.7 %), Germany (-10.1 %) and Belgium (-11.2 %) significantly contracted further in 2021, as can be seen from figure 2.8. By con-

of the EU27, the EFTA and the UK in the year 2021 (ACEA 2022a). Their corresponding market shares in the year 2021 can be found in the caption of figure 2.8.

[12]The member states of the EU27 are defined in the List of Abbreviations.

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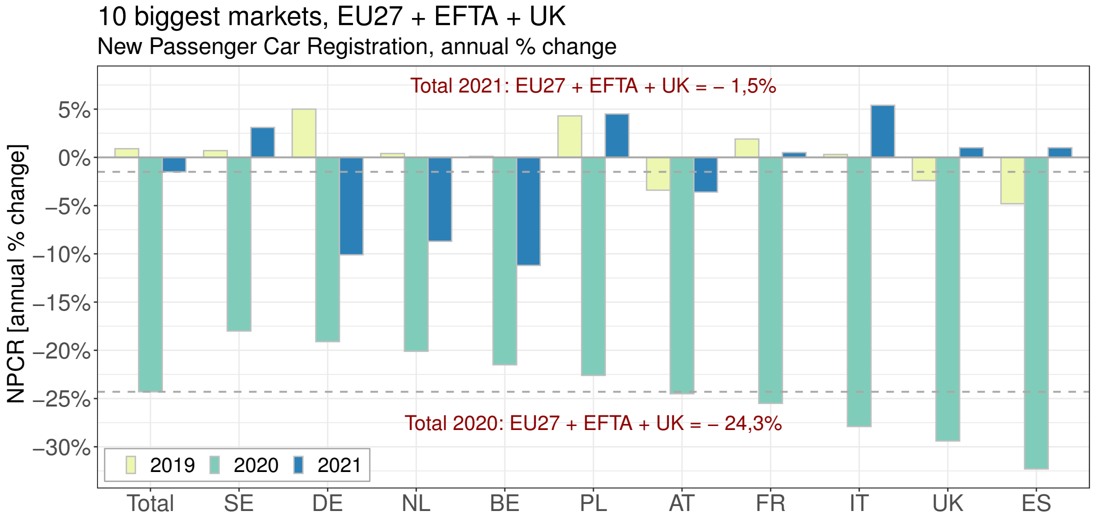


Figure 2.8: Ten Biggest Markets (EU+EFTA+UK), NPCR, annual per. change
**Total** (EU27+EFTA+UK), **SE** (Sweden, 2,6%), **DE** (Germany, 22,3%), **NL** (Netherlands, 2,7%), **BE** (Belgium, 3,3%), **PL** (Poland, 3,8%), **AT** (Austria, 2,1%), **FR** (France, 14,1%), **IT** (Italy, 12,4%), **UK** (United Kingdom, 14,0%), **ES** (Spain, 7,3%)
Data Source: (ACEA 2021e), (ACEA 2022a)

sidering new passenger car registrations on an aggregate basis, the drastic effects of the semiconductor crises on car supply in the second half of 2021 exceeded the positive results from the first half of the year. Hence aggregated registrations of the EU27, the EFTA, and the UK, contracted by 1,5% in the year 2021, despite already record-low 2020 levels.

Covid-19's year-to-year impact on new passenger car registrations in the EU14, the EFTA, and the UK of the biggest brand[13] of 10 different automotive groups is depicted in figure 2.9. Like the 2020 Covid-19 impact on the stated markets, all depicted OEMs suffered losses in the range of -15% to -35% compared to 2019. Ford suffered the biggest contraction of 33,64%, followed by Nissan (-26,5%), and Hyundai (-26,5%) in 2020. The new passenger car registrations of Peugeot (-23,2%), Renault (-23,1%), Volkswagen (-23,0%) and Mercedes (-20,0%) declined in a range of -20% to -25%, while BMW, Volvo, and Toyota were settled at the lower end of the impact range, with drops of 19,1%, 16,4%, and 14,4% respectively. New passenger car registrations of all OEMs, which sell cars in the EU14, the EFTA, and the UK, in total declined by 24,5% in comparison to 2020. As stated before for the biggest markets, new passenger car registrations of the depicted ten OEMs were generally heavily influenced by the intensifying semiconductor shortages in the second half of 2021. Yet, Hyundai (19,5%) and

[13]The ten automotive brands depicted in figure 2.9 covered a market share of 53,89% of the new passenger car registration in the EU14, the EFTA, and the UK in the year 2021 (ACEA 2022b). Their corresponding market shares of the brands in the year 2021 can be found in the caption of figure 2.9.

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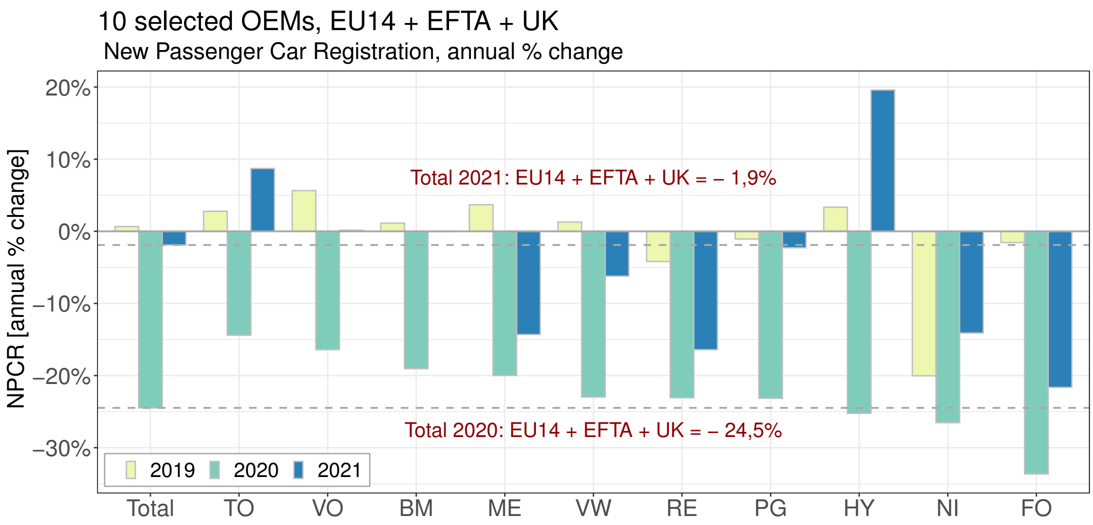


Figure 2.9: Ten OEMs (EU14+EFTA+UK), NPCR, annual per. change
**Total** (EU14+EFTA+UK), **TO** (Toyota, 5,5%, Toyota Group), **VO** (Volvo, 2,5%, Volvo), **BM** (BMW, 6,0%, BMW Group), **ME** (Mercedes, 5,6%, Daimler), **VW** (Volkswagen, 11,1%, VW Group), **RE** (Renault, 5,9%, Renault Group), **PG** (Peugeot, 6,5%, STELLANTIS), **HY** (Hyundai, 4,1%, Hyundai Group), **NI** (Nissan, 2,2%, Nissan), **FO** (Ford, 4,5%, Ford)
Data Source: (ACEA 2021f), (ACEA 2022b)

Toyota (8,7%) could close the year 2021 with a plus, however, in comparison to low 2020 levels, especially in the case of Hyundai. Volvo and BMW closed the year 2021 more or less at par with 0,15% and -0,02%, while Peugeot (-2,3%), Volkswagen (-6,2%), Nissan (-14,1%), Mercedes (-14,3%), Renault (-16,1%) and Ford (-21,6%) significantly contracted further in 2021, as can be seen from figure 2.9. By considering new passenger car registrations of all OEMs, which sell cars in the EU14, the EFTA, and the UK, on an aggregate basis, the supply chain shortages led to a further contraction of 1,9% in 2021 compared to 2020.

### 2.4.1 Remarks on Covid-19 NPCR Impact Evaluation

The previous section gave an overview of the impact of Covid-19 and resulting after-effects on European new passenger car registrations (NPCR) by ten different countries and OEMs in reference to a year-to-year comparison. However, to evaluate the effects of the pandemic and resulting after-effects on NPCR in an adequate way, the establishment of a clear baseline is required. To establish this baseline, suitable time series models (SARIMA-models) will be fitted in R to datasets of the ACEA - for NPCR by country (ACEA 2021e) and by manufacturer, (ACEA 2021f) in Europe - for a specified pre-Covid time-frame. By fitting adequate time series models a specified pre-Covid-19 time frame, the long-term systematic pattern (trend, seasonality) can be separated from the short-term dis-

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ruption due to Covid-19. In the next step, the time series models will be used to forecast stochastic events of new passenger car registrations in Europe for different OEMs and countries for a specified post-Covid-19 time frame. Hence, the forecasted events can be considered as realizations of new passenger car registration, which are neglecting the disruptive Covid-19 effects, and just consider prior time-series variability. This approach allows for an adequate evaluation of the quantitative Covid-19 impact through the calculation of the difference between the observed new passenger car registrations and the forecasted realization in the specified post-Covid time frame.

Following this, the next chapter 3 is dedicated to time series analysis and forecasting and sets the theoretical framework for this evaluation approach. Readers, who are familiar with time series analysis and forecasting might skip this chapter or use it as a repetition of their knowledge. Based on the theory of time series analysis and forecasting, chapter 4 of this thesis is concerned with the quantitative evaluation of Covid-19's impact on new passenger car registrations by country and by OEM, measured against pre-Covid time series variability exhibited in the European automotive industry.

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# 3 Time Series Analysis and Forecasting

The following chapter is dedicated to time series analysis and forecasting and sets the theoretical framework for the numerical studies presented in chapter 4. The first section 3.1 gives a general overview of forecasting methods and provides related basic terminology, with a focus on quantitative forecasting methods, and especially on stochastic time series models. Following this, section 3.2 gives a definition of the quantitative forecasting process in reference to this thesis. Section 3.3 is dedicated to preliminary time series analysis and covers topics, like general time series pattern, stationarity, autocorrelation, transformations, and trend and seasonal adjustments. Based on that, the theory of ARIMA models, which are used for forecasting in chapter 4, will be discussed in section 3.4. Finally, section 3.5 is dedicated to the ARIMA modeling approach, where order selection, parameter estimation, information criteria, residual analysis and forecast accuracy evaluation will be discussed in detail. Beyond that, practical examples related to the topic of the thesis and the numerical studies presented in chapter 4 will be stated.

## 3.1 Forecasting Models: Overview and Basic Terminology

Forecasting is very important in a variety of fields such as economics, finance, risk management, operations management, industrial process control, politics, physics, engineering, medicine, and natural and social sciences in general (Montgomery et al. 2015, p.2). Additionally, decision-makers from business and industry should link their goals and planning tasks to adequate short-, medium- and long-term forecasts. Such decisions may range from production scheduling, personnel planning, planning of marketing activities, capacity planning of production lines to long-term strategic investments, like the building of a new manufacturing plant.(Hyndman and Athanasopoulos 2018, p.14). In this thesis, forecasting will be used to establish a clear baseline for the evaluation of Covid-19's impact on new passenger car registrations in Europe, as will be explained in this chapter.

Forecasting methods can be classified broadly into two approaches - *quantitative forecasting methods* and *qualitative forecasting methods* (Montgomery et al. 2015,

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p.4). The decision, which of the two methods has to be used is dependent on the availability of historical data. Qualitative forecasting methods are based on expert judgment and are often used when historical data are incomplete or not available at all; also, quite often in combination with quantitative models (Hyndman and Athanasopoulos 2018, p.16). Since reliable datasets of the ACEA - for NPCR by country (ACEA 2021e) and by manufacturer (ACEA 2021f) in Europe - are available back to the year 1990, quantitative methods will be used in this thesis for forecasting.

### 3.1.1 Quantitative Forecasting Methods

A variety of quantitative forecasting models exist, which are often tailored to specific disciplines and purposes, while each method has different properties, accuracies, advantages, and disadvantages. The great part of quantitative forecasting models however, uses either *cross-sectional data*, gathered at a single point in time, or *time series data*, gathered at regular time-intervals (Hyndman and Athanasopoulos 2018, p.16). The further focus is on models using time series data, while a *time series* can be defined as a set of past observations of a variable of interest, which are ordered chronologically, while the ordered axis doesn't have to be necessary time (Montgomery et al. 2015, p.2). When the observations are taken continuously over time, we speak of a *continuous* time series. In the case that the observations are made only at specific points in time, which are usually equally spaced, we speak of a *discrete* time series (Chatfield and Xing 2019, p.8).

In general, quantitative forecast methods can be further classified into *regression models*, *time series models*, and a combination of the features of the two approaches, referred to *dynamic regression models*[1] (Hyndman and Athanasopoulos 2021, p.19). Regression models are based on relationships between the variable of interest, also called the dependent variable, and one or more predictor variables, also called the independent variables (Hyndman and Athanasopoulos 2018, p.105). Because the assumption here is, that the prediction variables explain the driving forces that cause the observations of the variable of interest, these models are sometimes also called *causal forecasting models* or *explanatory models* (Montgomery et al. 2015, p.5). In contrast, time series models are based on the assumption that future realizations of the variable of interest can be described by some characteristics of past data, like trends, seasonal and cyclical patterns (Cowpertwait and Metcalfe 2009, p.2). Another important characteristic of most

[1] More information on dynamic regression models can be found in Hyndman and Athanasopoulos (2021, pp.319–341).

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time series is, that adjacent observations are usually dependent, which is also known as *serial dependence* or *autocorrelation* (see section 3.3.3). A great part of the methodology of *time series analysis* and models deals with the explanation of this dependence, which makes the development of stochastic and dynamic models for time series data necessary (Box et al. 2016, p.1).

### 3.1.2 Stochastic Time Series Models

Following the previous statement, we can differentiate between *deterministic* and *stochastic* time series and time series models. A deterministic time series is one that can be predicted exactly, or in other words, which can be determined exactly by a mathematical function (Box et al. 2016, p.22). In practice, however, this is usually not the case. A more realistic assumption is, that future realizations of a time series are only partly explainable by past observations. Hence, it will be assumed that future realizations of a variable of interest can be described by a probability distribution which is conditional on a knowledge of past values. Under this assumption, we speak of a stochastic time series (Chatfield and Xing 2019, p.8). Models which are dedicated to the description of the probability structure of a sequence of observations are referred to *stochastic processes*, *stochastic time series models* or in short just *time series models* (Box et al. 2016, p.19).

Lehman and Groenendaal (2019, pp.132-133) broadly classify stochastic time series models into tree types, *Autoregressive Moving Average (ARMA)* models, *Autoregressive Conditional Heteroskedasticity (ARCH and GARCH)* models and *Geometric Brownian Motion (GBM)* models.[2] Box and Jenkins (1970) developed a general strategy for time-series forecasting and extended ARMA models to *Autoregressive Integrated Moving Average (ARIMA)* models, to cope with non-stationary time series data (see section 3.3.2), and by the incorporation of seasonal terms to *Seasonal ARIMA (SARIMA)* models. As a result of this major contribution, ARIMA models are also well known as *Box-Jenkins models* (Chatfield and Xing 2019, p.123). Another famous forecasting method which was introduced by Brown (1959), Holt (1957) and Winters (1960) is *exponential smoothing*. ARIMA and exponential smoothing models are two of the most widely used methods for time series forecasting and can be considered as complementary approaches. While the focus of ARIMA models is on the description of the autocorrelation in the time series data, the emphasis of exponential smoothing models is placed

[2] ARCH, GARCH and GBM models are widely used in finance, however not in the further scope of this thesis. The interested reader can find more information on this kind of stochastic time series models in Box et al. (2016, pp.361-377), Chatfield and Xing (2019, pp.303-321) and Hull (2012, pp.280-297)

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on the description of the trend and seasonal pattern in the data (Hyndman and Athanasopoulos 2021, p.265).[3] Beyond that, we can distinguish between, *univariate* and *multivariate* time series models. In contrast to univariate time series models, multivariate approaches, like *Vector Autoregression (VAR)* models, *Vector Autoregressive Moving Average (VARMA)* models, or *Vector Autoregressive Integrated Moving Average (VARIMA)* models, integrate additionally to the serial dependences within each series (autocorrelation), also the interdependencies between different series (cross-correlation)[4].

The further focus in this thesis is placed on SARIMA models, which will be fitted in R to monthly datasets of the ACEA - for new passenger car registrations by country (ACEA 2021e) and by manufacturer (ACEA 2021f) - to establish a clear baseline for the evaluation of Covid-19's impact on new passenger car registrations in Europe. The following sections, therefore, give the theoretical background on times series analysis and forecasting related to SARIMA models to get a better understanding of the forecasting approach used in chapter 4.

## 3.2 The Quantitative Forecasting Process

A classical quantitative forecasting process follows the steps as depicted in figure 3.1. The *problem definition* in this thesis, is in line with the methodical framework and the research questions of sections 1.1 and 1.2. Hence, to evaluate the effects of the pandemic and resulting after-effects on European new passenger car registrations in an adequate way, the establishment of a clear baseline is required. To establish this baseline, suitable time series models have to be fitted to datasets of new passenger car registrations (NPCR) in Europe for a sufficiently long pre-Covid-19 time frame. This approach then allows for an adequate evaluation of the quantitative Covid-impact through the calculation of the differences between the observed NPCR and the forecasted events in a specified post-Covid time frame.

In a further step, *data collection* is of particular interest. In the data gathering process, it is important, that historical data are taken from reliable sources and that the data are available for a sufficiently long time, which contains enough

[3]Seasonal ARIMA models, showed in almost all cases better results than Exponential Smoothing Models in forecasting NPCR by country (ACEA 2021e) and by OEM (ACEA 2021f) in Europe. Therefore, it was decided to place further focus on SARIMA models. The interested reader can find however more information on exponential smoothing and related innovations state space models in Hyndman and Athanasopoulos (2021, pp.227-263).

[4]The interested reader can find more information on multivariate time series models in Box et al. (2016, pp.505-558) or Chatfield and Xing (2019, pp.323-349).

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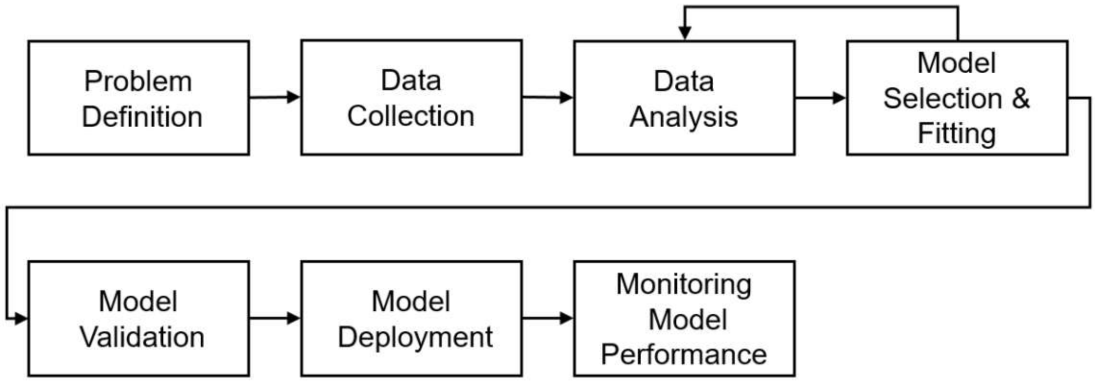


Figure 3.1: The Quantitative Forecasting Process
Adapted from (Montgomery et al. 2015, p.14)

representative information for forecasting. In this context, datasets of the ACEA - for new passenger car registrations by country (ACEA 2021e) and by manufacturer (ACEA 2021f) in Europe - will be used, for specified long pre-Covid time-frames (2003-2018 for countries, 2001-2018 for manufacturers).

The next crucial step in the forecasting procedure is *data analysis*, which demonstrates the basis for the selection of an appropriate forecasting model. In this step, the basic patterns of a time series, like a trend, seasonal and cyclical patterns as well as outliers, erroneous or missing values are observed by a graphical representation of the data in time plots. Other important topics in this step are, how strong the relationships between different variables of interest are, the computation of autocorrelations, possible data transformations, and trend and seasonal adjustments (Hyndman and Athanasopoulos 2021, p.22). A detailed description of this step, with examples in reference to the numerical studies presented in chapter 4, will be given in the next section 3.3 Preliminary Time Series Analysis.

Based on the findings from data analysis, the *selection* of one or more eligible models and their *fitting* to the data takes place. Fitting in this context means, the estimation of the unknown parameters of the model, normally by the least squares method (see section 3.5.2) (Montgomery et al. 2015, p.15). An explanation of the selected models (SARIMA) and the fitting process of the respective model parameters are stated in sections 3.4 and 3.5 respectively. Additionally, a method for checking whether a fitted model is able to capture all available information will be denoted in chapter 3.5.4 in more detail. *Model validation* represents the evaluation of the model performance. A good model validation should go beyond measurements of the fit for the historical time series data. Therefore, the magnitude of the forecast errors in reference to data that haven't been used for the

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fitting process is of special interest. Model validation will be discussed in section 3.5.5. If applicable, *model deployment* means the handover of the developed forecasting method to the customer, while *monitoring model performance* represents an ongoing task of revalidation after the model is deployed (Montgomery et al. 2015, pp.15-16).

## 3.3 Preliminary Time Series Analysis

The following section is dedicated to preliminary time series analysis, which demonstrates the basis for the selection of an appropriate forecasting model, as illustrated in figure 3.1. Hence time series pattern, stationarity, autocorrelation, transformations, and trend and seasonal adjustments will be discussed in the following, which in turn forms the basis for further sections.

### 3.3.1 Time Series Patterns

Different patterns, in particular *trends*, *seasonality* and *cycles* are elementary features of many time series. A discussion of this basic time series features and their visual identification in *time plots* will therefore be given next in more detail.

*Trend:* A trend in a time series can be defined as long-term increase or decrease in the data over time, or in more general terms, by a long-term change in the mean level (Chatfield and Xing 2019, p.16). A trend doesn't have to be linear, however, a linear increase or decrease is often a reasonable approximation (Cowpertwait and Metcalfe 2009, p.5).

*Seasonality:* A time series follows a seasonal pattern if it exhibits variation which is influenced by seasonal factors such as a specific time of the year, certain months, a specific day of the week, or any other fixed period. An important note is that a seasonal pattern is always of a fixed and known frequency (Hyndman and Athanasopoulos 2018, p.31).

*Cycle:* In contrary to a seasonal pattern, a cycle prevails when fluctuations are not of a fixed frequency (Hyndman and Athanasopoulos 2018, p.31). Such oscillations appear typically as a result of economic conditions and are usually connected to so-called business cycles, which may range from 2 to up to 10 years (Chatfield and Xing 2019, p.16).

*The Time Plot:* An initial step in time series analysis is usually the visualization of the data in a time plot, i.e., to plot past observations of the variable of interest

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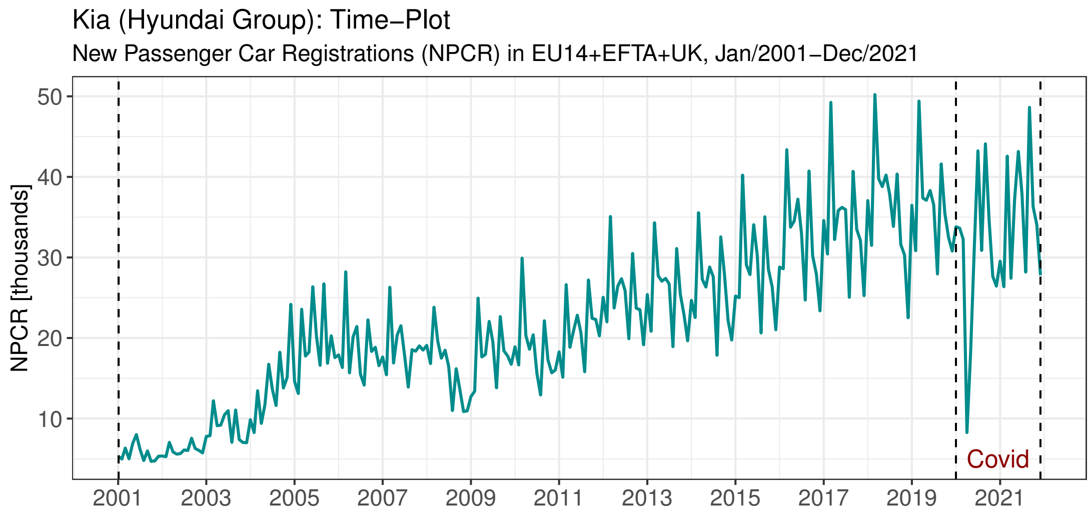


Figure 3.2: Kia: Time Plot, NPCR in EU14+EFTA+UK, Jan/2001-Dec/2021
Data Source NPCR: (ACEA 2021f), (ACEA 2022b)

over time of observation. By visualizing the data, the occurrence of the previously mentioned patterns (trend, seasonality, cycles) as well as extreme values (outliers), erroneous values, unequal spacing, or missing values can be detected immediately (Shmueli and Lichtendahl Jr 2016, p.28). As an example, a time plot of Kia's new passenger car registrations (NPCR) in the EU14[5], the EFTA[6] and the United Kingdom (UK) is plotted monthly from January 2001 to December 2021 in figure 3.2. With a look at the time plot, there is a distinct seasonal pattern observable. Additionally, a general upward trend can be noticed, especially in the years 2001 through 2005, and 2011 through 2019. Furthermore, we can detect slight up- and downward movements with a length of approximately 2-3 years, which are a sign for business cycles. The impact of the Financial Crisis and the resulting European Debt Crisis can be observed by the drop in 2008, and the more or less constant level of the NPCR between 2008 and 2011. Moreover, the impact of the Corona-Pandemic is clearly visible by the drastic drop of the NPCR at the beginning of the year 2020.

### 3.3.2 Stationary Time Series

We speak of a *stationary*[7] time series if its characteristics are not affected by the time at which the series is observed. Or more accurately, a time series $\{y_t\}$ is

[5]The member states of the EU14 are defined in the List of Abbreviations.
[6]The member states of the EFTA are defined in the List of Abbreviations.
[7]From a mathematical point of view, we can also differentiate between *strictly stationary* times series and *second-order* or *weak stationarity*. The interested reader can find a mathematical definition of both terms in Chatfield and Xing (2019, pp.42-44)

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stationary if for all $n$, the distribution of $(y_t, ..., y_{t+n})$ is not dependent on time $t$ (Hyndman and Athanasopoulos 2018, p.225). A stationary time series has therefore no systematic change in mean (trend), no periodic variation (seasonality), and no systematic change in variance (Chatfield and Xing 2019, p.17). Hence, in a stationary time series, there are no predictable patterns in the long-run and in a time plot, a stationary time series looks roughly horizontal (Hyndman and Athanasopoulos 2018, p.226). However, a stationary time series might contain cyclical behavior. The rationale for this is that cycles in contrast with seasonal patterns are not predictable. In other words, they are not of a fixed frequency, which means that it's not defined where the peaks and troughs of the cycles will be until we observe the realizations of the time series (Hyndman and Athanasopoulos 2018, p.225).

Stationarity of time series data is a requirement for many traditional time series models, however in reality most of the time series are *non-stationary* (Nielsen 2019, p.82). Subsequently, it is required in many cases to transform non-stationary time series into stationary ones, by removing the trend, the seasonal behavior and by stabilizing the variance (Chatfield and Xing 2019, p.17). Such transformations and adjustments will be explained in more detail in section 3.3.4 and 3.3.5 of this chapter.

### 3.3.3 Autocorrelation and Autocorrelation Function

The *correlation coefficient* measures the degree of a linear relationship between two variables. The *autocorrelation coefficient* however, measures the extent of correlation between observations of a time series which are apart from each other at different distances, also called *lagged values* (Hyndman and Athanasopoulos 2018, p.40). The calculation of the sample autocorrelation coefficient $r_k$ at *lag* $k$ is illustrated in equation 3.1 below:

$$r_k = \frac{\sum\limits_{t=k+1}^{T} (y_t - \bar{y}) \cdot (y_{t-k} - \bar{y})}{\sum\limits_{t=1}^{T} (y_t - \bar{y})^2} \tag{3.1}$$

where $y_t$ represents an observation at time $t$, in a set of observations at discrete time points $(t = 1 \dots T)$, and $\bar{y} = \sum_{t=1}^{T} x_t / T$ represents the sample mean. Following this, $r_1$ for example, represents the autocorrelation coefficient for the observation pairs $(y_t, y_{t-1})$ which are one time interval apart. Or more generally, $r_k$ represents the autocorrelation coefficient for the observation pairs $(y_t, y_{t-k})$



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which are $k$ time intervals apart. As for the correlation coefficient, the values of the autocorrelation coefficient $r_k$ will always be in the range of -1 and +1 (Chatfield and Xing 2019, p.30). A practical tool for the interpretation of the autocorrelation coefficients of a time series is the *autocorrelation function (ACF)*, also known as *correlogram*. In an ACF plot, the sample autocorrelation coefficients $r_k$ are plotted against the lag $k$ for $k = 1 \dots K$ (Chatfield and Xing 2019, p.30), as illustrated for the new passenger car registrations of Kia in the EU14, the EFTA and the UK until lag 36 in figure 3.3 below[8].

*Significant Autocorrelation in ACF Plots*

A time series $\{y_t\}$ which is completely random, also designated to a *white noise series*, is a series of independent observations which have the same distribution for which we typically assume a mean of zero and a variance $\sigma_y^2$ (Box et al. 2016, p.28). Because we have independent observations, we expect the autocorrelation coefficients $r_k$ close to zero for $k \neq 0$ for a white noise series. An additional property of a white noise series is that the values of the autocorrelation coefficients are approximately normally distributed with $r_k \sim \mathcal{N}(0, 1/T)$. Therefore, we can expect that 95% of the values of $r_k$ lie between $\pm 1,96/\sqrt{T}$ (Chatfield and Xing 2019, p.31). In figure 3.3 these bounds are represented by the dashed blue lines. Following this, if one or more large values of $r_k$ are outside this range, or if considerably more than 5% of the values lie outside this range, the autocorrelation in the series is significant, which means that the series is most probably not

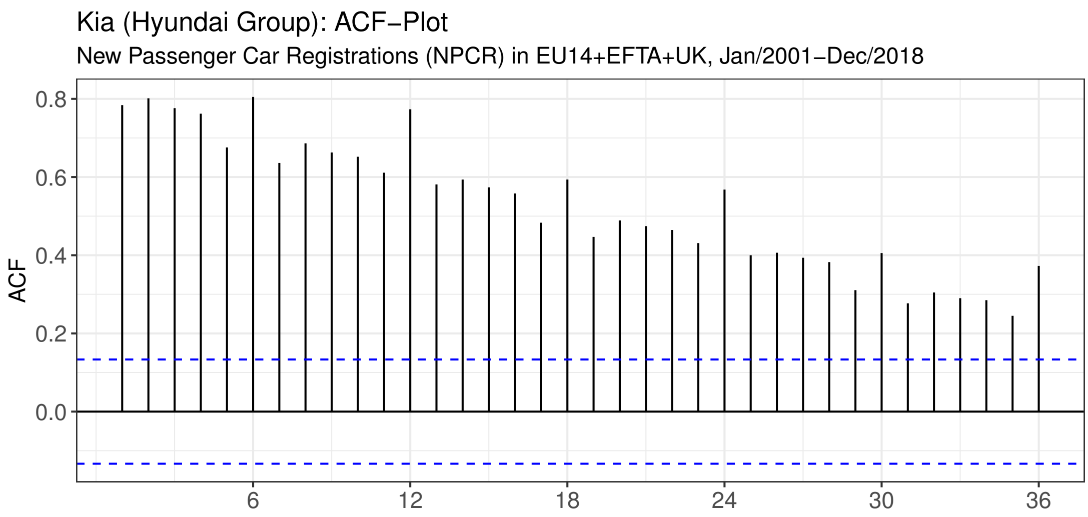


Figure 3.3: Kia: ACF-Plot, NPCR in EU14+EFTA+UK, Jan/2001-Dec/2018
Data Source NPCR: (ACEA 2021f), (ACEA 2022b)

[8] The ACF plot was generated with R by the usage of the ACF() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

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white noise (Hyndman and Athanasopoulos 2018, p.43). As highlighted in the ACF plot in figure 3.3, the values of $r_k$ at all lags ($k = 1 \ldots 36$) are all above the upper bound, which points out that there is significant autocorrelation in the time series of Kia's NPCR.

*Non-Stationary Time Series in ACF Plots*

As mentioned in section 3.3.2 a time series is non-stationary if it shows a systematic change in mean (trend). A trend can be identified in an ACF plot, if the autocorrelations are large and positive for small lags and slowly decrease as the lags increase (Hyndman and Athanasopoulos 2018, p.42). The reason for this is, that because of the trend, observations of one side of the mean are usually followed by a large number of observations on the same side of the mean (Chatfield and Xing 2019, p.33). It was noticed additionally in section 3.3.2, that times series which contain a systematic periodic variation (seasonality) are non-stationary as well. Seasonality in ACF plots is typically represented by larger autocorrelation coefficients for the seasonal lags, at multiples of the seasonal frequency as for other lags (Hyndman and Athanasopoulos 2018, p.42). In the ACF plot of KIA's NPCR depicted figure in 3.3, an overlay of a trend and seasonality can be observed. The slowly decreasing values of $r_k$ as the lag increases is due to the trend, while the oscillating shape with higher values for the seasonal lags (e.g., lag 12), and their multiples, results from the seasonality in the data.

It must be mentioned, however, that ACF plots of non-stationary time series are not very meaningful, especially when the trend and/or the seasonal pattern dominate all other characteristics. Much more can be inferred from the autocorrelation function (ACF) plot, as well as from the partial autocorrelation function (PACF) plot of stationary time series data, as will be explained in section 3.5.1. Therefore any systematic part (trend, seasonality, systematic change in variance) in a time series should be removed before calculating $r_k$ (Chatfield and Xing 2019, p.33). How to remove a systematic change in variance, a trend, and seasonal variation from a time series, to make non-stationary data stationary, will therefore be explained in the next two sections 3.3.4 and 3.3.5.

### 3.3.4 Transformations

Before a statistical analysis of a time series is conducted, it can be useful to transform or adjust the data, while an initial time plot of the data often gives hints on what kind of transformation or adjustment might be appropriate. Typically, there a three main reasons for a transformation, like taking logarithms or square

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roots of the raw data. The first one is the stabilization of the variance, the second one is to make the seasonal effect additive and the third one is to make the data in a time series normally distributed (Chatfield and Xing 2019, p.18).

*Stabilization of the Variance*

It is quite common, that the variance is not constant in time series data. In the case where we have a time series with a trend and the variance increases with the mean, a transformation might be useful. A logarithmic transformation is appropriate for the stabilization of the variance if the standard deviation increases linearly with the mean (Montgomery et al. 2015, p.46). However, when the variance is changing in a time series that contains no trend, a distributional transformation has generally no advantage. In this case, it is a better approach to choose a model which considers changing variance over time (Chatfield and Xing 2019, p.18).

*To Make the Seasonal Effect Additive*

If the magnitude of the seasonal effect increases with a trend in a times series, it is useful to transform the data in a way that makes the seasonal effect constant. In this case, we designate the seasonal effect as *additive*. On the other hand, the seasonal effect is said to be *multiplicative*, if it is directly proportional to the mean. Again, a logarithmic transformation is advisable here, which converts a multiplicative seasonal effect into an additive one (Chatfield and Xing 2019, p.18).

*To Make the Data Normally Distributed*

An assumption in many statistical procedures to perform effectively and for time series modeling and forecasting is that the data are normally distributed. At least the assumption that the data are symmetric and not too much kurtotic (fat-tailed) should be satisfied (Mills 2019, p.13). In practice, however, this is frequently not the case in observed time series data. A transformation is also not always helpful in making the data normally distributed and it may be required to use a different error distribution for modeling the data (Chatfield and Xing 2019, p.18).

*Box-Cox Transformion*

Transformations like taking square roots or cube roots, also called *power transformations*, might be useful as well, even though they are not so interpretable as logarithmic transformations (Hyndman and Athanasopoulos 2018, p.55). A well

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know family of power transformations, which includes the natural logarithmic transformation (i.e., to the base $e$) as a special case, was introduced by Box and Cox (1964). A modified Box-Cox transformation, which allows also for negative values of $y_t$, given that $\lambda > 0$, was proposed by Bickel and Doksum (1981) as illustrated in equation 3.2 below:

$$w_t = \begin{cases} \log(y_t) & \lambda = 0 \\ sign(y_t)|y_t|^{\lambda} - 1)/\lambda & \lambda \neq 0 \end{cases} \tag{3.2}$$

where $w_t$ refers to the transformed value of $y_t$. The transformation of a time series with a $\lambda$ that makes the seasonal variation constant across a time series generally simplifies the forecasting model (Hyndman and Athanasopoulos 2018, p.55). Regularly used values of $\lambda$ to transform time series data are $\lambda = 0,5$ which represents a square root transformation, $\lambda = 0$ which performs the natural logarithmic transformation, $\lambda = -0,5$ which leads to a reciprocal square root transformation, $\lambda = -1$ which conducts an inverse transformation, and $\lambda = 1$ where no transformation takes place (Montgomery et al. 2015, p.47). When we use a transformation in a forecasting model, first forecasts based on the transformed data are generated. In the next step, the data have to be back-transformed to get forecasts on the original scale (Hyndman and Athanasopoulos 2021, pp.129-130), as illustrated in equation 3.3:

$$y_t = \begin{cases} \exp(w_t) & \lambda = 0 \\ sign(\lambda w_t + 1)|\lambda w_t + 1|^{1/\lambda} & \lambda \neq 0 \end{cases} \tag{3.3}$$

The same also holds for a specified prediction interval: the interval is first computed on the transformed scale and then back-transformed to the original scale. The prediction interval's probability coverage is maintained by the method depicted in 3.3. One issue however when using a Box-Cox transformation is that the prediction interval will be no longer symmetric around the point forecast after the back-transformation. In fact, the point forecasts will typically be the median rather than the mean of the forecast distribution, which might be acceptable in some cases. The higher the value of the forecast variance is, the larger is this bias. Following this, if an approximation of the back-transformed mean is required, the method depicted in equation 3.4 should be applied: where $\hat{w}_{T+h|T}$ represents the h-step forecast mean on the transformed-scale, $\sigma_h^2$ is the h-step forecast variance on the transformed scale and $\hat{y}_{T+h|T}$ depicts the h-step forecast mean on the original-scale, based on a set of observations at the discrete time points $t = 1 \dots T$ (Hyndman and Athanasopoulos 2021, pp.130-131).

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$$\hat{y}_{T+h|T} = \begin{cases} \exp(\hat{w}_{T+h|T})\left[1 + \frac{\sigma_h^2}{2}\right] & \lambda = 0 \\ (\lambda \hat{w}_{T+h|T} + 1)^{1/\lambda}\left[1 + \frac{\sigma_h^2(1-\lambda)}{2(\lambda \hat{w}_{T+h|T}+1)^2}\right] & \lambda \neq 0 \end{cases} \tag{3.4}$$

### 3.3.5 Trend and Seasonal Adjustments

It is often of special interest in (preliminary) time series analysis to study the long-run or permanent patterns of a time series and its shorter-run, more transitory behavior, separately (Mills 2019, p.23). Two approaches that are dedicated to this separation are time series *decomposition* and *differencing*, which will be explained in the following two sections in more detail.

#### 3.3.5.1 Decomposition

Time series decomposition is dedicated to the separation of a time series into its particular components, which is done in most cases to get a better understanding of the data. However, it can also be used for forecasting. The basic components of a time series, like a trend, seasonality, and cycles were introduced in section 3.3.1. In time series decomposition, the trend and the cycles are usually combined to a single component, which is designated as the *trend-cycle* (Hyndman and Athanasopoulos 2018, p.159). In reference to time series decomposition, we will speak about three components, the *trend-cycle component* $T_t$, the *seasonal component* $S_t$, and a *remainder component* or more specific a *random error component* $\varepsilon_t$.

Subsequently, we can define two major types of decomposition models for a time series $\{y_t\}$ with a set of discrete observations at the time points $t = 1 \dots T$ - an *additive decomposition* model, illustrated in equation 3.5, and a *multiplicative decomposition* model, depicted in equation 3.6 (Montgomery et al. 2015, p.55):

$$y_t = S_t + T_t + \varepsilon_t \tag{3.5}$$

$$y_t = S_t \cdot T_t \cdot \varepsilon_t \tag{3.6}$$

In the case that the magnitude (amplitude) of the seasonal variation does not vary with the level of the time series, the additive decomposition model is applicable. If the seasonal variation is proportional to the level of the time series, which typically appears in economic data, the multiplicative decomposition model is

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appropriate (Hyndman and Athanasopoulos 2018, p.160). Alternatively to multiplicative decomposition, first a transformation of the data can be applied, which makes the seasonal effect adequately constant over time, which then allows for the application of a generally easier to handle additive approach (Chatfield and Xing 2019, p.26).

A variety of decomposition models exist, some of the most prominent are, *classical* decomposition which has its origin about one century ago, *X11* decomposition, which was established by the US Census Bureau and Statistics Canada, the *SEATS* (Seasonal Extraction in ARIMA Time Series) method, which was developed at the Bank of Spain and the *STL* (Seasonal and Trend decomposition using Loess[9]) decomposition (Hyndman and Athanasopoulos 2021, pp.76-84).[10] STL decomposition is a widely applied approach and has many advantages over other decomposition models. Some of the strengths are that the seasonal component can change over time, the rate of this seasonal change (season window) and the smoothness of the trend cycle (trend cycle window) can be set by the user, and the approach is also quite robust to outliers. One disadvantage is that the method is only applicable for additive decomposition (Hyndman and Athanasopoulos 2021, pp.82-83).

*Kia: STL-Decomposition of NPCR*

For a better understanding of the components of a time series a STL decomposition is illustrated in figure 3.4. With a look at Kia's time plot of NPCR in figure 3.2, the seasonal effect appears to increase approximately proportionally with the level of the series, which indicates a multiplicative approach. Since the STL method is generally based on additive decomposition, a logarithmic transformation[11] was applied to convert the multiplicative seasonal effect into an additive one.[12] In panel one of the STL decomposition[13] depicted in figure 3.4, the natural

[9] Loess demonstrates a method for the estimation of non-linear relationships (Hyndman and Athanasopoulos 2021, pp.82)

[10] A detailed discussion of the mentioned decomposition models is not in the purpose of this thesis; however, a general explanation of the models can be found in Hyndman and Athanasopoulos (2021, pp.59-87). A detailed description of X11 and SEATS decomposition is presented in Dagum and Bianconcini (2016) and for the STL method in the original paper of Cleveland et al. (1990).

[11] A $\lambda$ of -0,04212604 was calculated for the time series of Kia's NPCR illustrated in figure 3.2 with the *Guerrero Method* (Guerrero 1993), by the usage of the guerrero() feature in R, which is part of the fable package (R 2021a) and a sub-package of the tidyverse package (R 2021b). The $\lambda$ is very close to 0, which justifies a natural logarithmic transformation.

[12] The usage of a log transformation is equivalent to the application of the multiplicative decomposition approach because: $y_t = S_t \cdot T_t \cdot \varepsilon_t \;\approx\; \log\, y_t = \log\, S_t + \log\, T_t + \log\, \varepsilon_t$.

[13] STL decomposition was conducted with R by the usage of the STL() model of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b). The trend



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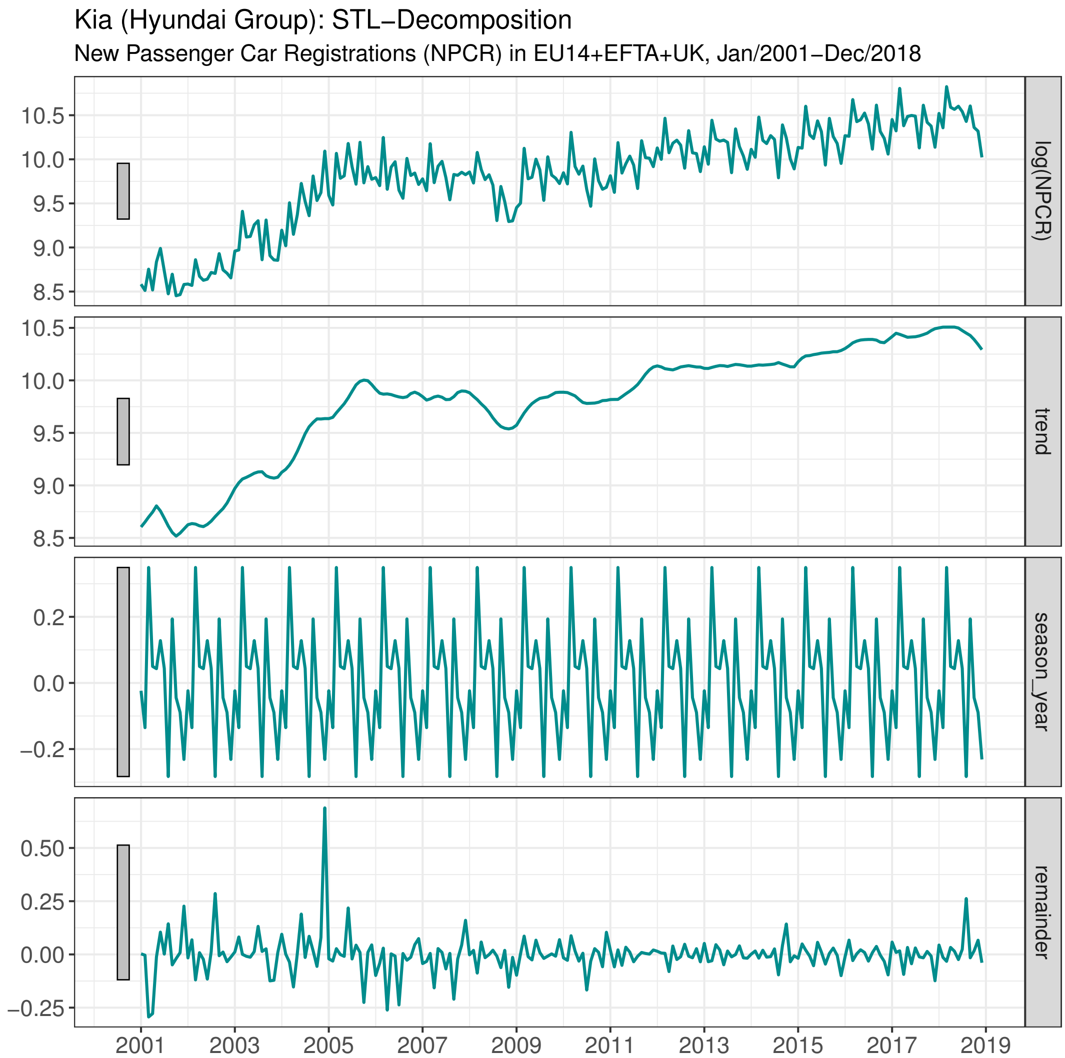


Figure 3.4: Kia: STL-Decomposition, NPCR in EU14+EFTA+UK
Data Source NPCR: (ACEA 2021f), (ACEA 2022b)

logarithm of Kia's NPCR data is calculated, which makes the seasonal effect approximately constant in comparison to the data on the original scale illustrated in figure 3.2. Panel two, three and four illustrate the trend-cycle component $T_t$, the seasonal component $S_t$ and the random error component $\varepsilon_t$.[14]

#### 3.3.5.2 Differencing

As was mentioned in section 3.3.2, stationarity of a time series is a prerequisite for many classical time series models. A way of converting a non-stationary time

cycle window was set to a value of 7 and the season window to periodic, i.e. identical across years.

[14] The components $T_t$, $S_t$, $\varepsilon_t$ of the STL decomposition illustrated in figure 3.4 are on the log-scale. In practice it would be required therefore, to back-transform the components, as described in section 3.3.4, to obtain the values on the original scale

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series into a stationary one is to compute the differences of successive observation, which is known as *differencing*. Transformations, like log transformations explained in section 3.3.4, can be helpful for the stabilization of the variance in time series. Differencing however can be useful for the stabilization of the mean in time series by eliminating changes in the level, which removes or at least reduces trend and seasonality (Hyndman and Athanasopoulos 2018, p.227).

*Regular Differencing*

A widely used method that generally works well for removing the trend of a time series is differencing (Chatfield and Xing 2019, p.25). The differencing approach for removing a trend is sometimes also referred to *regular differencing* to make it distinguishable from *seasonal differencing*, which will be explained later in this section. Computing the differences between observations of a times series which are one time interval apart (lag 1) is called *first-order differencing* and creates a new time series $\{y'_t\}$. The differenced series $\{y'_t\}$ represents the change between successive observations in the original series (Hyndman and Athanasopoulos 2018, p.227), as is illustrated in equation 3.7 below:

$$y'_t = y_t - y_{t-1} \tag{3.7}$$

Sometimes however, first-order differencing is not enough to remove the trend sufficiently. In this case it might be necessary to difference the series $\{y'_t\}$ as second time, which is also known as *second-order differencing*. However, it is almost never necessary to go beyond second-order differencing to generate a stationary time series (Hyndman and Athanasopoulos 2018, p.229).

*The Random Walk Model*

Under the assumption, that the differenced series is white noise (see section 3.3.3) we can rewrite equation 3.7 as follows:

$$y_t - y_{t-1} = \varepsilon_t \tag{3.8}$$

where $\varepsilon_t$ represents white noise, i.e. $\varepsilon_t \sim \mathcal{N}(0,\, \sigma_y^2)$. Rearranging equation 3.8 leads to a stochastic process known as the *random walk model* (Hyndman and Athanasopoulos 2018, p.228), as illustrated in equation 3.9.

$$y_t = y_{t-1} + \varepsilon_t \tag{3.9}$$

Especially in finance and economics, random walk models are widely used ap-

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proaches for non-stationary data. Random walks are characterized by long periods of an up or downward moving trend and sudden and unpredictable changes in one direction. The assumption in a random walk model is, that future movements are not predictable.[15] Hence, the forecasted values are equal to the last observation plus a white noise error term, and therefore equally likely to go up or down (Hyndman and Athanasopoulos 2018, p.228). If we allow the differences to have a non-zero mean, this leads to a related model denoted as *random walk with drift*, where c represents the average of the changes between successive observations, as depicted in equation 3.10. In the case that c is a positive value, the time series $\{y_t\}$ tends to move upwards. However, if c is a negative value the time series $\{y_t\}$ tends to move downwards (Hyndman and Athanasopoulos 2018, p.228).

$$y_t = c + y_{t-1} + \varepsilon_t \tag{3.10}$$

*Seasonal Differencing*

In addition to removing a trend in a time series, differencing is also suitable for removing seasonality by taking the *seasonal differences*. We get the seasonally differenced series by computing the difference of an observation and the previous observation from the same season (lag $m$), where $m$ represents the number of seasons (Hyndman and Athanasopoulos 2018, p.229), as illustrated below in equation 3.11:

$$y'_t = y_t - y_{t-m} \tag{3.11}$$

While regular differencing represents the change between successive observations, seasonal differences represent the change between observations from one year to the next (Hyndman and Athanasopoulos 2018, p.232). If we have monthly data with an annual season ($m = 12$), it follows, that the values of the seasonally differenced series would be equal to $y'_t = y_t - y_{t-12}$ for a set of observations at the discrete time points $t = 1 \dots T$. Under the assumption that the seasonally differenced series is white noise, we get forecasts which are equal to the observation from the last season plus a white noise error term (Hyndman and Athanasopoulos 2018, p.229), as illustrated in equation 3.12:

$$y_t = y_{t-m} + \varepsilon_t \tag{3.12}$$

It might be necessary to take the second-order seasonal differences in some cases to make a time series stationary, however, it is almost never necessary to go

[15] Random walk models in finance and economics are consistent with the *weak form of market efficiency*, a term introduced in the famous article of (Fama 1970, p.388).

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beyond that, as for regular first- and second-order differencing.

*Removing Trend and Seasonality*

If we analyze a time series that contains both a trend and seasonal variation, we first apply seasonal differencing to remove the seasonal pattern. This might be already sufficient to make the time series stationary, especially when the seasonal pattern is dominant. In the case however, where the seasonal differenced series appears to be non-stationary still, we remove the trend in a second step by differencing one or more times using regular differencing (Montgomery et al. 2015, p.55).

#### 3.3.5.3 Tests for Regular and Seasonal Differencing

Differencing can be applied sequentially in a subjective way until the differenced series appears to be stationary. However, a more objective way to determine whether and how often differencing is required are *unit root test*.

*Unit Root Tests*

A unit root test is a statistical hypothesis test of stationarity, which points out whether differencing is required or not (Hyndman and Athanasopoulos 2018, p.232). A variety of unit root test exist, the most prominent might be the *Augmented Dickey-Fuller Test* (Dickey and Fuller 1979), the *Phillips-Perron Test* (Phillips and Perron 1988) and the *Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test* (Kwiatkowski et al. 1992). Hyndman and Athanasopoulos (2021, p.272) recommend the KPPS Test, which states the null hypothesis, that a time series is stationary around a deterministic trend (Kwiatkowski et al. 1992, p.159). Hence, we search for evidence, that the null hypothesis can be rejected, indicated by a small p-value (e.g. $< 0,05$), which in turn would lead to the conclusion that differencing is required to make the time series stationary. In a further step, we can apply the KPPS Test again to the differenced series to see whether second-order differencing is required to make the time series stationary. This procedure can be repeated until the null hypothesis cannot be rejected anymore and we can conclude that the time series is stationary Hyndman and Athanasopoulos (2018, pp.232-233).

*Test for Seasonal Strength*

A measure that can be used for determining whether seasonal differencing is required is based on STL-decomposition, which was discussed in section 3.3.5.1.

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Besides a variety of other features which can be derived from time series decomposition, seasonal strength $F_S$ can be defined as illustrated in equation 3.13 below Hyndman and Athanasopoulos (2021, p.93):

$$F_S = max\left(0, 1 - \frac{Var(\epsilon_t)}{Var(S_t + \epsilon_t)}\right) \tag{3.13}$$

where $F_S$ is calculated in reference to the detrended time series, $S_t$ represents the seasonal component, and $\varepsilon_t$ the remainder component. The value of $F_S$ ranges from 0 to 1. Hence, a times series with a value close to 0, contains almost no seasonal pattern, while strong seasonality is represented by a value close to 1. This is because $Var(\epsilon_t)$ will be much smaller than the term $Var(S_t + \epsilon_t))$ in this case Hyndman and Athanasopoulos (2021, p.93). In reference to the determination of the appropriate number of seasonal differences, a threshold value for $F_S$ of 0,64 is suggested. Hence, in the case that $F_S \geq 0,64$, seasonal differencing will be applied until a value of $F_S < 0,64$ is reached Hyndman and Athanasopoulos (2021, p.273).

*Kia: Stationary, Twice Difference log NPCR*

As stated in section 3.3.2, stationarity of time series data is a requirement for many traditional time series models. However, in reality, most of the time series are non-stationary (Nielsen 2019, p.82). Subsequently, it is required in many cases to transform non-stationary time series into stationary ones, by removing the trend, the seasonal behavior and by stabilizing the variance (Chatfield and Xing 2019, p.17), as will be explained by the example of Kia's new passenger car registrations (NPCR) in the following. Panel one, on the top of figure 3.5, illustrates the time series of Kia's NPCR in the EU14, The EFTA, and the UK from Jan/2001-Dec/2018. As noted for the STL-decomposition depicted in 3.3.5.1, the variance of the seasonal pattern is increasing approximately proportionally with the level of the series, which indicates a logarithmic transformation[16] to stabilize the variance of the seasonal pattern. Hence in panel two of figure 3.5, the natural logarithm of Kia's NPCR is calculated, which makes the seasonal effect approximately constant in comparison to the data on the original scale depicted in panel one. As mentioned in the previous section 3.3.5.2, if we analyze a time series that contains both a trend and seasonal variation, as it appears in the case of Kia's NPCR, we first apply seasonal differencing to remove the seasonal pat-

[16] A $\lambda$ of -0,04212604 was calculated for the time series of Kia's NPCR, illustrated at the top of figure 3.5, with the *Guerrero Method* (Guerrero 1993), by the usage of the guerrero feature in R, which is part of the fable package (R 2021a), a sub-package of the tidyverse package (R 2021b). The $\lambda$ is very close to 0, which suggests a natural logarithmic transformation.

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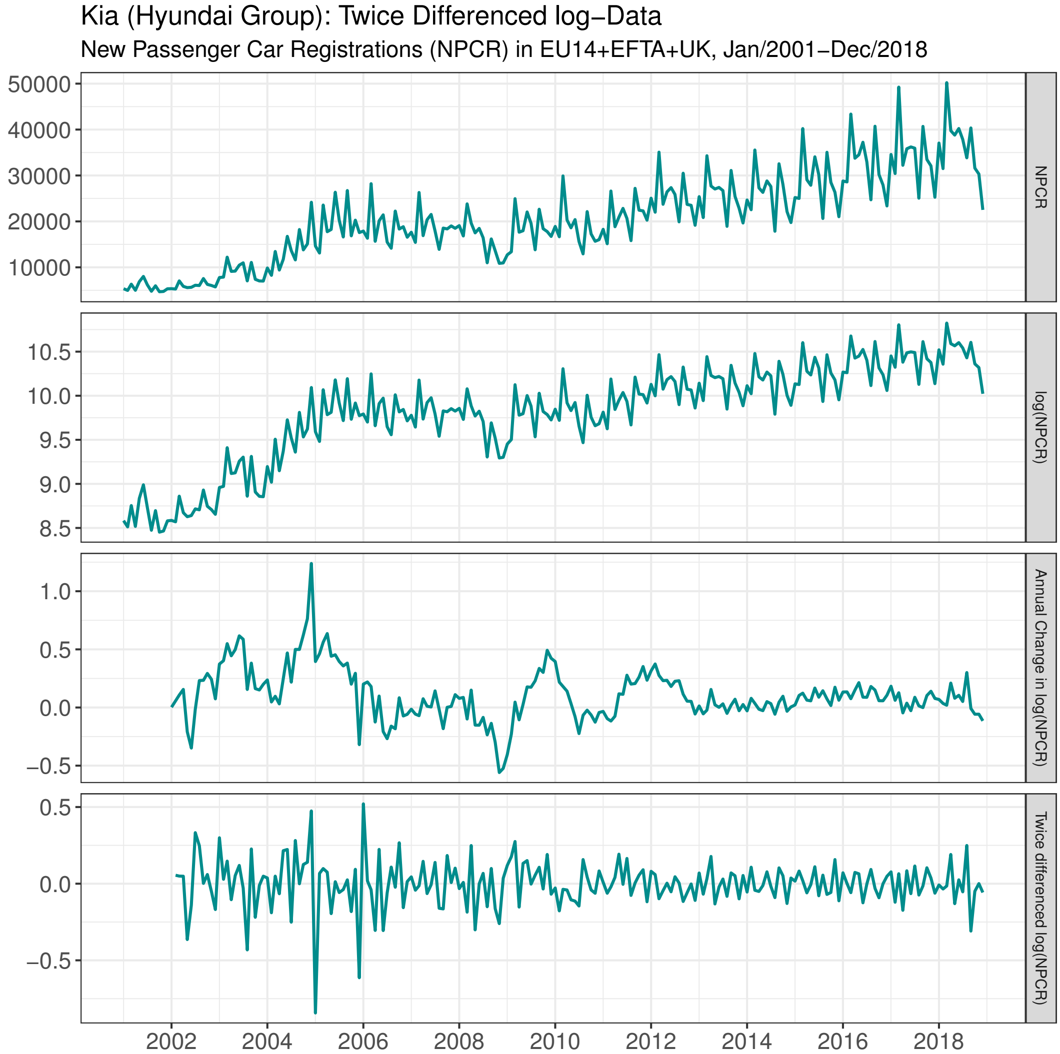


Figure 3.5: Kia: Twice Differenced Log Data, NPCR in EU14+EFTA+UK
Data Source NPCR: (ACEA 2021f), (ACEA 2022b)

tern. In this context, tests for seasonal strength were conducted in R[17] to the natural log values of Kia's NPCR, which indicated that one seasonal difference is required. Following this, panel three of figure 3.5 depicts, the first-order seasonal differenced series (lag $m = 12$) of Kia's log NPCR. Following this, KPPSs tests were applied to the log of the seasonal differenced series of Kia's NCPR in R[18], which proposed, that a further regular difference should be taken to make the series stationary. Finally, panel four of 3.5 states in reference to the applied unit root tests, the stationary twice differenced log NPCR of Kia.

[17] The determination of the appropriate number of seasonal differences was conducted in R by the usage of the unitroot_nsdiffs() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

[18] The determination of the appropriate number of regular differences was conducted in R by the usage of the unitroot_ndiffs() function of the fable package (R 2021a), which a sub-package of the tidyverse package (R 2021b).

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## 3.4 ARMA and ARIMA Models

In the following section the theory of Autoregressive Integrated Moving Average Models (ARIMA) models, which will be used for forecasting in chapter 4, will be derived. The components of ARIMA models, Autoregressive (AR) models, Moving Average (MA) models, and the resulting Autoregressive Moving Average (ARMA) model will be explained in the sections 3.4.1, 3.4.2 and 3.4.3. Following this, Non-Seasonal and Seasonal ARIMA models will be discussed in more detail in section 3.4.4.

### 3.4.1 Autoregressive Models

While in a multiple regression model the variable of interest is regressed on separate predictor variables, we forecast the variable of interest $y_t$ in an *Autoregressive (AR)* model by a regression of $y_t$ on past values or lagged values of $y_t$, which is indicated by the prefix *autoregressive* (Chatfield and Xing 2019, p.52). Following this, an autoregressive model of order $p$, known as an AR(p) model can be expressed as illustrated in equation 3.14 below:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \tag{3.14}$$

where $c$ represents a constant and $\varepsilon_t$ represents a white noise process with a mean of 0 and variance $\sigma_y^2$. Autoregressive models are useful for the description of a variety of time series patterns. While a change of the parameters $\phi_1 \dots \phi_p$ leads to different time series patterns, a change in the variance of the error term $\varepsilon_t$, will only influence the scale of the series (Hyndman and Athanasopoulos 2018, p.235). Beyond that, the application of autoregressive models is generally restricted to stationary data (see section 3.3.2), which makes some constraints on the values of the parameters $\phi_1 \dots \phi_p$ necessary. The stationarity constraints for an AR(1) and AR(2) model are illustrated in equation 3.15 and 3.16below (Hyndman and Athanasopoulos 2018, p.236):

$$\text{AR}(1)\!: -1 < \phi_1 < 1 \tag{3.15}$$

$$\text{AR}(2)\!: -1 < \phi_2 < 1, \phi_1 + \phi_2 < 1 \tag{3.16}$$

The stationarity constraints for an autoregressive model of an order $p \geq 3$ are more complicated and beyond the scope of this thesis. However, the interested reader can find more information regarding this topic in Chatfield and Xing (2019, pp.56-59) or Box et al. (2016, pp.54-55).

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### 3.4.2 Moving Average Models

In an Autoregressive model explained before, we forecast the variable of interest $y_t$ by a regression of $y_t$ on past values of $y_t$. In a *Moving Average (MA)* model, however, we use the forecast errors in a regression-like model. Furthermore, each value of $y_t$ can be considered as a weighted moving average of past forecast errors, which explains the prefix *moving average* (Hyndman and Athanasopoulos 2018, p.236). Hence, a moving average model of order $q$, also denoted to a MA(q) model, can be written as illustrated in equation 3.17 below:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ ... \ + \theta_q \varepsilon_{t-q} \tag{3.17}$$

where $c$ represents a constant and $\varepsilon_t$ represents a white noise process with mean zero and variance $\sigma_y^2$. Similar as described before in reference to autoregressive models, a change of the parameters $\theta_1 \ldots \theta_p$ leads to different time series patterns, while a change in the variance of the error term $\varepsilon_t$ will only have an effect on the scale of the series (Hyndman and Athanasopoulos 2018, p.237).

No restriction on the parameters $\theta_1 \ldots \theta_p$ are required for a finite-order MA process to be stationary. However, it is generally useful to state restriction on the values of $\theta_1 \ldots \theta_p$ to make sure, that an MA process fulfills a condition which is designated as *invertibility* (Chatfield and Xing 2019, p.49). The invertibility constraints for a MA(1) and a MA(2) model are depicted in equation 3.18 and 3.19 below (Hyndman and Athanasopoulos 2018, p.237):[19]

$$\text{MA(1)}: -1 < \theta_1 < 1 \tag{3.18}$$

$$\text{MA(2)}: -1 < \theta_2 < 1, \theta_1 + \theta_2 > -1, \theta_1 - \theta_2 < 1 \tag{3.19}$$

### 3.4.3 Autoregressive Moving Average Models

A combination of an AR and a MA process leads to an *Autoregressive Moving Average (ARMA)* model. Hence, an autoregressive moving average model which contains $p$ AR terms and $q$ MA terms is designated as an ARMA model of orders $(p, q)$ and can be stated as follows (Chatfield and Xing 2019, p.59):

$$y_t = c + \phi_1 y_{t-1} + \ ... \ + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \ ... \ + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{3.20}$$

[19] A more detailed explanation of invertibility of a MA process is stated in Appendix A.



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where $c$ represents a constant and $\varepsilon_t$ represents a white noise process with mean zero and variance $\sigma_y^2$. An important feature of an ARMA model is, that a stationary time series, can often be modeled sufficiently with less parameters by an ARMA process than by a single MA or AR process (Chatfield and Xing 2019, p.60). In this context, the use of an ARMA process is consistent with the *principle of parsimony*, i.e., all other things being equal, we want to apply a model with as few parameters as possible for an adequate representation (Box et al. 2016, p.15).

### 3.4.4 Autoregressive Integrated Moving Average Models

The previously described ARMA model is restricted to stationary time series data. However, as described in section 3.3.2, in reality, most of the time series are non-stationary. A way of stabilizing the variance by transformations was explained in section 3.3.4, while removing a trend and seasonality to make a time series stationary was explained in sections 3.3.5.2 and 3.3.5.3 respectively. If we combine differencing with an ARMA model to deal with non-stationary data, we get an *Autoregressive Integrated Moving Average (ARIMA)* model, as will be explained in the next sections.

#### 3.4.4.1 Non-Seasonal ARIMA Model

If we combine regular differencing with an ARMA model to deal with non-stationary data which contain a trend, we get an *Autoregressive Integrated Moving Average (ARIMA)* model for non-seasonal data (Hyndman and Athanasopoulos 2018, p.238). The term *"integrated"* is used because the model which is fitted to the stationary differenced time series has to be summed or *"integrated"* to generate a model for the non-stationary original series (Chatfield and Xing 2019, p.63). Hence integration can be considered as the reverse of differencing in this case (Hyndman and Athanasopoulos 2018, p.238). In general terms, an ARIMA model of orders $(p, d, q)$ can be defined a as a process, which $d^{th}$ order difference generates a stationary ARMA(p,q) model (Montgomery et al. 2015, p.363). Following this, an ARIMA model, where $y'_t$ represents the regular first-order differenced series, is stated below in equation 3.21 (Hyndman and Athanasopoulos 2018, p.238):

$$y'_t = c + \phi_1 y'_{t-1} + \ ... \ + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \ ... \ + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{3.21}$$



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where $c$ represents a constant and $\varepsilon_t$ represents a white noise process with mean zero and variance $\sigma_y^2$. The mentioned stationary constraints for AR processes stated in section 3.4.1 and the invertibility constraints for MA processes stated in section 3.4.2, generally also apply for ARMA and ARIMA models (Hyndman and Athanasopoulos 2018, p.239). Furthermore, some of the models, which were discussed in previous sections, can be represented by ARIMA models, as illustrated in table 3.1 below:

| Stoch. Process | ARIMA model |
|---|---|
| White Noise | ARIMA(0,0,0) with no constant |
| Random Walk | ARIMA(0,1,0) with no constant |
| Random Walk with Drift | ARIMA(0,1,0) with a constant |
| Autoregression | ARIMA(p,0,0) |
| Moving Average | ARIMA(0,0,q) |

Table 3.1: Special Cases of ARIMA Models
Adapted from Hyndman and Athanasopoulos (2018, p.238)

In the case we form some more complicated ARIMA models, it is generally easier to work with the backshift notation. Hence if $y'_t$ in equation 3.21 is replaced by $y'_t = (1-B)^d$, where $B$ represents the *backward shift operator*[20] and $d$ represents the order of regular differences (Montgomery et al. 2015, p.363), we get an ARIMA(p,d,q) model, as stated in equation 3.22 below (Hyndman and Athanasopoulos 2018, p.239):

$$\underset{\substack{\uparrow \\ \text{AR(p)}}}{(1-\phi_1 B + \dots + \phi_p B^p)} \; \underset{\substack{\uparrow \\ \text{d differences}}}{(1-B)^d y_t} \; = \; c + \underset{\substack{\uparrow \\ \text{MA(q)}}}{(1+\theta_1 B + \dots + \theta_q B^q)\varepsilon_t} \tag{3.22}$$

#### 3.4.4.2 Seasonal ARIMA Model

The ARIMA model presented in equation 3.22 is restricted to non-seasonal data. If we enhance an ARIMA model to deal with seasonal data, we speak of a *Sea-*

[20] The backward shift operator $B$ is very useful in reference to lags of time series. $By_t = y_{t-1}$, so that, by $B$ operating on $y_t$, the data are shifted back one time period. In the same way, with $B(By_t) = B^2 y_t = y_{t-2}$, the data are shifted back two time periods, while for seasonal data on a monthly basis ($m = 12$), a lag of 12 month can be represented as $B^{12} y_t = y_{t-12}$. Beyond that, the backward shift operator can be used for the representation of differencing, since the first-order difference can be represented as $y'_t = y_t - y_{t-1} = y_t - By_t = (1-B)y_t$, additionally, the second-order difference can be represented as $y''_t = y_t - 2y_{t-1} + y_{t-2} = (1-2B+B^2)y_t = (1-B)^2 y_t$, or in a general form, the $d^{th}$-order difference can be stated as $(1-B)^d y_t$ (Hyndman and Athanasopoulos 2018, pp.234-235).

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*sonal ARIMA (SARIMA)* model (Chatfield and Xing 2019, p.103). As illustrated below, a SARIMA model includes additional seasonal terms which are added to the ARIMA model for non-seasonal data (Hyndman and Athanasopoulos 2018, p.257):

$$\begin{array}{ccc} \text{SARIMA} & (p,d,q) & (P,D,Q)_m \\ & \uparrow & \uparrow \\ & \text{non-seasonal part} & \text{seasonal part} \end{array} \tag{3.23}$$

where $m$ represents the number of observations per year, e.g., for monthly data $m = 12$. In this context, lower case notation is used for the non-seasonal part, while we use upper case notation for the seasonal part of the model. The seasonal part of the SARIMA model includes backward shift operators for the seasonal period $m$, apart form that, the terms are generally similar to the non-seasonal part of the model and are simply multiplied by the non-seasonal terms (Hyndman and Athanasopoulos 2018, p.257). An example of an ARIMA(1,1,1)(1,1,1)$_{12}$ model is illustrated below in equation 3.24 for a better understanding:

$$(1-\phi_1 B)(1-\Phi_1 B^{12})(1-B)(1-B^{12})y_t = (1+\theta_1 B)(1+\Theta_1 B^{12})\varepsilon_t \tag{3.24}$$

## 3.5 The ARIMA Modeling Approach

The Seasonal ARIMA(p,d,q)(P,D,Q)[m] models, which have been used to establish an adequate baseline for the evaluation of Covid-19's impact on European new passenger car registrations (NPCR) in chapter 4, have been fitted in R by the usage of the ARIMA() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b). The ARIMA() function is based on variations of the Hyndman-Khandakar algorithm (Hyndman and Khandakar 2008), in which a combination of unit root tests and the minimization of the AICc and MLE is conducted to obtain an ARIMA model with their corresponding orders and parameters. The next section 3.5.1 gives some information about how the orders of an ARIMA model can be derived from ACF and PACF plots of stationary time series, section 3.5.2 states how the corresponding parameters of the model are estimated for a given set of orders, while section 3.5.3 comprises information on model-selection statistics, like the AIC, the AICc, and the BIC.

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### 3.5.1 Order Selection

In reference to equation 3.23, the orders for regular differencing $d$ and seasonal differencing $D$ can be derived in a subjective way or by the use of unit root tests, as was explained in section 3.3.5.3. For the following example, which refers to monthly new passenger car registrations (NPCR) of BMW in the EU14, the EFTA, and the UK, unit root tests will be applied for the determination of the appropriate number of regular and seasonal differences, to get a stationary time series. With a look a the time series of BMW's NPCR in panel one at the top of figure 3.6, the variance of the seasonal pattern is increasing approximately proportional with the level of the series. Hence, a logarithmic transformation is used to stabilize the variance of the seasonal pattern, as depicted in panel two of figure 3.6. The repeated tests for seasonal strength[21] and the KPPS-tests[22] indicated, that one seasonal difference (m = 12) applied to the log NPCR of BMW is enough to obtain a stationary time series. From this it follows, that the orders of differencing to obtain a stationary series are $d = 0$ and $D = 1$ in the BMW example. The stationary seasonal differenced log NPCR of BMW is depicted in panel three of figure 3.6.

Additionally, the plots of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF)[23] of stationary time series can give information about the non-seasonal orders $p, q$ and the seasonal orders $P, Q$ of ARIMA(p,d,q)(P,D,Q)[m] models. If $p$ and $q$ are both positive, the plots do not help in finding suitable values. However, if the stationary series follows a non-seasonal ARIMA(p,d,0) or ARIMA(0,d,q) model, the orders of the non-seasonal AR and MA components can be derived from the ACF and the PACF plot as follows (Hyndman and Athanasopoulos 2018, p.243):

[21] The determination of the appropriate number of seasonal differences was conducted in R by the usage of the unitroot_nsdiffs() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

[22] The determination of the appropriate number of regular differences was conducted in R by the usage of the unitroot_ndiffs() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

[23] The partial autocorrelation function PACF, states a measure for the relationships of $y_t$ and $y_{t-k}$ after the effects of the lags (k=1,2,3, ... , k-1) are removed. An estimation of each partial autocorrelation $\alpha_k$ can be obtained by fitting autoregressive models of orders p=1,2,3, etc., separately. This is because the estimate of the last coefficient $\phi_k$ of an autoregressive AR(k) model is equal to the $k^{th}$ partial autocorrelation coefficient $\alpha_k$ of the PACF. In practice however, the partial autocorrelation coefficients of the PACF are calculated by algorithms that are more efficient (Hyndman and Athanasopoulos 2021, p.283). The PACF plot was generated with R by the usage of the PACF() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

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**1. Non-seasonal AR part:** In the case, that the data can be described by an ARIMA(p,d,0) model, the ACF and the PACF plot of the differenced series exhibit the following pattern:

- *"The ACF is exponentially decaying or sinusoidal;*
- *there is a significant spike at lag p in the PACF, but none beyond lag p."* (Hyndman and Athanasopoulos 2018, p.243)

**2. Non-seasonal MA part:** Beyond that, the data can be described by an ARIMA(p,d,0) model, if the ACF and the PACF plot of the differenced series exhibit the following pattern:

- *"There is a significant spike at lag q in the ACF, but none beyond lag q;*
- *the PACF is exponentially decaying or sinusoidal."* (Hyndman and Athanasopoulos 2018, p.243)

**3. Seasonal AR part:** Additionally, a seasonal AR component of the model can be derived from the seasonal lags of the ACF and PACF plots of the stationary series. A Seasonal ARIMA(0,0,0)(1,0,0)[12] model exhibits, as for example:

- *"An exponential decay in the seasonal lags of the ACF (i.e., at lags 12, 24, 36, etc.);*
- *a spike at lag 12 in the PACF but no other significant spikes."* (Hyndman and Athanasopoulos 2018, p.257)

**4. Seasonal MA part:** Furthermore, the order of the seasonal MA component of a model can be derived for a ARIMA(0,0,0)(0,0,1)[12] model, if the ACF and PACF plot of the stationary data exhibit:

- *"A spike at lag 12 in the ACF but no other significant spikes;*
- *an exponential decay in the seasonal lags of the PACF (i.e., at lags 12, 24, 36, etc.)."* (Hyndman and Athanasopoulos 2018, p.257)

With a look at the plots at the bottom of figure 3.6, a significant spike at lag 3 in the PACF is observable, which indicates a non-seasonal AR(3) component of the model. Beyond that, we can see a significant spike at lag 12 in the ACF as well as in the PACF, which could indicate both, a seasonal AR(1) and/or a seasonal MA(1) component of the model. Consequently, we could start with an ARIMA(3,0,0)(1,1,0)[12], an ARIMA(3,0,0)(0,1,1)[12] or an ARIMA(3,0,0)(1,1,1)

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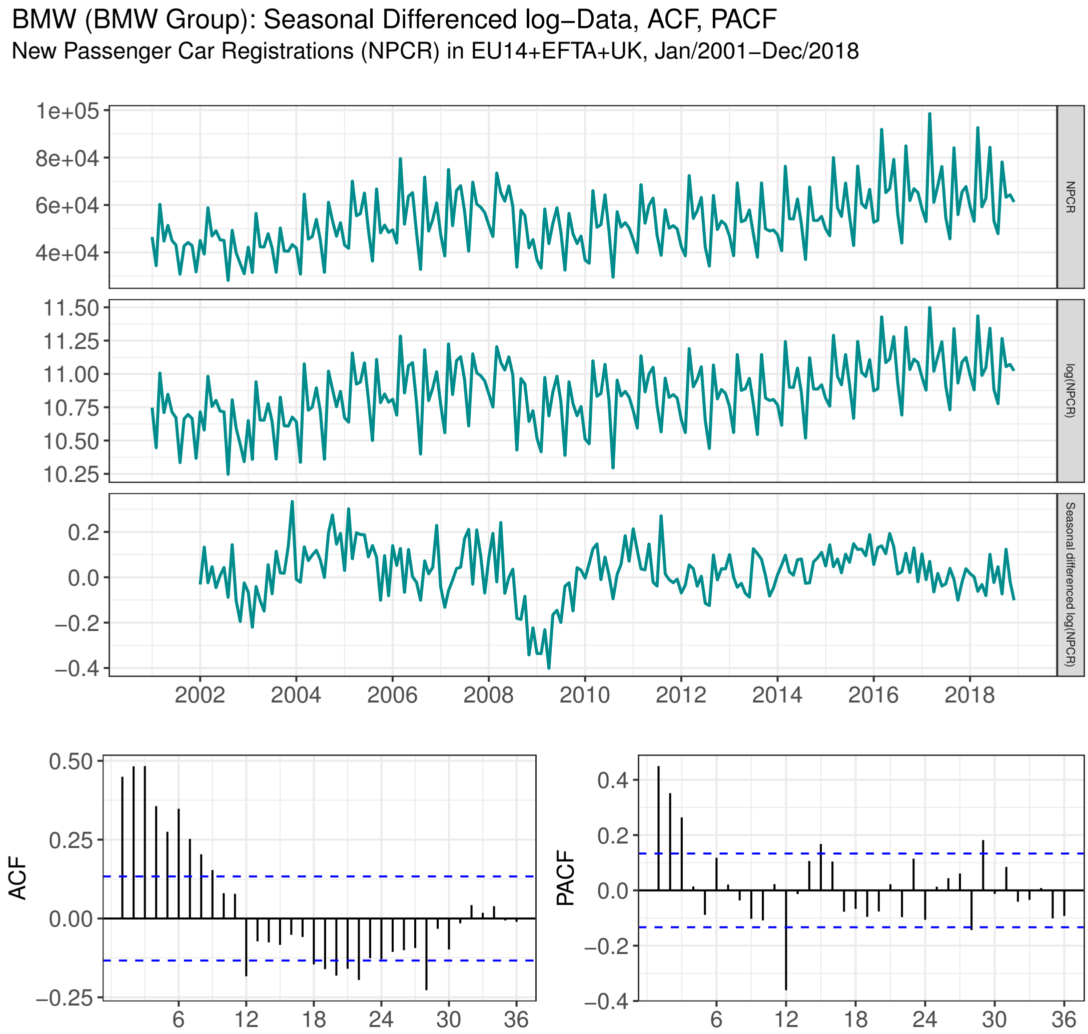


Figure 3.6: BMW: Seasonal Differenced Log NPCR, ACF, PACF
Data Source NPCR: (ACEA 2021f), (ACEA 2022b)

[12] model for a further evaluation. The best model which could be found under the usage of the ARIMA() function in R, was an ARIMA(3,0,0)(0,1,1)[12] model which incorporated a natural log transformation. The syntax of the model indicates a non-seasonal AR(3) component, first-order seasonal differencing with a lag $m = 12$, and a seasonal MA(1) component. It will be explained in the next sections how different competing models can be evaluated.

### 3.5.2 Parameter Estimation

Given that the orders of a non-seasonal ARIMA(p,d,q) or a seasonal ARIMA (p,d,q)(P,D,Q)[m] model have been selected, the parameters c, $\phi_1 \dots \phi_p, \theta_1 \dots \theta_q$, $\Phi_1 \dots \Phi_P, \Theta_1 \dots \Theta_Q$ have to be estimated. Nowadays, this estimation is done by modern software packages, like the fable package (R 2021a) of R, which has been

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used in this thesis. The estimation of the parameters in modern software packages is generally based on *maximum likelihood estimation (MLE)*. This approach estimates the values of the parameters in a way, so that the probability of obtaining the data, which have been observed, is maximized. MLE for ARIMA models is basically similar to the *least squares* estimates, and is obtained by minimizing the sum of the squared residuals[24] in a set of observations at discrete time points $t = 1 \ldots T$ (Hyndman and Athanasopoulos 2018, p.245):

$$min. \sum_{t=1}^{T} \varepsilon_t^2 \tag{3.25}$$

### 3.5.3 Information Criteria

In general, we often have several competing models which can be used for forecasting a given time series. However, it is not useful to choose just the model which provides the best fit by minimizing the sum of the squared residuals. This comes from the fact that the sum of the squared residuals will typically decrease with an increasing number of parameters, without considering, if the additional complexity of the model pays off. One widely used model-selection statistics, which selects the best fitting model in respect to the likelihood function L, while it is preventing overfitting by a penalty term which is increasing with the number of parameters used in the model, is the *Akaike's Information Criterion* (AIC) (Chatfield and Xing 2019, pp.97-98):

$$\text{AIC} = -2\ln(L) + 2r \tag{3.26}$$

where $r$ is the number of parameters used for fitting the model. For an ARIMA(p,d,q) model, $r$ would be $p + q + k + 1$, with $k = 1$ for $c \neq 0$, and $k = 0$ for $c = 0$, while an additional parameter is added which considers the variance of the residuals (Hyndman and Athanasopoulos 2018, p.245). Furthermore, the likelihood function can be approximated by $T\ \ln(S/T)$, where S is the the sum of the squared residual and $T$ denotes the number of observations $t = 1 \ldots T$. However, for small samples the AIC tends to be biased in a way, that too many predictors are selected. A biased-corrected version of the AIC, denoted by AICc, where the term $2r$ is replaced by $2rT/(T - r - 1)$, has therefore been developed, as illustrated in

[24]In this context, the sum of the squared residuals is equal to the sum of the squared differences between the observed values and the fitted values provided by the model.

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equation 3.27 (Chatfield and Xing 2019, p.98):

$$\text{AICc} = -2\ln(L) + \frac{2rT}{(T-r-1)} \tag{3.27}$$

Another widely used model-selection criterion, which penalizes additional parameters used to fit a model in a more restrictive way, is the *Bayesian Information Criterion* (BIC). In the BIC, the term $2r$ from the AIC is replaced by $(r+r\ \ln T)$ as depicted in equation 3.28 (Chatfield and Xing 2019, p.98):

$$\text{BIC} = -2ln(L) + (r + r - \ln T) \tag{3.28}$$

The presented model-selection criteria allow for a numerical-valued ranking in a set of competing models, where the best model is represented by the smallest AIC, $\text{AIC}_c$ or BIC value (Chatfield and Xing 2019, p.98). Additionally, information criteria are also widely used in iterative approaches implemented in modern software packages for the determination of the order of ARIMA models, where a good model is obtained by minimizing the preferred information criterion. However, it is important to consider, that the proposed criteria are not useful for selecting the adequate orders of differencing $(d, D)$, but only for selecting appropriate values of $p, q$ and/or $P, Q$. This comes from the fact, that differencing is changing the data, which are the basis for the calculation of the likelihood function $L$. This makes models with different orders of differencing not comparable. The general approach is therefore, to select the order of differencing first, e.g. by the appliance of unit root tests, as stated in section 3.3.5.2. In a next step then, the information criteria can be used for the selection of $p, q$ and/or $P, Q$ (Hyndman and Athanasopoulos 2018, p.246).

### 3.5.4 Residual Analysis

There is a consensus, that all models are wrong in some way. However, models which demonstrate a reasonable fit to the time series data, which were used for the parameter estimation, and do not violate underlying model assumptions, can be quite useful (Montgomery et al. 2015, p.136), Hence we must check whether the fitted model is able to capture all available information and describes the data in an adequate way. In most statistical modeling approaches, this is generally done by an analysis of the *residuals*, which result from the differences between the *observations* and the *fitted values* (Chatfield and Xing 2019, p.107), as illustrated in equation 3.29 below.

$$e_t = y_t - \hat{y}_{t|t-1} \tag{3.29}$$



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The fitted values, denoted by $\hat{y}_{t|t-1}$, are the forecasts of $y_t$ which are based on all previous observations of a time series ($y_1 \ldots y_{t-1}$) and represent in most cases one-step ahead forecasts. However, fitted values are usually not true forecasts, because all observations, including future observations, are used for the estimation of the parameters of a corresponding time series model. Furthermore, we can state that the residuals $e_t$ represent what is left after fitting a model to a time series. If a transformation has been used in the modeling approach, we generally look at the residuals on the transformed scale. In this case, the residuals are designated as *innovation residuals*, however, if no transformation has been used, they are identical to the regular residuals (Hyndman and Athanasopoulos 2021, p.115). The (innovation) residuals of a good forecasting method generally have the following properties:

**1.** The (innovation) residuals are uncorrelated (no autocorrelation), otherwise there would be some information left which should be used for forecasting.

**2.** The (innovation) residuals have a mean of zero, otherwise the forecasts would be biased (Hyndman and Athanasopoulos 2018, p.59).

Generally, any forecasting method which violates these two conditions can be improved. However, this does not mean that forecasting methods, which fulfill the stated conditions, cannot be improved anymore. Additionally, two further conditions for the residuals can be stated, which are useful but generally not necessary:

**3.** The (innovation) residuals show a constant variance, which is also know as *homoscedasticity*.[25]

**4.** The (innovation) residuals are approximately normal distributed (Hyndman and Athanasopoulos 2018, p.59).

A modeling approach that doesn't fulfill conditions three and four cannot necessarily be improved, although their fulfillment makes the calculation of prediction intervals easier. In some cases, a Box-Cox transformation might be helpful to fulfill these conditions (see section 3.3.4). In other cases, more elaborative approaches like *bootstrapping* have to be applied for the calculation of prediction intervals (Hyndman and Athanasopoulos 2021, p.126-129).

To get a better understanding of residual analysis, an example based on the ARIMA (3,0,0)(0,1,1)[12] model which has been fitted to the monthly new passenger car registrations (NPCR) of BMW in the EU14, the EFTA and the UK,

[25] The opposite, i.e. a change in the variance in a time series is also known as *heteroscedasticity*.

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is illustrated in figure 3.7. The model has been fitted to the time series data from Jan/2001-Dec/2018, the rational for this will be explained in the next section

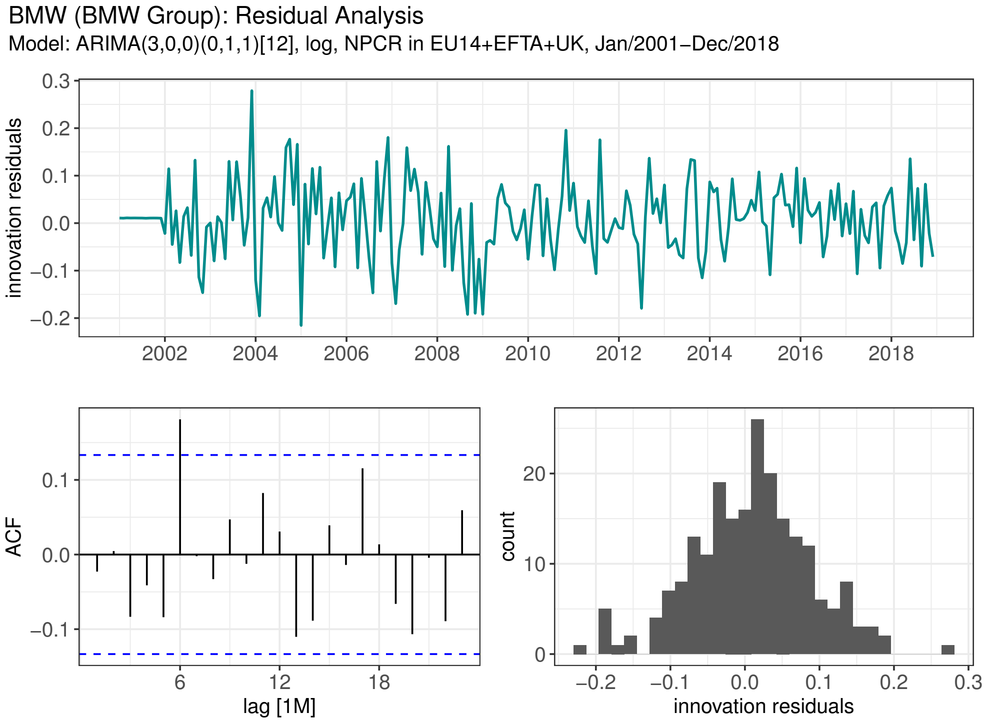


Figure 3.7: BMW: NPCR, Residual Analysis, ARIMA(3,0,0)(0,1,1)[12], log
Data Source NPCR: (ACEA 2021f), (ACEA 2022b)

3.5.5 Evaluating Forecast Accuracy. Since a natural logarithmic transformation has been used in the modeling approach, we must look at the innovation residuals. The resulting series of the innovation residuals of the fitted seasonal ARIMA model, an ACF plot and a histogram of the innovation residuals is depicted in figure 3.7. The illustrated graphs indicate that the selected model captures most of the available information. We have a mean of the innovation residuals of approximately zero and the ACF plot suggests that we have almost no significant autocorrelation in the series of residuals, except for one significant spike at lag 6. Additionally, we can observe an approximate constant variance in the histogram and the time plot of the residuals, except for some outliers. The assumption of a normal distribution for the calculation of the prediction intervals can therefore be considered as reasonable.

### 3.5.4.1 Portmanteau Tests for Autocorrelation

In the BMW example, stated in figure 3.7, we looked at the ACF plot of the innovation residuals to see whether the spikes are within the required boundaries. In doing so, we implicitly conducted multiple hypothesis tests. Each of these

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hypothesis tests, however, has a small probability of giving a false positive. Hence, if the number of tests we are doing is increasing, the probability that at least one of these tests gives a false positive is rising. We could assume therefore that the residuals contain significant autocorrelation, when they do not (Hyndman and Athanasopoulos 2021, pp.120-121). To overcome this problem, *portmanteau tests* state a more formal statistical test for autocorrelation, by looking at the first $l$ autocorrelation coefficients as a whole, to indicate whether the model is appropriate or not Box et al. (2016, p.121). The *Ljung-Box test*[26] (Ljung and Box 1978) is a well-known portmanteau test, which is depicted below in equation 3.30:

$$Q^* = T(T+2)\sum_{k=1}^{l}(T-k)^{-1}r_k^2 \tag{3.30}$$

where $T$ defines the number of observations, $l$ represents the maximum lag which is considered, and $r_k$ is the autocorrelation coefficient at lag $k$. Hyndman and Athanasopoulos (2021, p.121) suggest a value for $l = 10$ for non-seasonal data and a value of $l = 2m$ for seasonal data, where $m$ defines the period of seasonality.

If the model is inappropriate, the null hypothesis, that the series of (innovation) residuals can be considered as white noise, is rejected. Hence some $r_k$ have a big positive or negative value, which results in a large value of $Q^*$. However, if the fitted model is appropriate, in a sense that the null-hypothesis cannot be rejected, each $r_k$ has a small value close to 0, and $Q^*$ will be small. In this case, it is possible to show that $Q^*$ has approximately a $\mathcal{X}^2$-distribution with $(l - K)$ degrees of freedom, where $K$ represents the number of parameters of the model (Hyndman and Athanasopoulos 2021, p.121). Therefore, we are looking for evidence that the null hypothesis can be rejected, indicated by a small p-value (e.g. $< 0,05$). The ARIMA (3,0,0)(0,1,1)[12] model of the BMW example has a non-seasonal AR(3) components and a seasonal MA(1) component, so the number of parameters $K = 4$. Since we have seasonal data, the maximum lag which is considered is set to $l = 2 \cdot 12 = 24$, which results in 20 degrees of freedom. By conducting the Ljung-Box test in R[27], we get a p-value of 0,101 (p $\geq 0,05$), which indicates that the null hypothesis cannot be rejected, so the series of innovations residuals is most probably white noise. In other words, the SARIMA model of BMW captures most probably all information, at least in reference to the Ljung-Box test.

[26] The Ljung-Box test is closely related to another well-known portmanteau tests, the so-called *Box-Pierce test* (Box and Pierce 1970).

[27] The Ljung-Box test was conducted in R by the usage of the augment() and the features() function, with lag = 24 and dof = 4. The functions are part of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

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### 3.5.5 Evaluating Forecast Accuracy

However, good model validation should go beyond measurements of the fit for the historical time series data, which have been discussed in the previous section 3.5.4. Hence, the magnitude of the (innovation) residuals is not a good indicator for the size of the true *forecast errors* (Hyndman and Athanasopoulos 2018, p.64). More meaningful for the evaluation of the forecast accuracy is the magnitude of the forecast errors, which refer to data that haven't been used for the fitting process of the model (Montgomery et al. 2015, p.15). As to compare different models, the out-of-sample performance is generally evaluated by dividing the available data into two different sets - *training data*, which are used for the fitting process of the model, and *verification data* which are used for the evaluation of the forecast accuracy. Since the verification data have not been used in the model fitting process, this approach is providing a good indication of how well the model is forecasting in comparison to new data (Hyndman and Athanasopoulos 2018, p.64).

Following this, the forecast errors can be defined as the differences between the forecasts, based on a model which has been fitted to the training data, and the observations of the verification data, as stated in equation 3.32 below (Hyndman and Athanasopoulos 2018, p.66):

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T} \tag{3.31}$$

where $\{y_1, \dots, y_T\}$ defines the training data, $\{y_{T+1}, y_{T+2}, \dots\}$ represents the verification data, and $\hat{y}_{T+h|T}$ are the h-step forecasts of the model, which has been fitted to the training data. In summary, the following differences between (innovation) residuals and forecast errors can be stated. The (innovation) residuals are calculated from the training data and are based on one-step-ahead forecasts. On contrary, forecasts errors are calculated from the verification data and refer generally to h-step forecasts (Hyndman and Athanasopoulos 2021, p.136).

Furthermore, we can distinguish between *scale-dependent* errors, such as the *mean absolute error* (MAE) or the *root mean squared error* (RMSE), and *percentage errors*.[28] The general percentage error is defined as $p_t = 100e_t/y_t$, where $e_t$ designates the forecast error at time t and $y_t$ represents an observed value at time $t$, both with reference to the verification data set. For the evaluation of

[28]The interested reader can find a detailed description of a variety of scale-dependent and percentage errors in Montgomery et al. (2015, pp.64-74) or Hyndman and Athanasopoulos (2021, pp.137-141).

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forecast accuracy in this thesis, the *mean absolute percentage error* (MAPE) was used, which is defined as follows (Hyndman and Athanasopoulos 2021, p.137):

$$MAPE = mean(|p_t|) \tag{3.32}$$

The evaluation of the forecast accuracy of the BMW example is stated in figure 3.8. Panel one at the top of figure 3.8 depicts the training data set (Jan/2001-Dec/2018) of BMW's monthly new passenger car registrations (NPCR) in the EU14, the EFTA, and the UK, which has been used for fitting the ARIMA (3,0,0)(0,1,1)[12] model. The left part of panel two, at the bottom of figure 3.8, depicts the pre-Covid-19 verification data (Jan/2019-Dec/2019), which have been used for the evaluation of the forecast accuracy. In the BMW example, the corresponding average MAPE in reference to the verification data (Jan/2019-Dec/2019) is 6,69%, while in general, a MAPE < 15% has been considered as

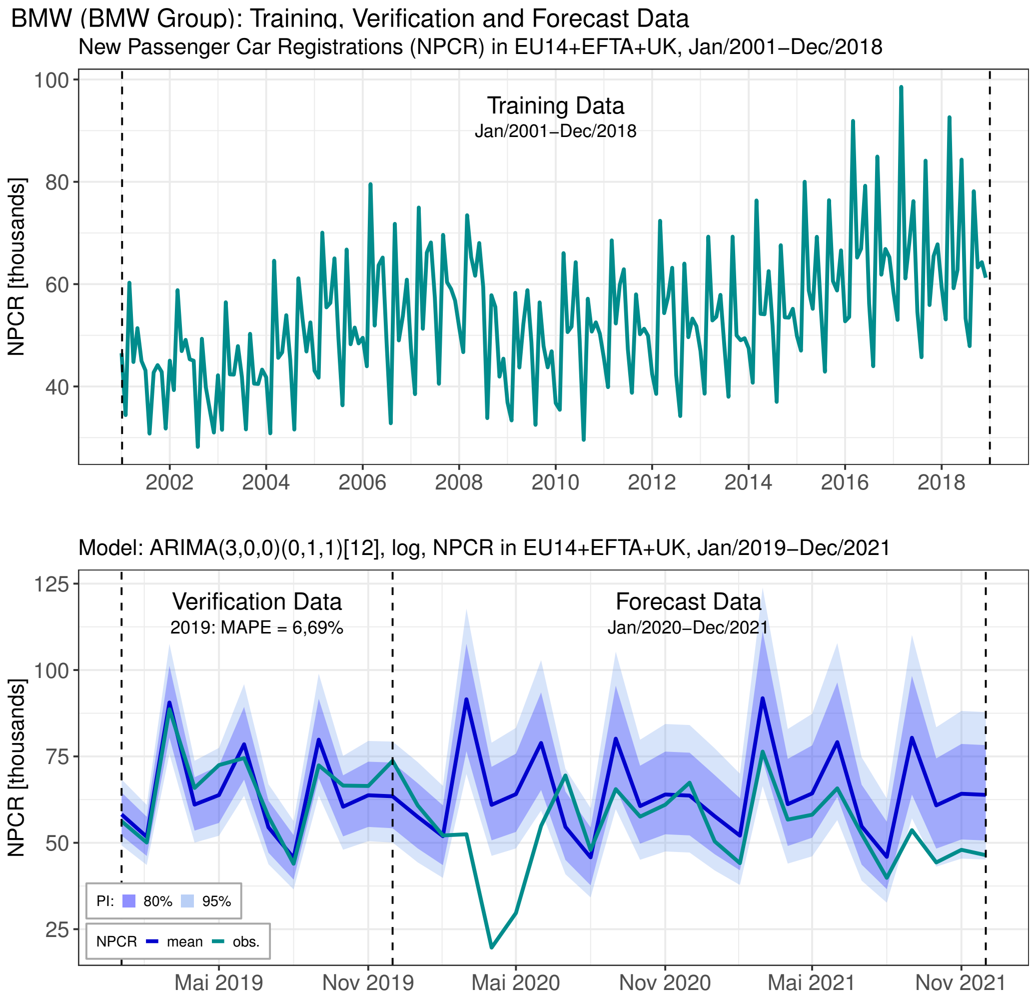


Figure 3.8: BMW: NPCR, Training, Verification and Forecast Data
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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acceptable. Additionally, the left part of panel two, illustrates the forecasting horizon (Jan/2020-Dec/2021), in which Covid-19's impact on new passenger car registrations in Europe will be evaluated for a variety of countries and other OEMs in the numerical studies of chapter 4.

Yet, to evaluate the effects of the Covid-19 pandemic and resulting after-effects on new passenger car registrations (NPCR) adequately, the establishment of a good baseline NPCR forecast for each country and OEM is required. To establish these baseline forecasts, suitable time series models will be fitted in R to datasets of the ACEA - for NPCR by countries (ACEA 2021e) and by manufacturers ((ACEA 2021f) in Europe - for a specified pre-Covid time-frame. However, as mentioned in section 3.1 of this chapter, a variety of time series models exist like Autoregressive Integrated Moving Average (ARIMA) models, Autoregressive Conditional Heteroskedasticity (ARCH and GARCH) models, Geometric Brownian Motion (GBM) models, and Exponential Smoothing and related innovations state-space models (ETS), while each method has different properties, accuracies, advantages, and disadvantages. Hence, it is required to fit several time series models, select the best fitting one, and evaluate its forecast accuracy. In the next step, the model with the best forecasting accuracy will be used as a baseline forecast evaluating the quantitative Covid-19 impact on NPCR for a corresponding country or OEMs, as will be explained in the following chapter 4 of this thesis in more detail.

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# 4 Numerical Studies

The following chapter is concerned with the evaluation of the quantitative impact of Covid-19 and resulting after-effects on European new passenger car registrations (NPCR) in relation to the research questions, stated in section 1.2. The first section 4.1 gives a summary of the approach which was used for the evaluation, in connection with the theory of time series analysis and forecasting, presented in chapter 3. Following this, sections 4.2 and 4.3 are dedicated to the quantitative evaluation of Covid-19's impact on European NPCR by countries and by OEMs respectively, which will be measured against the pre-Covid-19 time series variability exhibited in the automotive industry.

## 4.1 Covid-19 NPCR Impact Evaluation

It is required to establish a clear baseline for the quantitative evaluation of the impact of Covid-19 and resulting after-effects on European new passenger car registrations. As to establish this baseline suitable time series models (SARIMA models) have been fitted in R to datasets of the ACEA - for NPCR by country (ACEA 2021e) and by manufacturer (ACEA 2021f) in Europe - for a specified pre-Covid time-frame (Jan/2003-Dec/2018 for countries, Jan/2001-Dec/2018 for manufacturers). In many of the investigated time series, the variance of the seasonal pattern appears to increase approximately proportional with the level of the series, which indicates an appliance of a logarithmic transformation for the stabilization of the variance of the seasonal pattern (see 3.3.4). Following this, generally, four different types of models have been originally considered:

1. Seasonal ARIMA models
2. Seasonal ARIMA models with a log-transformation
3. Exponential Smoothing models
4. Exponential Smoothing models with a log-transformation

Seasonal ARIMA models (with and without log-transformation) however, showed in almost all cases better results than Exponential Smoothing models in forecasting European NPCR by country and by OEM. Following this, further focus was placed on SARIMA models.

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The fitting of the Seasonal ARIMA(p,d,q)(P,D,Q)[12] models (see section 3.4.4.2) to the pre-Covid-19 training data was conducted in R by the usage of the ARIMA() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b). The ARIMA() function is based on variations of the Hyndman-Khandakar algorithm (Hyndman and Khandakar 2008), in which a combination of unit root tests and the minimization of the AICc (see section 3.5.3) and MLE (see section 3.5.2) is conducted to obtain an ARIMA model (Hyndman and Athanasopoulos 2021, p.285). The algorithm employs a stepwise search to traverse the model space, rather than taking account for every possible combination of p, q, P, and Q, and includes approximations to speed up the model search. However, it is possible that the minimum AICc model might not be found by using these approximations and the stepwise search. So options to avoid the approximations and the stepwise search, as to traverse a much larger model space, are provided (Hyndman and Athanasopoulos 2021, pp.285-287).[1] Most of the best fitting models for forecasting European NPCR of different countries and OEMs have been found with the option to avoid the approximations and the stepwise search.

The integrated selection of the right number of regular and seasonal differences (d,D) in the ARIMA() function is based on repeated unit root tests, (test for seasonal strength, KPPS-test, see section 3.3.5.3). From here on the orders of the non-seasonal AR and MA components (p,q) and of the seasonal AR and MA components (P,Q) of the model are chosen by a minimization of the AICc after the data have been D-times seasonally and d-times regularly differenced (see section 3.3.5.2), if appropriate (Hyndman and Athanasopoulos 2021, p.286). As a log-transformation has additinally been used to get a stationary time series, the forecasts on the transformed scale have been back-transformed in accordance with the bias-adjusted reversed Box-Cox transformation (see section 3.3.4). As a result, the point forecasts, in this case, represent approximations of the mean and not the median values, as for the models without a log-transformation. This has the advantage that the forecasts of the models which include a log-transformation are additive as well.

In the next step, the (innovation) residuals of the best fitting model of each approach were analyzed, as was explained in section 3.5.4. The observed series of (innovation) residuals were approximately normally distributed, with a mean close to zero and a roughly constant variance. Following this, prediction intervals

[1] The options to avoid the approximations and the stepwise search can be set by approximation=False and stepwise=False in the ARIMA() function (Hyndman and Athanasopoulos 2021, p.287).

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were calculated under the assumption of normally distributed NPCR, where the point forecast represents the mean of the corresponding distribution.[2] To check whether the series of (innovation) residuals contained remaining information (autocorrelation) which could be used for modeling, Ljung-Box tests (see section 3.5.4.1) were conducted for the best fitting models. In this context, the null hypothesis that the series of (innovation) residuals can be considered as white noise (i.e., contains no autocorrelation), was rejected for p-values $< 0,05$.

Apart from that, an evaluation of the forecast accuracy of the best fitting models was conducted, as stated in section 3.5.5. The evaluation of the forecast accuracy of the best fitting SARIMA model of each approach (with and without log-transformation) was evaluated in a pre-Covid-19 verification time frame (Jan/2019-Dec/2019), which has not been used for the fitting process of the model. The mean absolute percentage error (MAPE) was used as a measure for the forecast accuracy, while a MAPE $< 15\%$ has been considered acceptable. In a further step, the model with the lowest MAPE was then selected for forecasting European NPCR of a specific country or an OEM, in a specified post-Covid-19 time-frame (Jan/2020-Dec/2021). This approach then allows for an adequate evaluation of the quantitative Covid-19 impact on NPCR by countries and by OEMs through a comparison of the observed new passenger car registrations and the forecasted realization in the specified post-Covid time frame, as it will be presented next in sections 4.2 and 4.3.

## 4.2 Covid-19's Impact on NPCR in Europe by Countries

The following section is dedicated to the evaluation of the quantitative Covid-19 impact on NPCR in different countries of the EU27[3], the EFTA[4], and UK, based on the approach stated in section 4.1. The first section 4.2.1 gives an overview of the selected SARIMA models used for forecasting NPCR in the considered countries. Following this, section 4.2.2 states the results of the Covid-19 impact on NPCR for the considered countries in total and for each country, while a comparison of the results will be stated in section 4.2.3.

[2]Point forecasts and prediction intervals were generated in R with the forecast() and the hilo() function of the fable package (R 2021a), which is a sub-package of the tidyverse package (R 2021b).

[3]The member states of the EU27 are defined in the List of Abbreviations.

[4]The member states of the EFTA are defined in the List of Abbreviations.

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### 4.2.1 Countries: Selected Models for NPCR-Forecasting

The SARIMA models used for forecasting new passenger car registration (NPCR) in European countries, have been fitted and selected under the approach described in section 4.1. Based on datasets of the ACEA for monthly NPCR by country (ACEA 2021e), all countries of the EU27, the EFTA, and the UK were considered, for which data were available from Jan/2003-Dec/2021.[5] Following this, the best SARIMA model in reference to the MAPE, for each of the resulting 25 considered countries, is depicted in table 4.1. As stated in section 4.1, a MAPE $< 15\%$ has been considered as acceptable, which resulted in 21 countries being considered, and 4 countries that did not reach the target for the evaluation of Covid-19's impact on NPCR in the following sections 4.2.2 and 4.2.3.[6] The 21 selected countries depicted in table 4.1, cover most of the NPCR in the EU27, the EFTA and the UK, with an aggregate market share of 94,03% in the year 2021 (ACEA 2022a).

| Index | Country | FTA | Model | Trans. | p-value | MAPE |
|---|---|---|---|---|---|---|
| 1 | Spain | EU14 | ARIMA(3,1,0)(0,1,1)[12] | log | 0.014 | 3.85% |
| 2 | Poland | EU27 | ARIMA(2,1,1)(2,0,1)[12] w/ drift | - | 0.552 | 4.29% |
| 3 | Italy | EU14 | ARIMA(3,0,0)(0,1,2)[12] | - | 0.266 | 4.61% |
| 4 | Austria | EU14 | ARIMA(3,0,0)(0,1,2)[12] | - | 0.792 | 4.71% |
| 5 | United Kingdom | UK | ARIMA(2,0,2)(0,1,1)[12] | log | 0.058 | 5.03% |
| 6 | Finland | EU14 | ARIMA(3,0,0)(0,1,1)[12] | log | 0.973 | 5.07% |
| 7 | Portugal | EU14 | ARIMA(3,0,0)(0,1,1)[12] | - | 0.676 | 6.01% |
| 8 | Belgium | EU14 | ARIMA(0,0,3)(1,1,2)[12] w/ drift | - | 0.240 | 7.11% |
| 9 | Luxembourg | EU14 | ARIMA(2,0,0)(0,1,1)[12] | - | 0.319 | 7.50% |
| 10 | Switzerland | EFTA | ARIMA(3,0,0)(0,1,1)[12] | log | 0.102 | 7.61% |
| 11 | Czech Republic | EU27 | ARIMA(3,0,0)(0,1,2)[12] w/ drift | log | 0.168 | 8.06% |
| 12 | Slovakia | EU27 | ARIMA(0,1,4)(2,0,0)[12] | log | 0.185 | 8.46% |
| 13 | France | EU14 | ARIMA(3,0,2)(0,1,1)[12] | - | 0.116 | 8.63% |
| 14 | Germany | EU14 | ARIMA(2,0,2)(0,1,2)[12] | log | 0.317 | 10.38% |
| 15 | Netherlands | EU14 | ARIMA(1,0,1)(0,1,2)[12] | - | 0.983 | 10.38% |
| 16 | Greece | EU14 | ARIMA(0,1,1)(0,1,1)[12] | log | 0.240 | 11.44% |
| 17 | Lithuania | EU27 | ARIMA(2,1,2)(2,0,0)[12] | log | 0.023 | 11.57% |
| 18 | Denmark | EU14 | ARIMA(2,1,2)(2,0,0)[12] | log | 0.020 | 11.58% |
| 19 | Ireland | EU14 | ARIMA(2,0,2)(0,1,0)[12] | log | 0.165 | 13.31% |
| 20 | Norway | EFTA | ARIMA(5,1,0)(1,0,0)[12] | - | 0.175 | 13.87% |
| 21 | Estonia | EU27 | ARIMA(4,0,0)(0,1,1)[12] | - | 0.036 | 14.63% |
| 22 | Hungary | EU27 | ARIMA(2,1,1)(2,0,0)[12] | log | 0.103 | 16.87% |
| 23 | Sweden | EU14 | ARIMA(2,0,1)(0,1,1)[12] | log | 0.324 | 18.25% |
| 24 | Latvia | EU27 | ARIMA(1,0,3)(2,0,0)[12] w/ mean | log | 0.035 | 19.46% |
| 25 | Iceland | EFTA | ARIMA(3,0,2)(0,1,1)[12] | log | 0.064 | 23.00% |

Table 4.1: Countries: Selected Models for NPCR-Forecasting

For most of the models, it can be assumed that the available information which can be used for modeling is captured adequately since they have p-values in reference to the Ljung-Box test, which are significantly higher than 0,05. Only

[5] Slovenia was not considered because of a difference in the reported NPCR in the year 2020 of around 40% in reference to the ACEA reports (ACEA 2021e) and (ACEA 2022a).

[6] The results for Hungary, Sweden, Latvia and Iceland (MAPE $> 15\%$), which are not considered in the numerical studies of section 4.2.2 and 4.2.3, are stated in Appendix B.

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the models of Spain, Lithuania, Denmark, and Estonia show a p-value lower than 0,05, however, their corresponding MAPE is < 15%, which was decisive for the model selection.

### 4.2.2 Countries: Obs., Forecasts and Covid-Impact on NPCR

The following section deals with research question 1, depicted in section 1.2, regarding Covid-19's impact on European new passenger car registrations (NPCR) by the countries stated in table 4.1. First, the impact of Covid-19 and resulting after-effects on NPCR will be discussed on an aggregate basis for the 21 countries before the results of each country will be stated and compared. Hence, figure 4.1 below depicts the observed NPCR from Jan/2003-Dec/2021, based on datasets of the ACEA ((ACEA 2021e), (ACEA 2022a)) for the 21 countries in total. The data which were used for the fitting of the SARIMA models (Jan/2003-Dec/2018), the verification data (Jan/2019-Dec/2019), as well as the forecast horizon (Jan/2020-Dec2021) are separated by the respective dotted vertical lines.

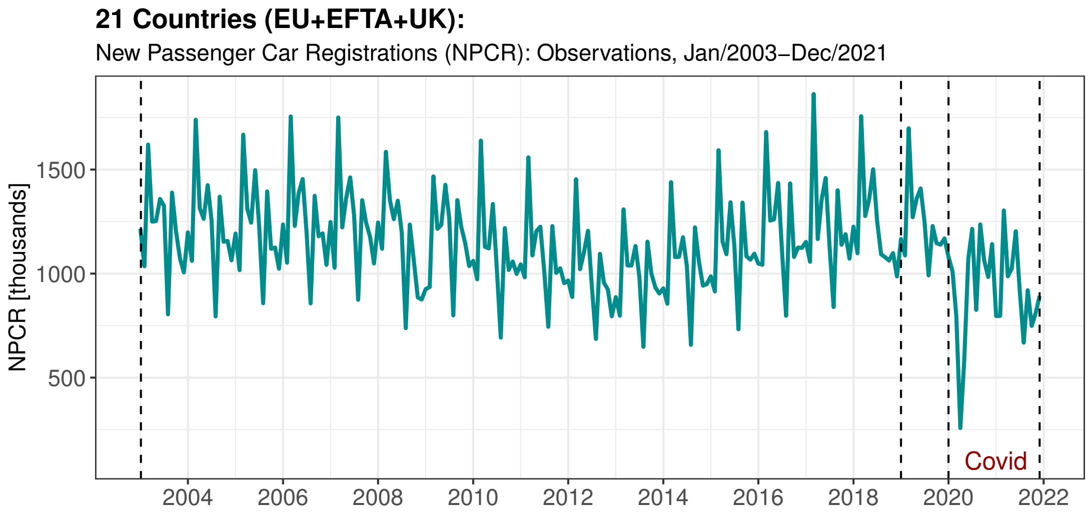


Figure 4.1: All 21 Countries, NPCR: Observations, Jan/2003-Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

As can be seen from figure 4.1, the market for NPCR in the 21 countries in total is quite saturated. New passenger car registrations were quite stable between 2003 and 2007. From 2008 through 2013, the impact of the Financial Crisis (2008-2009) and the resulting European Debt Crisis (2010-2013) is clearly visible, as well as the following recovery phase from 2014 through 2017. Beyond that, a beginning downward cycle in pre-Covid 2018 can be seen, as already noted earlier in section



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2.4 of this thesis. Additionally, the Covid-19 impact at the beginning of 2020 through 2021 is obvious, as depicted in figure 4.2 in more detail.

Figure 4.2 states the observed and the forecasted NPCR values of all 21 countries in total, while the data are illustrated for the verification time frame (Jan/2019-Dec/2019) with a corresponding MAPE of 5,53%, and for the forecast horizon (Jan/2020-Dec2021) in which the Covid-19 impact and resulting after-effects are evaluated.[7] The Covid-19 impact on NPCR in the forecast horizon is represented by the gap between the observed values (obs.) and the corresponding NPCR point forecasts (mean), which represent the mean of the assumed normal distributions. Additionally, the associated 80% and 95% prediction intervals (PI) are represented by the shaded light blue areas in figure 4.2. As illustrated in figure 4.2, the mean values of the NPCR forecasts for the verification time frame (Jan/2019-Dec/2019) are very close to the observed NPCR data (MAPE = 5,35%). Beyond that, the Covid-19 impact in spring 2020 is obvious since the observed NPCR values are well outside the lower end of the 95% prediction interval. After a strong recovery, the mean values of the NPCR forecasts are more or less at par with the observed NPCR values in the second half of 2020. However, in 2021, the observed NPCR values dropped below the mean values of the NPCR forecasts again and settled in the lower end of the 80% prediction interval.

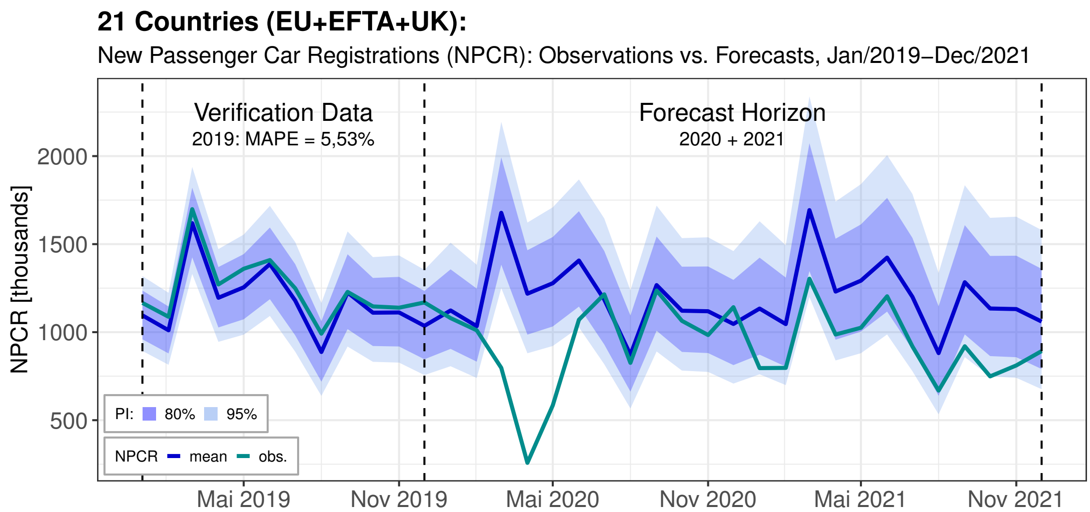


Figure 4.2: All 21 Countries, NPCR: Obs. vs. Forecasts, Jan/2019-Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

An evaluation of the Covid-19 impacts on European NPCR of the 21 countries, in absolute and percentage terms, is depicted in figures 4.3 and 4.4. In this con-

[7]The forecasted NPCR and the respective prediction intervals (PI) in figures 4.2, 4.3 and 4.4, result from the sum of the corresponding values of the individual models for the 21 countries.

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text, the expressions absolute (abs.) mean difference and percentage (per.) mean difference can be understood as follows: the abs. mean difference denotes the difference between an observed NPCR value in a given month and the corresponding forecasted mean value (obs. - mean), while the per. mean difference refers to the difference between an observed NPCR value and the forecasted mean value expressed as a percentage of the observed NPCR values (obs. - mean)/obs. in a certain month. A positive per. mean difference can therefore be considered as a percentage increase of the observed NPCR values in relation to pre-Covid-19 time series variability, while a negative value denotes a related decrease in observed NPCR.

With reference to figures 4.3 and 4.4, the impact of Covid-19 on NPCR in spring 2020, is clearly visible in absolute and percentage terms. It is suggested, that the spread of the virus and related lockdowns and containment measures contributed in March 2020 to a steep drop in NPCR, which reached its trough in April 2020 with a decline of -372,9% or -960'734 NPCR in relation to pre-Covid-19 time series variability. After this severe impact, a strong recovery phase can be noticed, up to a slight increase of 2,4% or 29'646 NPCR in July 2020. In the rest of 2020, the abs. and per. mean differences are slightly in the negative range, while a further plus of 8,4% or 95'524 NPCR, in relation to pre-Covid-19 time series variability, can be seen in December 2020. Yet, as it has been suggested by the analysis in section 2.3, the fast recovery in demand and the slower recovery of production capacities led to significant supply-demand mismatches in the global economy and especially in the automotive industry in the year 2021. In particu-

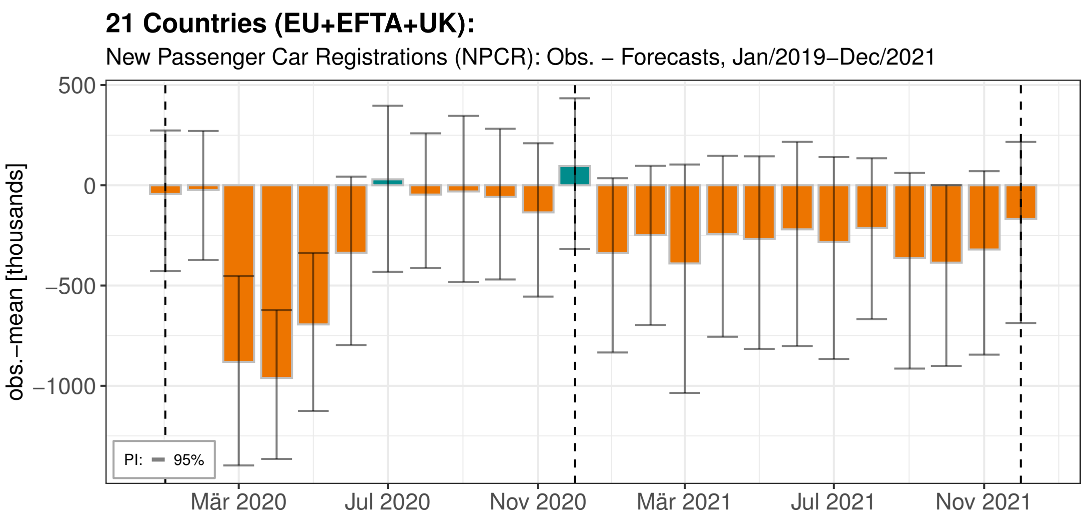


Figure 4.3: All 21 Countries, NPCR: Abs. Mean Differences, Jan/2020- Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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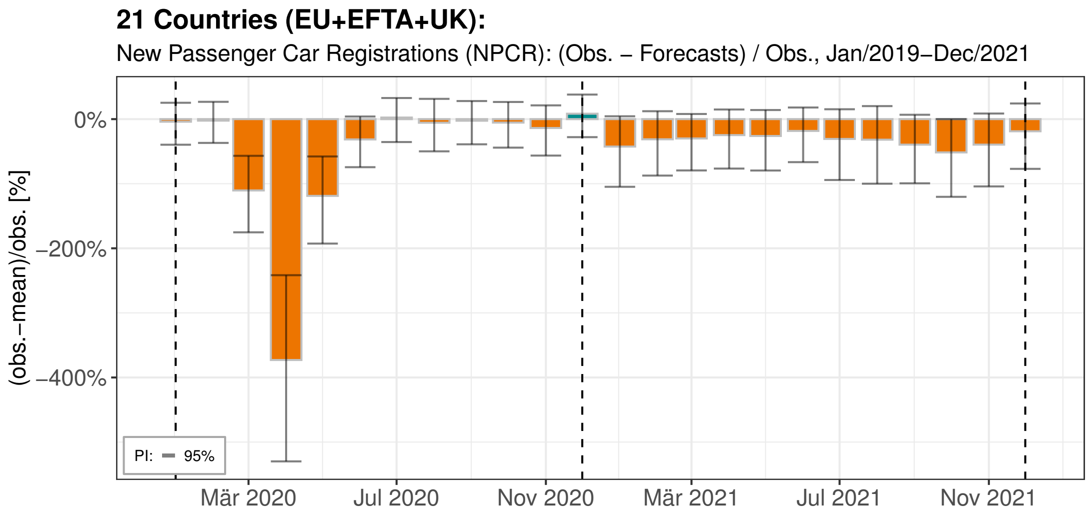


Figure 4.4: All 21 Countries, NPCR: Perc. Mean Differences, Jan/2020-Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

lar, the semiconductor shortages drastically intensified in the second half of 2021 and put strong downward pressure again on an already struggling automotive sector (OECD 2021a, pp.17-20). The suggested effects of the Covid-19 related semiconductor shortages in 2021 are visible as well in figure 4.3 and 4.4. Starting from a decrease in observed NPCR of -42.5% or -338'174 units in January 2021, compared to the forecasted aggregate mean values of the 21 European countries, the situation eased slightly by June 2021 with respect to the proposed evaluation approach. However, as shown in figures 4.3 and 4.4, the situation deteriorated again in the second half of 2021, with a maximum drop in NPCR of -51,5% or -385'705 units in October 2021, which can be related to the intensifying semiconductor shortages. By the end of the year the situation eased again slightly but it was still clearly in the negative range with differences of -18,8% or -167'701 NPCR in December 2021, compared to Pre-Covid-19 time series variability.

In the following, the evaluation of the Covid-19 impact on new passenger car registrations (NPCR), measured against pre-Covid-19 time series variability for each of the 21 considered countries, will be presented in figures 4.5 - 4.11. With regards to the described Covid-19 impact on NPCR for the 21 countries in total, the figures for the single countries can be read as follows: panel A of each figure illustrates the observed NPCR values based on datasets of the ACEA ((ACEA 2021e), (ACEA 2022a)) for a respective country. In this context, the data which were used for the fitting of the SARIMA models (Jan/2003-Dec/2018), the verification data (Jan/2019-Dec/2019), as well as the forecast horizon (Jan/2020-Dec2021) are separated by the respective dotted vertical lines.

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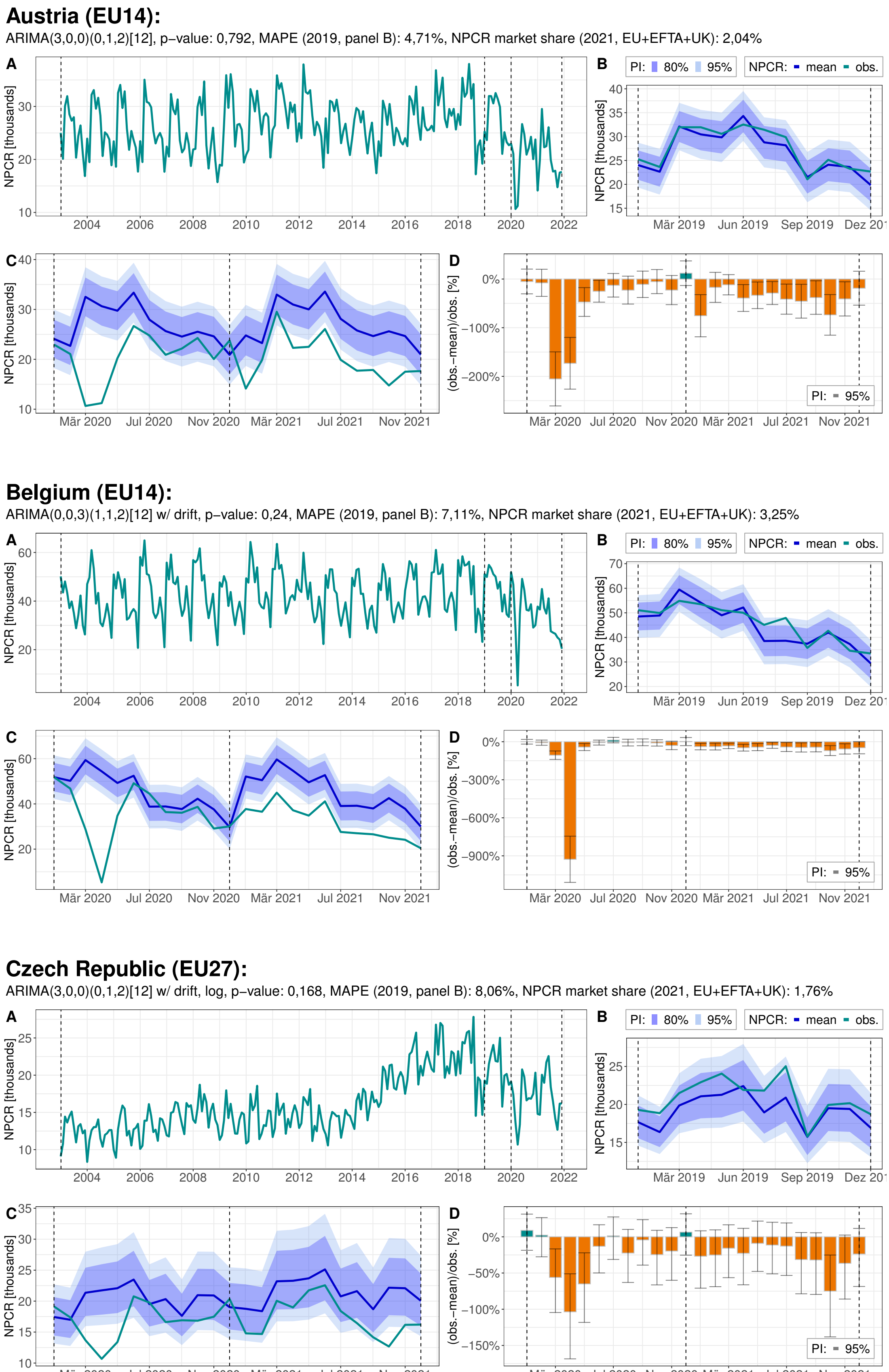


Figure 4.5: Covid-19's Impact on NPCR: Austria, Belgium, Czech Republic
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)



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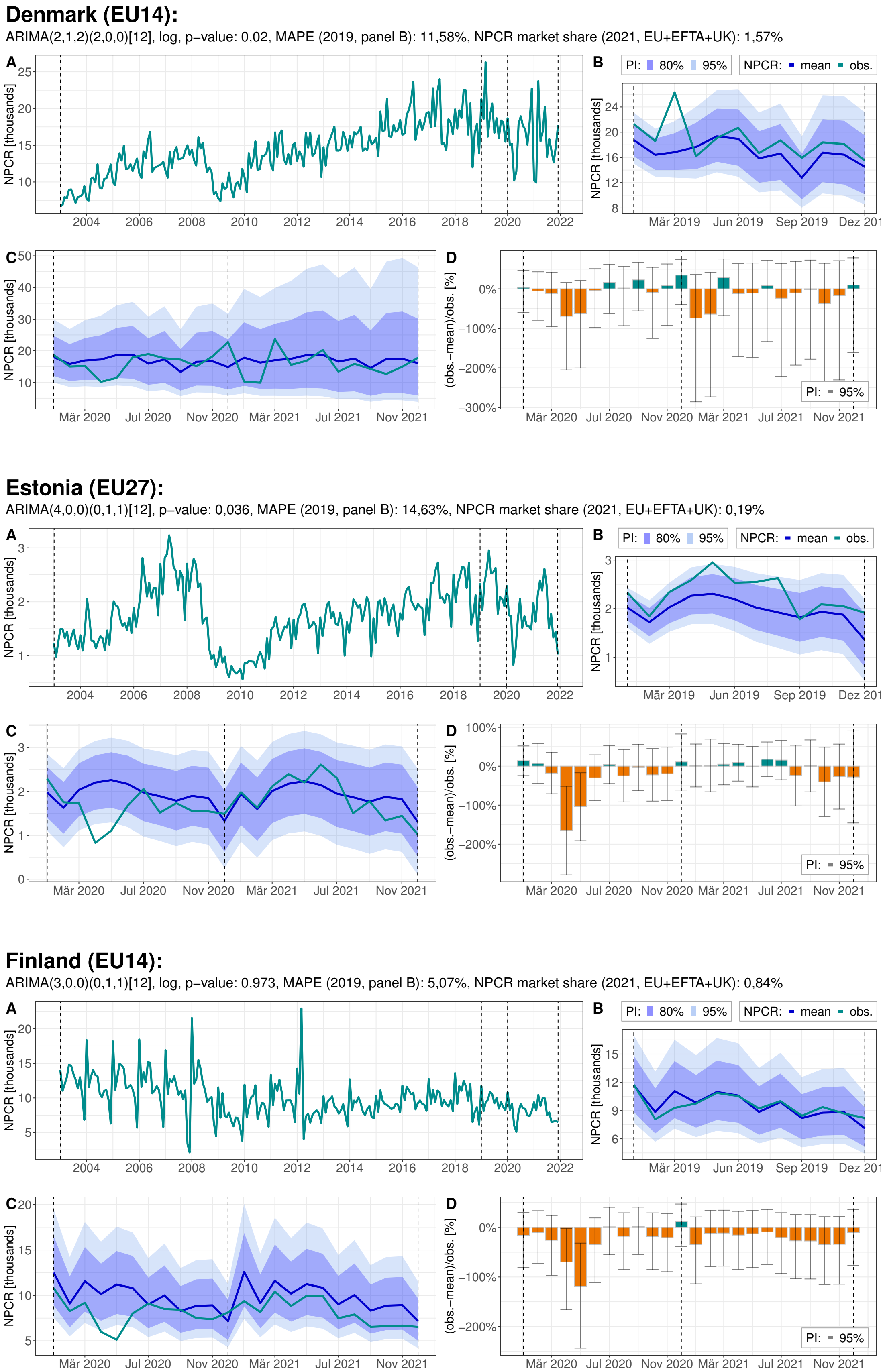


Figure 4.6: Covid-19's Impact on NPCR: Denmark, Estonia, Finland
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)



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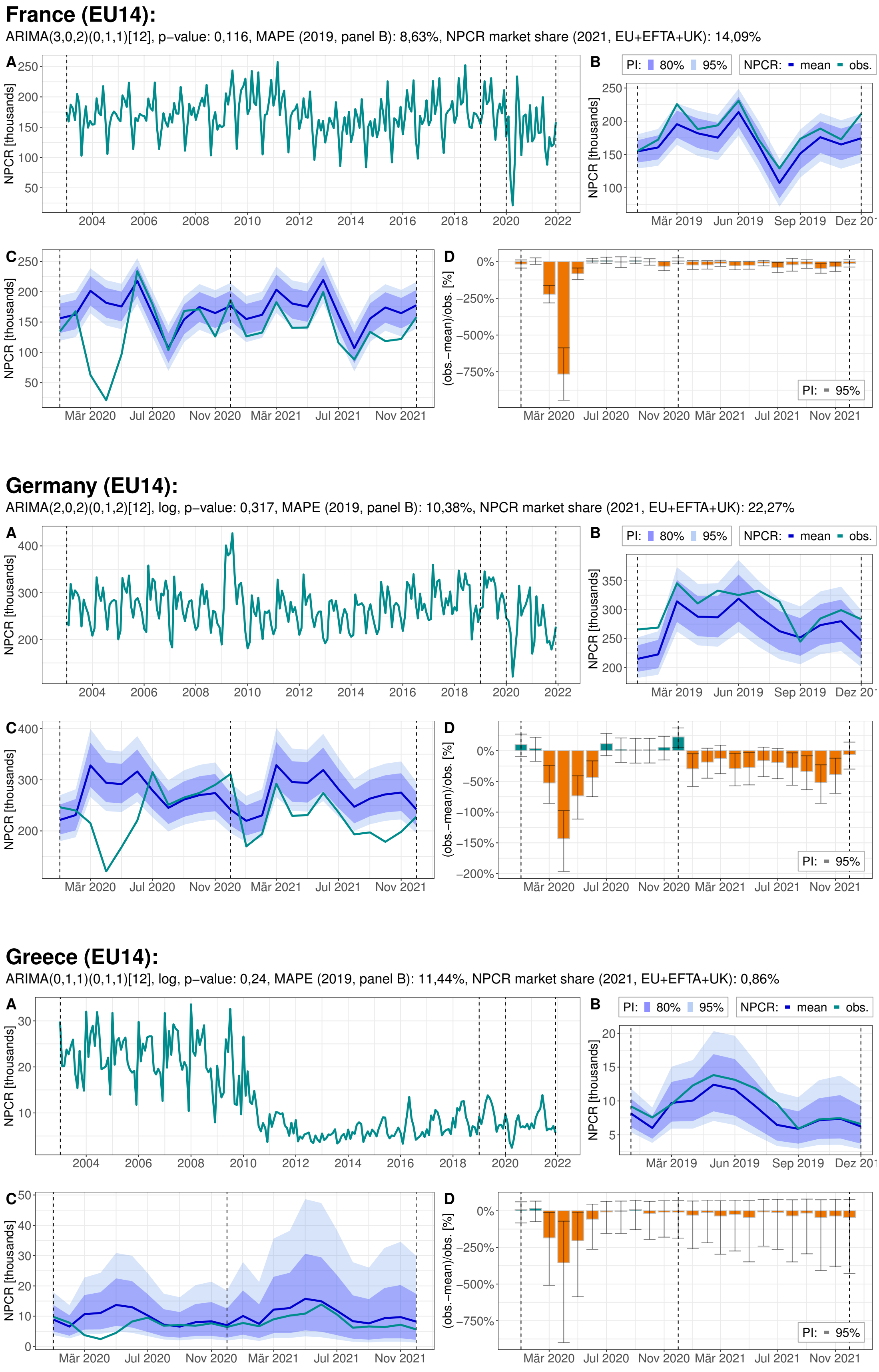


Figure 4.7: Covid-19's Impact on NPCR: France, Germany, Greece
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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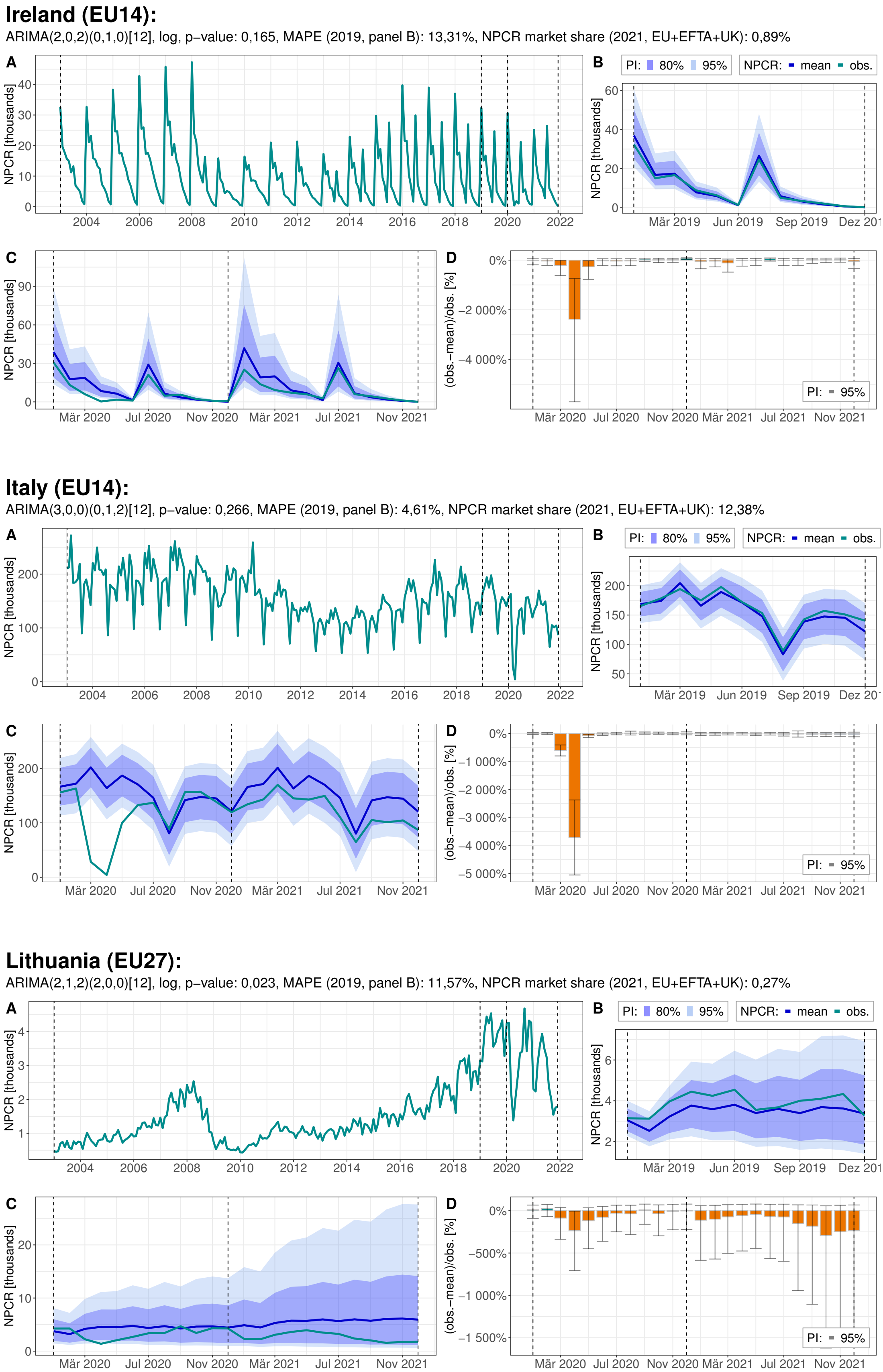


Figure 4.8: Covid-19's Impact on NPCR: Ireland, Italy, Lithuania
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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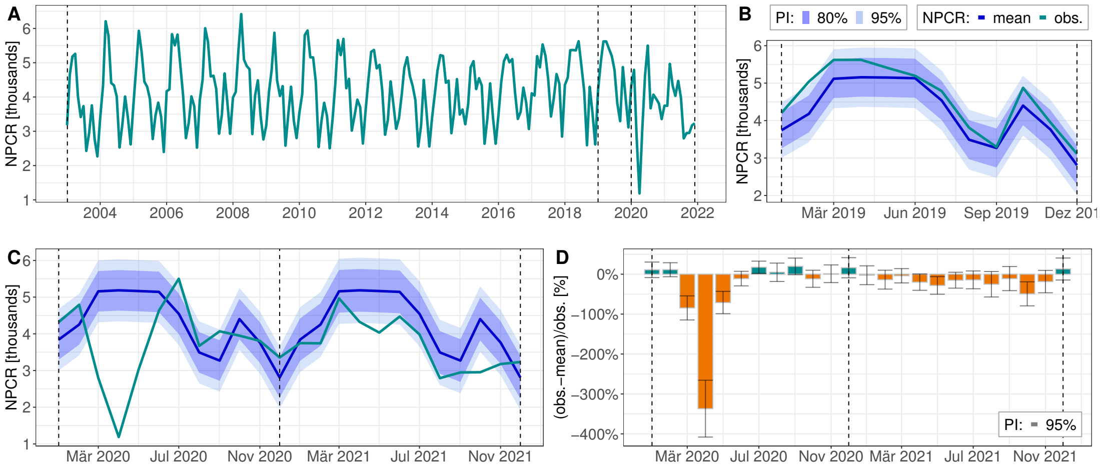
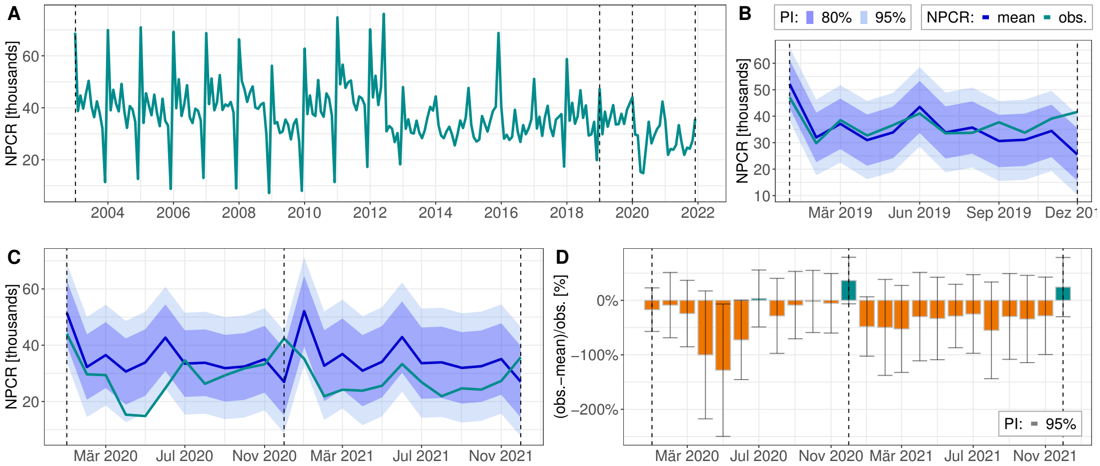
**Luxembourg (EU14):**

ARIMA(2,0,0)(0,1,1)[12], p–value: 0,319, MAPE (2019, panel B): 7,5%, NPCR market share (2021, EU+EFTA+UK): 0,38%




**Netherlands (EU14):**

ARIMA(1,0,1)(0,1,2)[12], p–value: 0,983, MAPE (2019, panel B): 10,38%, NPCR market share (2021, EU+EFTA+UK): 2,74%




**Norway (EFTA):**

ARIMA(5,1,0)(1,0,0)[12], p–value: 0,175, MAPE (2019, panel B): 13,87%, NPCR market share (2021, EU+EFTA+UK): 1,5%

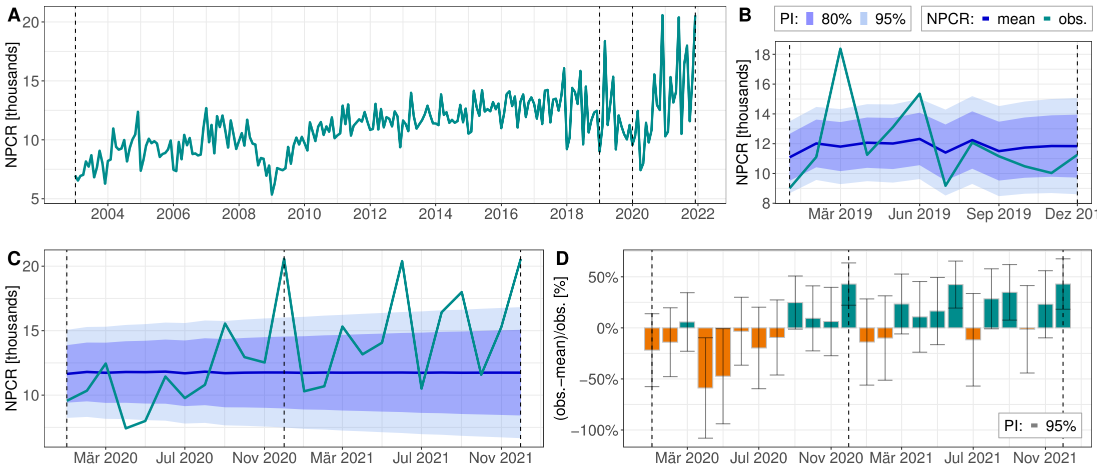



Figure 4.9: Covid-19's Impact on NPCR: Luxembourg, Netherlands, Norway
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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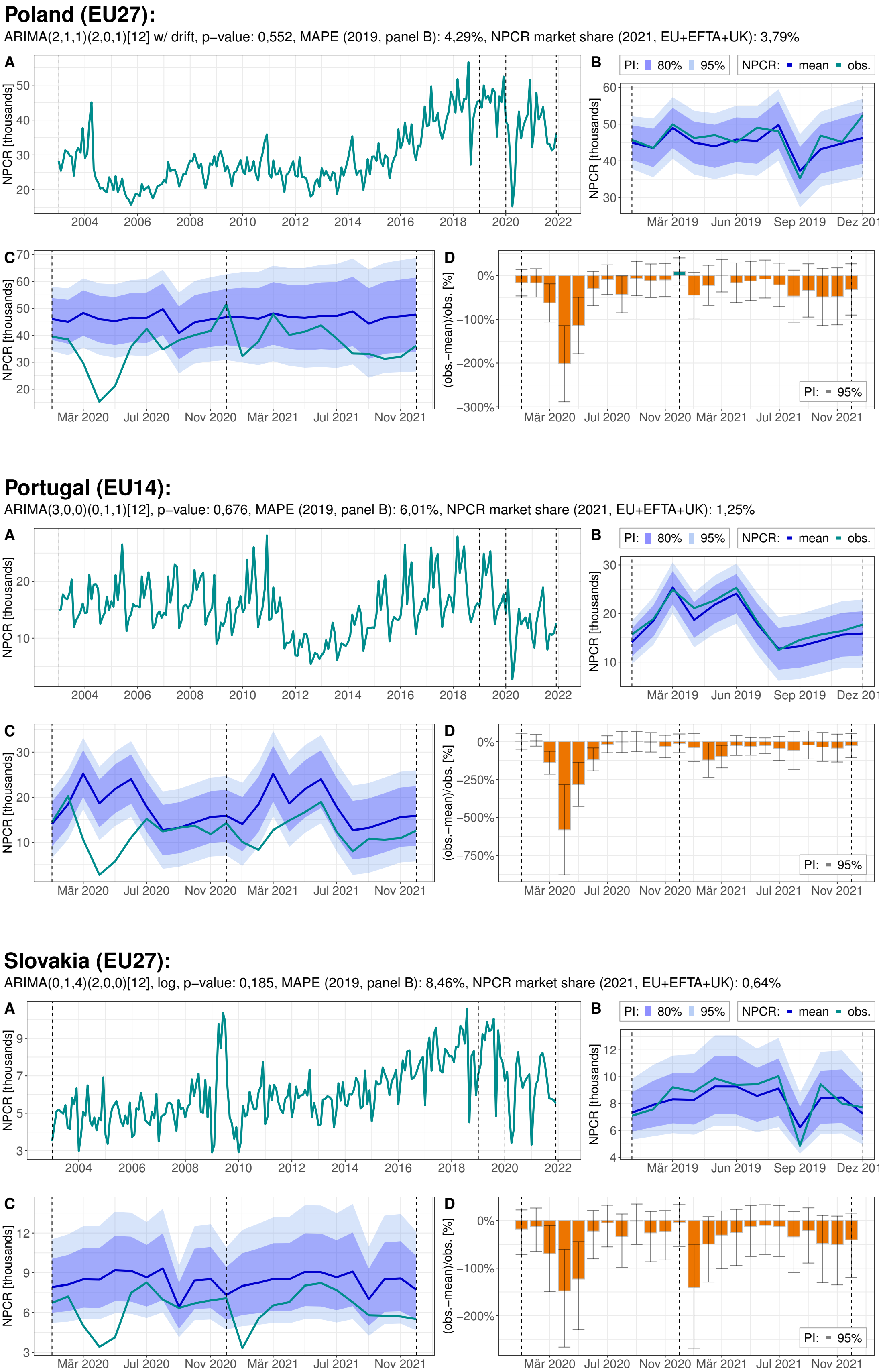


Figure 4.10: Covid-19's Impact on NPCR: Poland, Portugal, Slovakia
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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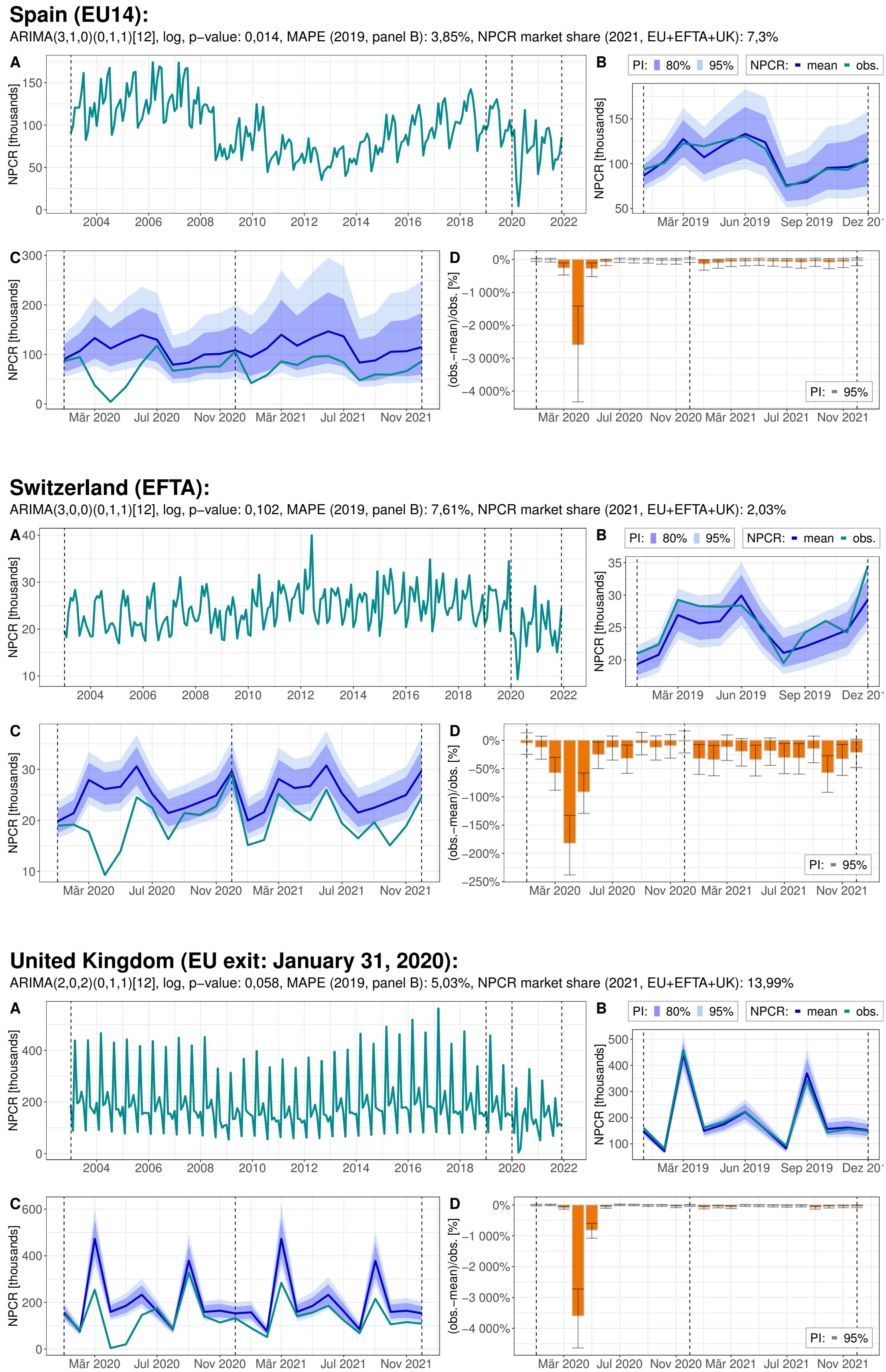


Figure 4.11: Covid-19's Impact on NPCR: Spain, Switzerland, United Kingdom
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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The comparison of the observed NPCR values and the forecasted values in reference to the verification time frame and the forecast horizon for each of the 21 countries are depicted in panels B and C respectively. Furthermore, the per. mean difference of the observed NPCR values and the forecasted mean values (obs. - mean)/obs., with the respective 95% prediction intervals are illustrated in panel D for each of the countries. Additionally, the best SARIMA model in reference to the MAPE, the p-value with regards to the Ljung-Box test, the corresponding MAPE, and the NPCR market share of a respective country in the EU27, the EFTA, and the UK in 2021, are stated in the caption at the top of each figure.

In reference to the analysis of section 2.3, it is suggested to consider the impact on NPCR in March, April, and May 2020 in relation to the Covid-19 induced macro-shock, followed by a recovery phase in the second half of 2020. Beyond that, the NPCR impact in 2021 can be observed concerning supply chain disruptions and related shortages and particularly in connection with the semiconductor shortages, which drastically intensified in the second half of 2021 (OECD 2021a, pp.17-20).

### 4.2.3 Countries: Comparison of Covid-Impact on NPCR

Based on the evaluation of the Covid-19 impact on NPCR for each country in figures 4.5 - 4.11, a comparison of the results will be provided in the following in relation to research question 2, stated in section 1.2. Following this, the countries will be compared in reference to their best and worst months, the number of positive and negative months, and their overall performance in relation to NPCR, measured against pre-Covid-19 time series variability.

#### 4.2.3.1 Countries: Worst and Best Months 2020 and 2021

First, a ranking of the worst and best months of the 21 European countries in 2020 and 2021, in reference to the Covid-19 impact on NPCR measured by the per. mean difference[8], is provided in figure 4.12. As can be seen from panel A of figure 4.12, almost all countries recorded their deepest Covid-19 impact on NPCR, in relation to pre-Covid-19 time series variability, in April 2020. According to the ranking, Italy shows the most severe impact with -3712,4% in April 2020, followed by the UK (04/20, -3592,2%) and Spain (04/20, -2587,3%). The per. mean

[8]See section 4.2.2 for an explanation of the per. mean difference. The following descriptions are related to the per. mean difference, however, the corresponding values of the 95% prediction intervals are stated in figure 4.12.

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difference in consideration of all 21 countries was -372,9% in April 2020, while Denmark (04/20, -68,9%) and Norway (04/20, -58,8%) show the lowest Covid-19 impact on NPCR in their worst month in 2020, in relation to the proposed evaluation approach. Panel B of figure 4.12 depicts the best month of each country in 2020 in reference to the per. mean difference. As illustrated, the values range from +73,4% for Ireland (12/20) and +42,9% for Norway (12/20) to -2,6% in Spain (12/20), which represents the worst-best month in 2020 in comparison to the other countries. The best month, considering all 21 countries in total, was in December 2020 with an increase of +8,4%, in relation to time series variability.

Beyond that, panel C states the ranking of the countries with regards to the worst month of the year 2021. As suggested by the analysis in section 2.3, the year 2021 was characterized by supply chain disruptions, and especially by semiconductor shortages in the automotive industry (OECD 2021a, pp.17-20). In this regard, Lithuania was affected most heavily with -292,2% in October 2021, followed by Slovakia (01/21, -141,0%) and Spain (01/2021, -125,9%). All 21 countries together recorded the highest impact in October 2021, with a decrease in NPCR of -51,5%, in relation to time series variability, while Finland (10/21, -34,2%) and Norway (01/21, -13,2%) showed the lowest worst impact in 2021. Finally, panel D of figure 4.12 refers to the best month of each country with regards to the per. mean difference. As can be seen, Ireland is ranked first with +49,1% in June 2021, followed by Norway (12/21, +42,9%) and Denmark (03/21, +28,3%), while the best month for all 21 countries in total was in June 2021 with a value of -18,3%. Furthermore, Spain with -33,1% in December 2021, and Lithuania with -45,1% in May 2021, are ranked in the lowest range.

#### 4.2.3.2 Countries: Positive and Negative Months 2020 and 2021

Table 4.2 states the number of positive and negative months of the 21 selected countries in reference to the proposed Covid-19 NPCR impact evaluation approach, stated in section 4.1. The results are illustrated in binary form and do not provide any information on the magnitude of the per. mean difference. Hence, a plus in the table designates a general increase in NPCR in relation to pre-Covid-19 time series variability, while a general decrease is denoted by a corresponding minus. In addition, the countries are ranked by the number of positive months in a year in descending order.

As illustrated in table 4.2, the effect of Covid-19 on NPCR is obvious for most of the countries from March 2020 through June 2020, except for the countries that were settled in the negative range even before the Covid-19 impact. However, the

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great part of the countries recovered at least to some extent in the second half of 2020, as it can be recognized by the pluses in that period. Overall, Germany performed best in the year 2020 with 8 positive months, followed by Luxembourg (7 pos.), Denmark (6 pos.), and Norway (5 pos.), while Slovakia, Spain, and Switzerland have performed worst with zero positive months, in reference to the proposed evaluation approach. In 2021, however, which was characterized by all kinds of shortages, and especially by semiconductors shortages, as it was suggested by the analysis presented in section 2.3, the situation looks different. In reference to figure 4.2, almost all countries, except for Norway, Estonia, Ireland Denmark, Luxembourg, and the Netherlands stayed completely in the negative range in 2021. It is interesting to see, however, that especially Norway and Estonia performed quite well with 8 and 7 positive months respectively in 2021.

#### 4.2.3.3 Countries: Overall Performance 2020 and 2021

The last comparison study of the 21 European countries is dedicated to the overall performance of each country in 2020, 2021, and over both years concerning NPCR measured by the per. mean difference.[9] Panel A of figure 4.13 depicts the overall performance of each country in 2020 ranked by the per. mean difference. As can be seen from panel A, out of the 21 European countries, only Norway records a slight increase of +0,2% of the observed NPCR in relation to pre-Covid-19 time series variability in 2020. All other countries are settled in the negative range, starting with -0,8% in Demark, followed by Germany with -11,5%, to countries with the most severe overall Covid-19 impact in 2020, like the UK with -46,4%, Ireland with -50,9% and Spain with -53,9% at the last rank. Furthermore, the impact of Covid-19 on all 21 countries in total has amounted to -27,4%, which demonstrates a decrease of 3’082’185 new passenger car registrations in the year 2020 in comparison to pre-Covid-19 time series variability exhibited in the European automotive industry. The impact of Covid-19 on NPCR in the year 2021 on the 21 considered European countries is depicted in panel B of figure 4.13. As in 2020, again only Norway shows a plus in the year 2021, however in comparison to 2020 a significantly higher one with +20,1%. The UK with -44,9% and Spain with -60,4% are again in the lowest range like in the year 2020, while Lithuania is at the last rank with a decrease of -115,2% in the year 2021, measured by the per. mean difference. All 21 countries on an aggregate basis recorded a

[9] See section 4.2.2 for an explanation of the per. mean difference. The following descriptions are related to the per. mean difference, however, the corresponding values of the 95% prediction intervals are stated in figure 4.13.

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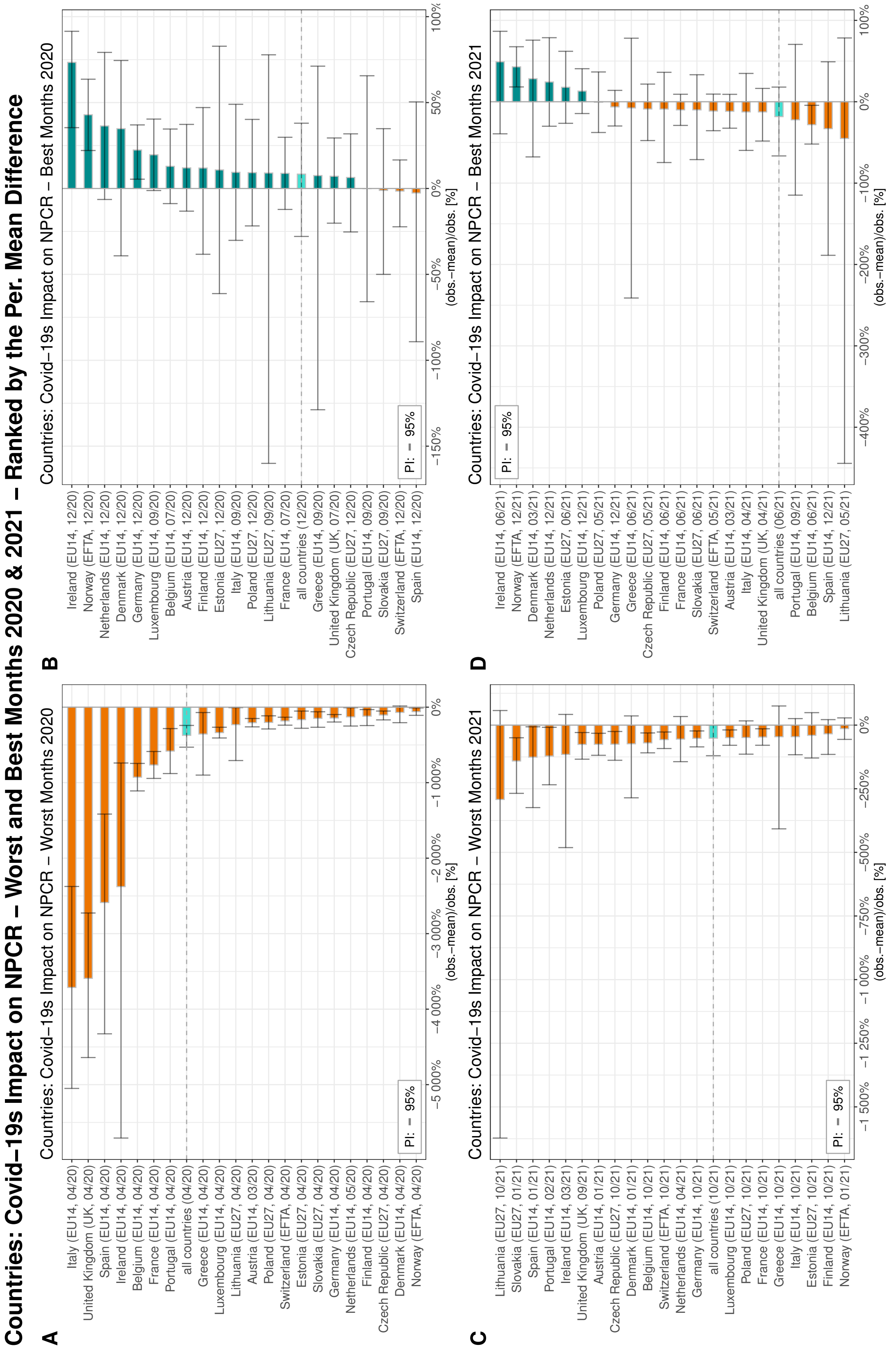


Figure 4.12: Countries, NPCR: Worst and Best Months, 2020, 2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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**2020**

| Index | country | FTA | 01/20 | 02/20 | 03/20 | 04/20 | 05/20 | 06/20 | 07/20 | 08/20 | 09/20 | 10/20 | 11/20 | 12/20 | pos. | neg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Germany | EU14 | + | + | - | - | - | - | + | + | + | + | + | + | 8 | 4 |
| 2 | Luxembourg | EU14 | + | + | - | - | - | - | + | + | + | - | + | + | 7 | 5 |
| 3 | Denmark | EU14 | + | - | - | - | - | - | + | + | + | - | + | + | 6 | 6 |
| 4 | Norway | EFTA | - | - | + | - | - | - | - | - | + | + | + | + | 5 | 7 |
| 5 | France | EU14 | - | + | - | - | - | + | + | - | + | - | - | + | 5 | 7 |
| 6 | Estonia | EU27 | + | + | - | - | - | - | + | - | - | - | - | + | 4 | 8 |
| 7 | Ireland | EU14 | - | - | - | - | - | - | - | - | + | + | + | + | 4 | 8 |
| 8 | Czech Republic | EU27 | + | + | - | - | - | - | + | - | - | - | - | + | 4 | 8 |
| 9 | Belgium | EU14 | + | - | - | - | - | - | + | - | - | - | - | + | 3 | 9 |
| 10 | Finland | EU14 | - | - | - | - | - | - | + | - | + | - | - | + | 3 | 9 |
| 11 | Greece | EU14 | + | + | - | - | - | - | - | - | + | - | - | - | 3 | 9 |
| 12 | Italy | EU14 | - | - | - | - | - | - | - | + | + | + | - | - | 3 | 9 |
| 13 | Lithuania | EU27 | + | + | - | - | - | - | - | - | + | - | - | - | 3 | 9 |
| 14 | United Kingdom | UK | - | + | - | - | - | - | + | + | - | - | - | - | 3 | 9 |
| 15 | all countries | - | - | - | - | - | - | - | + | - | - | - | - | + | 2 | 10 |
| 16 | Netherlands | EU14 | - | - | - | - | - | - | + | - | - | - | - | + | 2 | 10 |
| 17 | Portugal | EU14 | + | + | - | - | - | - | - | - | - | - | - | - | 2 | 10 |
| 18 | Austria | EU14 | - | - | - | - | - | - | - | - | - | - | - | + | 1 | 11 |
| 19 | Poland | EU27 | - | - | - | - | - | - | - | - | - | - | - | + | 1 | 11 |
| 20 | Slovakia | EU27 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 21 | Spain | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 22 | Switzerland | EFTA | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |

**2021**

| Index | country | FTA | 01/21 | 02/21 | 03/21 | 04/21 | 05/21 | 06/21 | 07/21 | 08/21 | 09/21 | 10/21 | 11/21 | 12/21 | pos. | neg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Norway | EFTA | - | - | + | + | + | + | - | + | + | - | + | + | 8 | 4 |
| 2 | Estonia | EU27 | + | + | + | + | - | + | + | - | + | - | - | - | 7 | 5 |
| 3 | Ireland | EU14 | - | - | - | - | - | + | - | - | + | + | + | - | 4 | 8 |
| 4 | Denmark | EU14 | - | - | + | - | - | + | - | - | - | - | - | + | 3 | 9 |
| 5 | Luxembourg | EU14 | - | - | - | - | - | - | - | - | - | - | - | + | 1 | 11 |
| 6 | Netherlands | EU14 | - | - | - | - | - | - | - | - | - | - | - | + | 1 | 11 |
| 7 | all countries | - | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 8 | Germany | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 9 | France | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 10 | Czech Republic | EU27 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 11 | Belgium | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 12 | Finland | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 13 | Greece | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 14 | Italy | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 15 | Lithuania | EU27 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 16 | United Kingdom | UK | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 17 | Portugal | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 18 | Austria | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 19 | Poland | EU27 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 20 | Slovakia | EU27 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 21 | Spain | EU14 | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 22 | Switzerland | EFTA | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |

Table 4.2: Countries, NPCR: Positive and Negative Months, 2020, 2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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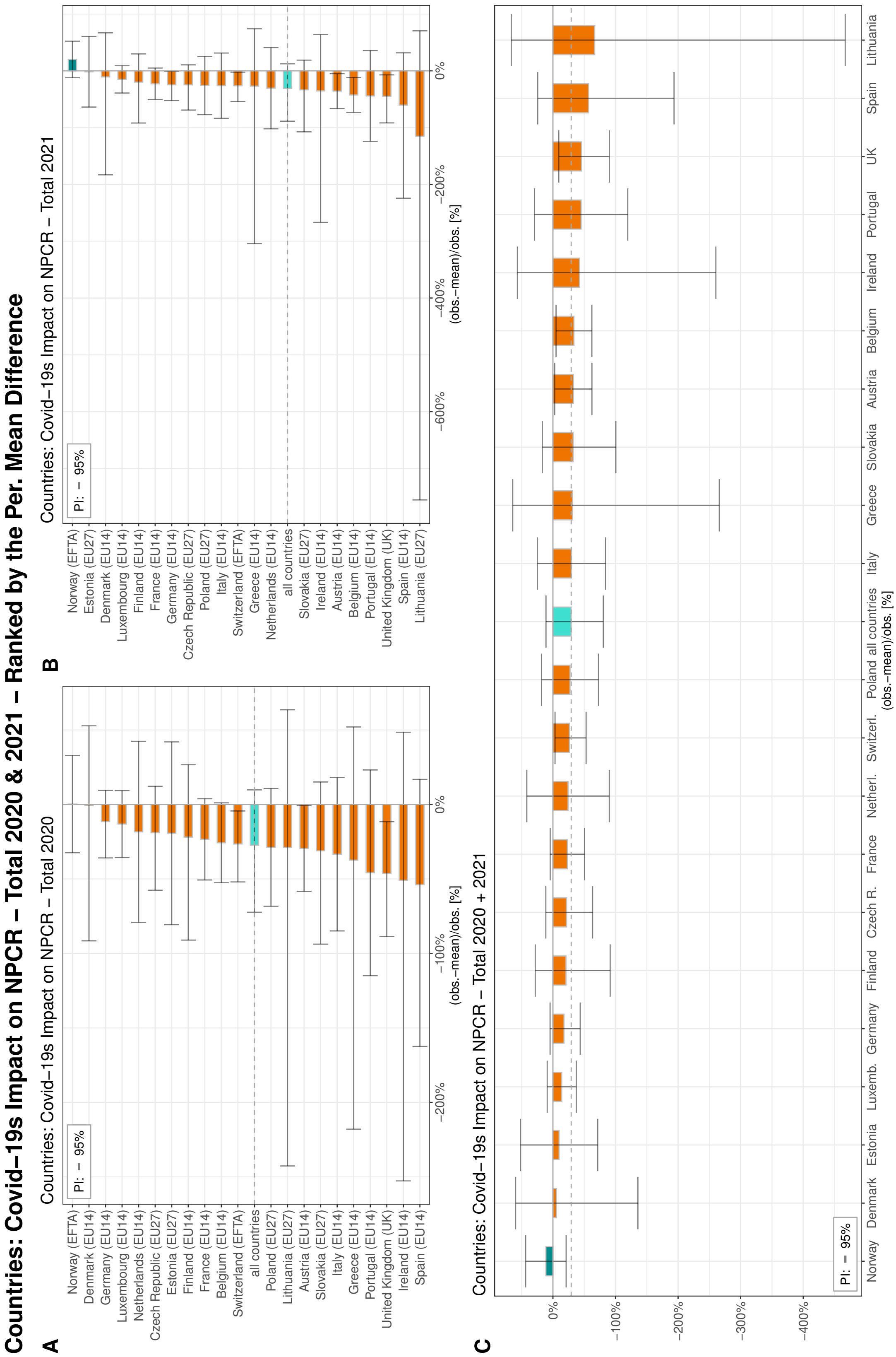


Figure 4.13: Countries: Covid-19s Impact on NPCR, Grand Total, 2020, 2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

decrease of -31,1% in the year 2021, which constitutes a corresponding decline of 3'439'513 NPCR in reference to the proposed evaluation approach. Following this, the overall impact on the 21 countries in 2021 (-31,1%) was even greater than in 2020 (-27,4%). It is suggested that this is a result of the semiconductor shortages, which drastically intensified in the second half of the year 2021.

The overall performance in reference to the per. mean difference of the 21 European countries over 2020 and 2021 in total, is illustrated in panel C of figure 4.13. As obvious from the figure, Norway is the only country with a plus of 11,2% over the considered post-Covid-19 time frame (Jan/2020-Dec/2021). Additionally, countries like Denmark (-5,5%), Estonia (-5,5%), Luxembourg (-14,1%) and Germany (-17,7%) are in the lowest Covid-19 impact range, while countries like Portugal (-45,0%), the UK (-45,6%), Spain (-57,2%), and Lithuania (-66,7%) have been affected most in reference to the proposed evaluation approach. The aggregate decline of all 21 countries in total in 2020 and 2021 in NPCR, in relation to pre-Covid-19 time series variability, amounts to -6'521'698 NPCR, which constitutes a corresponding per. mean difference of -29,2%.

Some speculations on potential causes for differences in the results proposed by the analysis of the observed countries will be stated in the last chapter of this thesis in section 5.2.

## 4.3 Covid-19's Impact on NPCR in Europe by OEMs

The next section provides the evaluation of the quantitative Covid-19 impact on new passenger car registrations (NPCR) in the EU14[10], the EFTA[11], and the United Kingdom (UK) subdivided by OEMs. Based on the evaluation approach stated in section 4.1, the first section 4.3.1 gives an overview of the selected SARIMA models used for forecasting NPCR of the considered OEMs. Following this, section 4.3.2 states the results of the Covid-Impact on NPCR for the considered OEMs in total and for each OEM, while a comparison of the results will be stated in section 4.3.3.

### 4.3.1 OEMs: Selected Models for NPCR-Forecasting

As for the numerical studies of the 21 considered European countries presented in the previous sections, SARIMA models have been fitted and selected in ref-

[10] The member states of the EU14 are defined in the List of Abbreviations.
[11] The member states of the EFTA are defined in the List of Abbreviations.

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erence to the approach stated in section 4.1, for forecasting new passenger car registration (NPCR) of different OEMs which are selling their cars in the EU14, the EFTA, and the UK. Based on datasets of the ACEA for monthly NPCR subdivided by OEMs (ACEA 2021f), all OEMs which are selling cars in the EU14,

| Index | OEM | Group | Model | Trans. | p-value | MAPE |
|---|---|---|---|---|---|---|
| 1 | Land Rover | Jaguar L. Rover | ARIMA(2,0,0)(0,1,1)[12] | log | 0.270 | 4.41% |
| 2 | Mercedes | Daimler | ARIMA(2,1,3)(0,1,1)[12] | - | 0.325 | 4.66% |
| 3 | Skoda | VW Group | ARIMA(3,0,0)(0,1,2)[12] w/ drift | - | 0.554 | 4.84% |
| 4 | Peugeot | STELLANTIS | ARIMA(2,1,0)(0,1,1)[12] | - | 0.054 | 5.28% |
| 5 | Fiat | STELLANTIS | ARIMA(3,0,0)(1,1,1)[12] | log | 0.062 | 5.59 |
| 6 | Audi | VW Group | ARIMA(1,0,0)(2,1,2)[12] w/ drift | log | 0.644 | 6.49% |
| 7 | BMW | BMW Group | ARIMA(3,0,0)(0,1,1)[12] | log | 0.101 | 6.69% |
| 8 | Hyundai | Hyundai Group | ARIMA(2,0,1)(0,1,1)[12] w/ drift | - | 0.061 | 6.74% |
| 9 | Kia | Hyundai Group | ARIMA(2,1,1)(2,1,1)[12] | log | 0.025 | 7.11% |
| 10 | Renault | Renault Group | ARIMA(3,0,2)(0,1,1)[12] | log | 0.301 | 7.88% |
| 11 | Volkswagen | VW Group | ARIMA(1,0,1)(2,1,2)[12] | - | 0.387 | 8.20% |
| 12 | Ford | Ford | ARIMA(3,0,0)(0,1,1)[12] w/ drift | - | 0.020 | 8.41% |
| 13 | Mitsubishi | Mitsubishi | ARIMA(1,0,1)(0,1,1)[12] | log | 0.699 | 9.19% |
| 14 | Mini | BMW Group | ARIMA(3,0,2)(0,1,1)[12] w/ drift | - | 0.220 | 10.33% |
| 15 | Mazda | Mazda | ARIMA(4,0,1)(0,1,1)[12] | - | 0.047 | 10.63% |
| 16 | Citroen | STELLANTIS | ARIMA(3,0,0)(0,1,2)[12] w/ drift | - | 0.013 | 10.71% |
| 17 | Honda | Honda | ARIMA(0,1,4)(0,1,1)[12] | log | 0.265 | 10.83% |
| 18 | Volvo | Volvo | ARIMA(3,0,0)(0,1,1)[12] | - | 0.756 | 11.92% |
| 19 | Nissan | Nissan | ARIMA(1,0,1)(0,1,1)[12] | log | 0.581 | 12.24% |
| 20 | Opel/Vaux. | STELLANTIS | ARIMA(3,0,0)(0,1,1)[12] w/ drift | - | 0.012 | 13.02% |
| 21 | Toyota | Toyota Group | ARIMA(3,0,0)(0,1,1)[12] | log | 0.07 | 14.36% |
| 22 | Seat | VW Group | ARIMA(3,1,1)(0,1,2)[12] | - | 0.395 | 16.99% |
| 23 | Alfa Romeo | STELLANTIS | ARIMA(2,0,2)(0,1,2)[12] w/ drift | log | 0.582 | 17.13% |
| 24 | Jeep | STELLANTIS | ARIMA(2,1,3)(1,0,0)[12] | - | 0.368 | 17.59% |
| 25 | Smart | Daimler | ARIMA(3,0,2)(0,1,1)[12] | log | 0.117 | 20.52% |
| 26 | Jaguar | Jaguar L. Rover | ARIMA(3,1,2)(0,1,1)[12] | - | 0.417 | 38.98% |

Table 4.3: OEMs: Selected Models for NPCR-Forecasting

the EFTA, and the UK, were considered, for which data were available from Jan/2001-Dec/2021. For each of the resulting 26 OEMs, which have been considered, the best SARIMA model in reference to the MAPE is stated in table 4.1. In reference to section 4.1, a MAPE $< 15\%$ has been contemplated as acceptable, which resulted in 21 OEMs being considered, while Seat, Alfa Romeo, Jeep, Smart, and Jaguar did not reach the target for the evaluation of Covid-19's impact on NPCR in the following sections 4.3.2 and 4.3.3.[12] Yet, in reference to datasets of the ACEA (ACEA 2022b), the 21 selected OEMs depicted in table 4.1, cover the great part of the NPCR in the EU14, the EFTA and the UK, with an aggregate market share of 84,79% in 2021.

As for the selected models of the 21 countries, it can be expected, that the available information which can be used for modeling is also captured adequately for the great part of the models of the considered OEMs. In reference to the Ljung-Box test, most models, except for Kia, Ford, Mazda, Citroen, and Opel/Vauxhall,

[12] The results for Seat, Alfa Romeo, Jeep, Smart, and Jaguar (MAPE $> 15\%$), which are not considered in the numerical studies of section 4.3.2 and 4.3.3, are stated in Appendix B.

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have a p-value that is significantly higher than 0,05. The corresponding MAPE is however < 15% for all the 21 models, which was decisive for the model selection.

### 4.3.2 OEMs: Obs., Forecasts and Covid-Impact on NPCR

Based on the SARIMA models stated in table 4.3, this section is dedicated to research question 1, as depicted in section 1.2, in reference to Covid-19's impact on European new passenger car registrations (NPCR) in the EU14, the EFTA, and the UK, subdivided by OEMs. As for the numerical studies in reference to European countries stated in section 4.2.2, first, the impact of Covid-19 and resulting after-effects on NPCR in the EU14, the EFTA, and the UK, will be discussed for the 21 OEMs on an aggregate basis. In the next step, the results for each OEM will be then stated and compared. Following this, figure 4.14 below illustrates the observed NPCR of the 21 considered OEMs in total from Jan/2001-Dec/2021 based on datasets of the ACEA ((ACEA 2021f), (ACEA 2022b)). The data which were used for the fitting of the SARIMA models (Jan/2001-Dec/2018), the verification data (Jan/2019-Dec/2019), as well as the forecast horizon (Jan/2020-Dec2021) are separated by the respective dotted vertical lines.

Like the illustrated data for the observed NPCR of the 21 countries in the EU27, the EFTA, and the UK, illustrated in figure 4.1, the observed NPCR in the EU14, the EFTA, and the UK of the 21 OEMs appear quite saturated in the considered time frame. As it can be seen from the figure, NPCR were quite stable between 2003 to 2007. In addition, the impact of the Financial Crisis (2008-2009) and the resulting European Debt Crisis (2010-2013) is clearly visible from 2008

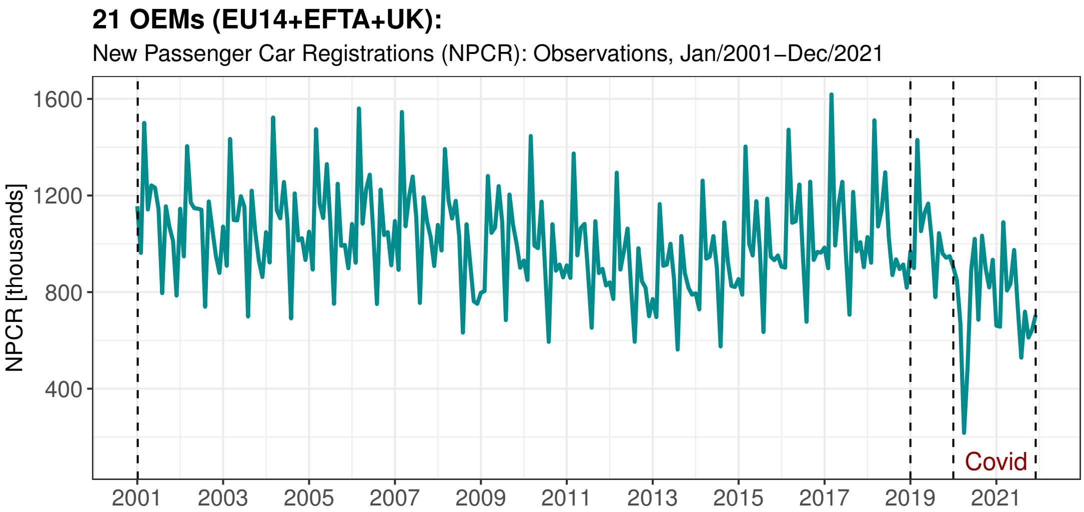


Figure 4.14: All 21 OEMs, NPCR: Observations, Jan/2001-Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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through 2013, as well as the following recovery phase from 2014 through 2017. Furthermore, a beginning downward cycle in pre-Covid 2018 can be seen, as for the data of NPCR in the 21 countries. Beyond that, the Covid-19 impact at the beginning of 2020 and through 2021 is clearly visible, which is illustrated in figure 4.15 in more detail.

Figure 4.15 depicts the observed and the forecasted NPCR values in the EU14, the EFTA, and the UK, for the 21 OEMs on an aggregate basis in the specified verification time frame (Jan/ 2019-Dec/2019) with a corresponding MAPE of 4,82%, and the forecast horizon (Jan/2020-Dec2021), in which the Covid-19 impact and resulting after-effects are evaluated. The Covid-19 impact on NPCR in the forecast horizon is represented by the gap between the observed values (obs.) and the corresponding NPCR point forecasts (mean).[13] Figure 4.15 can be interpreted in the same way as in the analysis for the 21 European countries stated in section 4.2.2 and shows generally the same patterns. Hence, the mean values of the NPCR forecasts for the verification time frame (Jan/2019-Dec/2019) are very close again to the observed NPCR data (MAPE = 4,82%). Furthermore, the Covid-19 impact in spring 2020 is clearly visible since the observed NPCR values are well outside the lower end of the 95% prediction interval. After a strong recovery, the mean values of the NPCR forecast distribution are more or less at par with the observed NPCR values in the second half of 2020. Yet, in 2021, the observed NPCR values dropped below the mean values of the NPCR

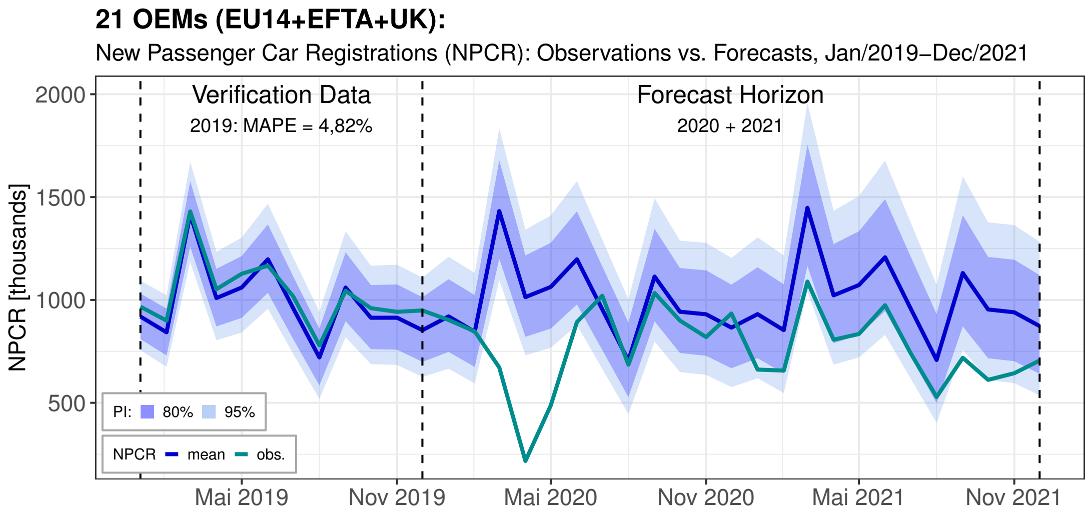


Figure 4.15: All 21 OEMs, NPCR: Obs. vs. Forecasts, Jan/2019-Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

[13]The associated 80% and 95% prediction intervals (PI) are represented by the shaded light blue areas in figure 4.15.

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forecasts again and settled in the lower end of the 80% prediction interval.

Based on the results depicted in figure 4.15, the evaluation of the Covid-19 impact on European NPCR of the 21 OEMs measured by the absolute (abs.) mean difference (obs. - mean), and the percentage (per.) mean difference (obs. - mean) /obs., is illustrated in figure 4.16 and 4.17 respectively.[14] As for the analysis of the Covid-19's impact on NPCR for the 21 European countries stated in section 4.2.2, it will be suggested, that the spread of the virus and related lockdowns and containment measures led in March 2020 to a steep drop in NPCR of the 21 OEMs in relation to pre-Covid-19 time series variability. Based on the proposed evaluation approach, the trough of the Covid-19 impact on NPCR of the 21 OEMs in total, was recorded in April 2020 with a decline of -367,0% or -796'586 units. The remaining results with regards to the considered post-Covid-19 time frame (Jan/2020-Dec/2021) are also quite similar to the analysis of the 21 countries stated in section 4.2.2. In this context, a strong recovery phase is visible as well for the NPCR of the 21 OEMs, after the initial Covid-19 induced macro-shock took place, which led to an increase in NPCR of 6,5% or 65'870 units in July 2020. For the remaining year 2020, the abs. and per. mean differences are slightly in the negative range as well, while a further plus of 7,3% or 68'549 NPCR in relation to pre-Covid-19 time series variability is recorded in December 2020.

In reference to the analysis of Covid-19's Impact on the Automotive Industry, stated in section 2.3, it will be suggested, like it was proposed for the numerical

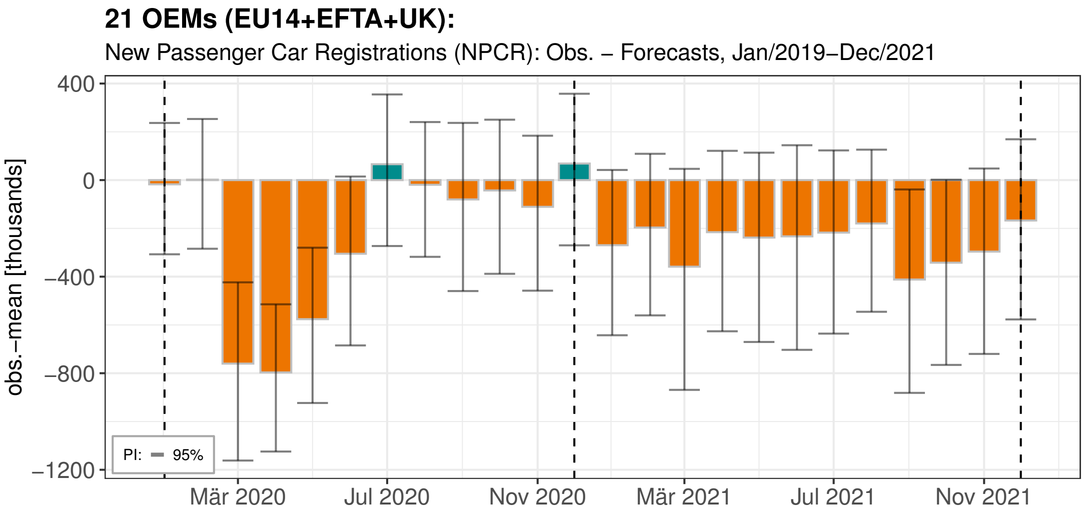


Figure 4.16: All 21 OEMs, NPCR: Abs. Mean Differences, Jan/2020- Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

[14]See section 4.2.2 for an explanation of the abs. mean difference and the per. mean difference.



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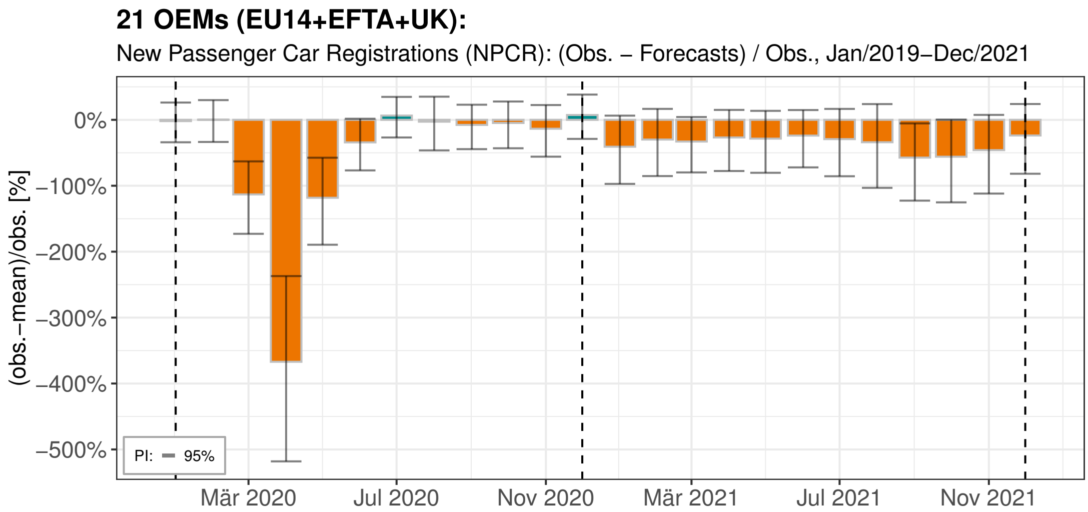


Figure 4.17: All 21 OEMs, NPCR: Perc. Mean Differences, Jan/2020-Dec/2021
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

studies on Covid-19's impact on NPCR by countries, that the year 2021 was characterized by a variety of shortages caused by the stronger than expected recovery in demand and the slower recovery of production capacities. In this context, especially the semiconductor shortages, which drastically intensified in the second half of 2021, put again strong downward pressure on an already struggling automotive industry (OECD 2021a, pp.17-20). Following this, the suggested impact of the Covid-19 related semiconductor shortages in the year 2021 on NPCR in the EU14, the EFTA and the UK for the 21 considerd OEMs, is again quite similar to the impact on NPCR in the 21 selected countires of the EU27, the EFTA and the UK, described in section 4.2.2. Hence, a decrease in observed NPCR of -40.8% or -269'736 units was recorded in January 2021, in reference to the proposed evaluation approach. Following this drop at the beginning of the year, the situation eased slightly until June 2021. However, the situation deteriorated again in the second half of the year 2021, most likely due to the intensifying semiconductor shortages in the automotive industry, which lead to a maximum decline in NPCR of -57,3% or -411'874 units in September 2021, in relation to time series variability. Towards the end of the year, the situation eased slightly again, but was still clearly in the negative range with per. and abs. mean differences of -23,7% or -167'358 NPCR respectively in December 2021.

In the following, the evaluation of the Covid-19 impact on new passenger car registrations (NPCR) in the EU14, the EFTA, and the UK, measured against pre-Covid-19 time series variability, for each of the 21 OEMs, stated in table 4.3, will be presented in figures 4.18 - 4.24. As was proposed for the studies on the



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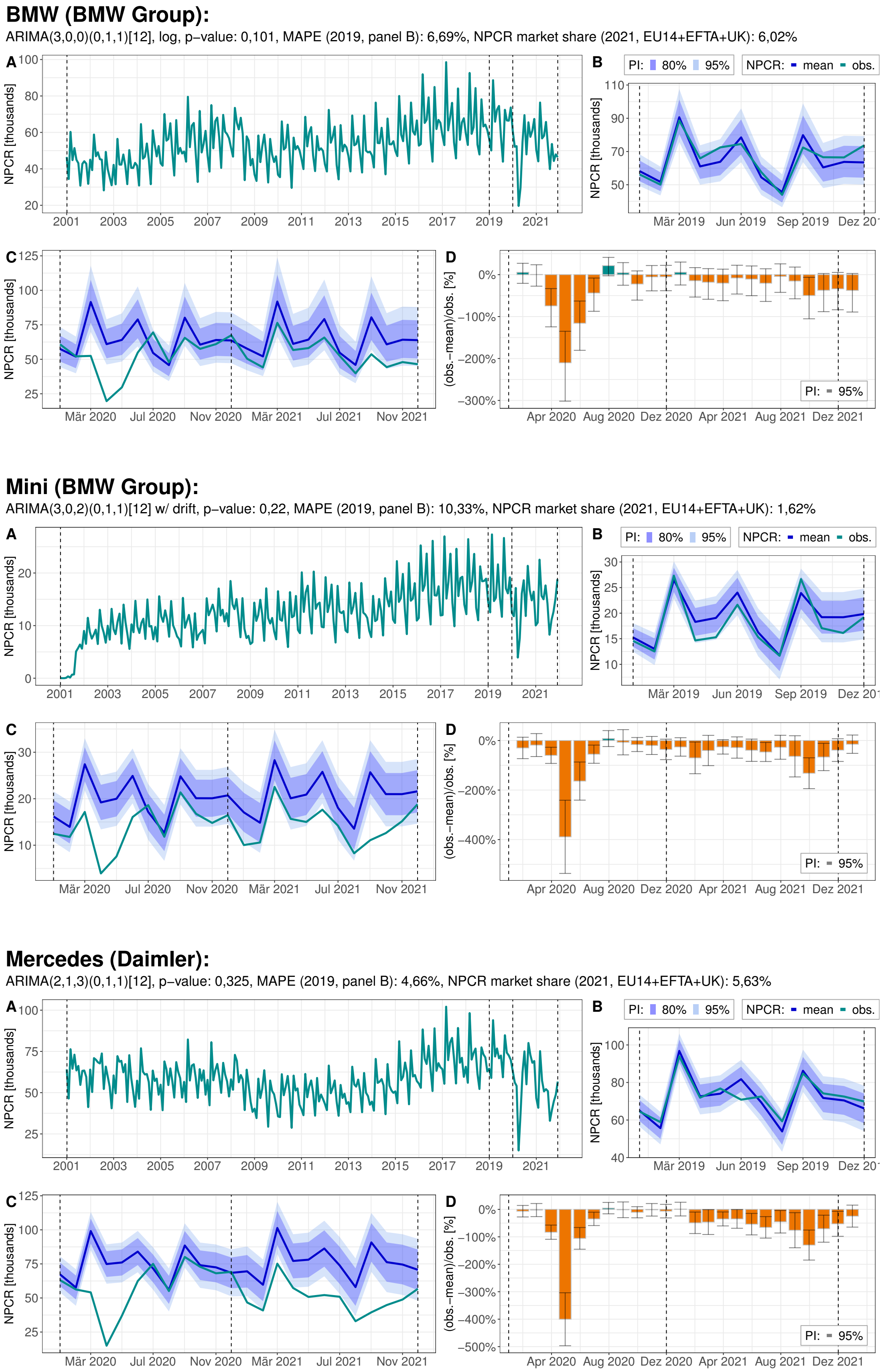


Figure 4.18: Covid-19's Impact on NPCR: BMW, Mini, Mercedes
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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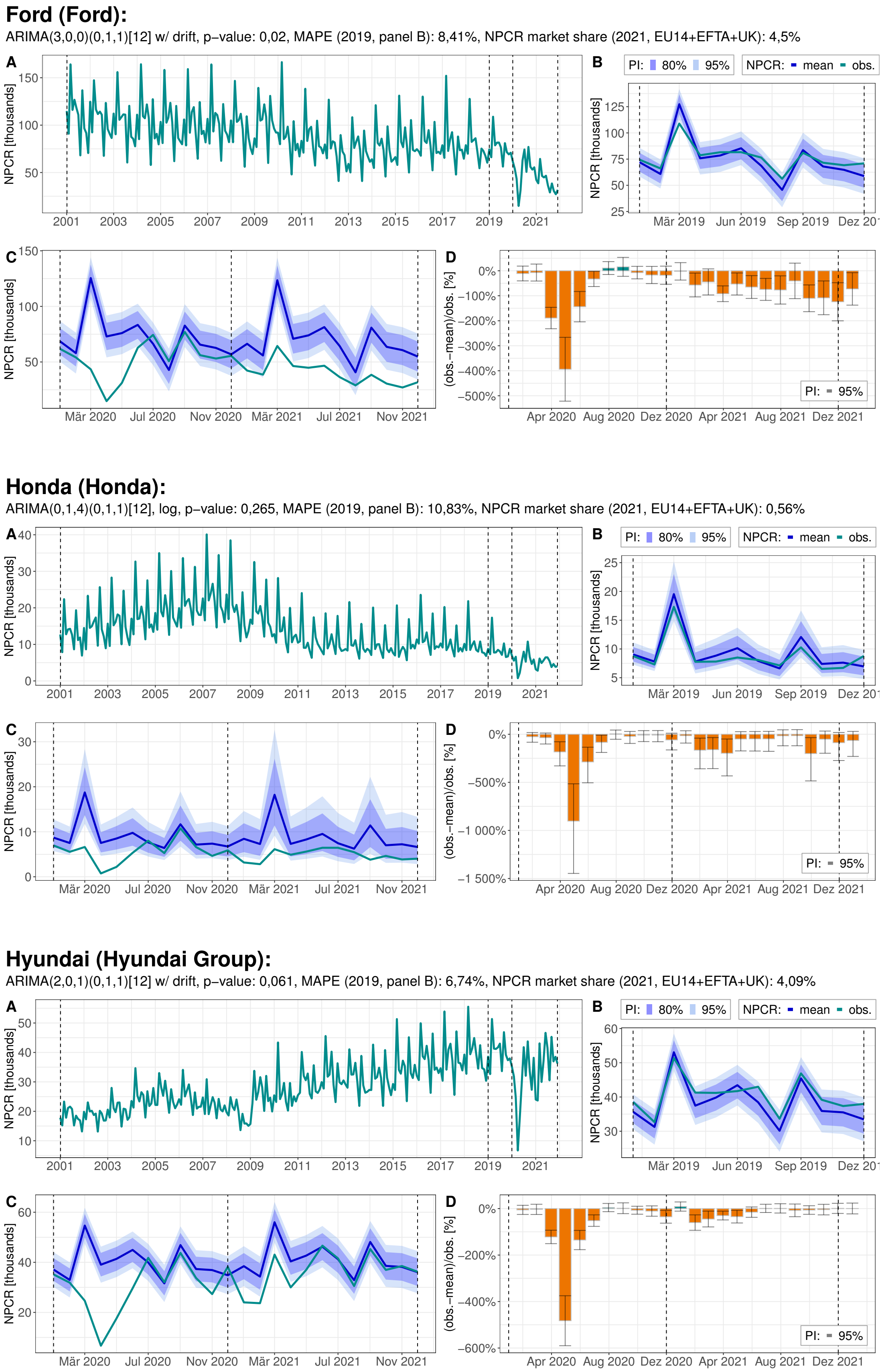


Figure 4.19: Covid-19's Impact on NPCR: Ford, Honda, Hyundai
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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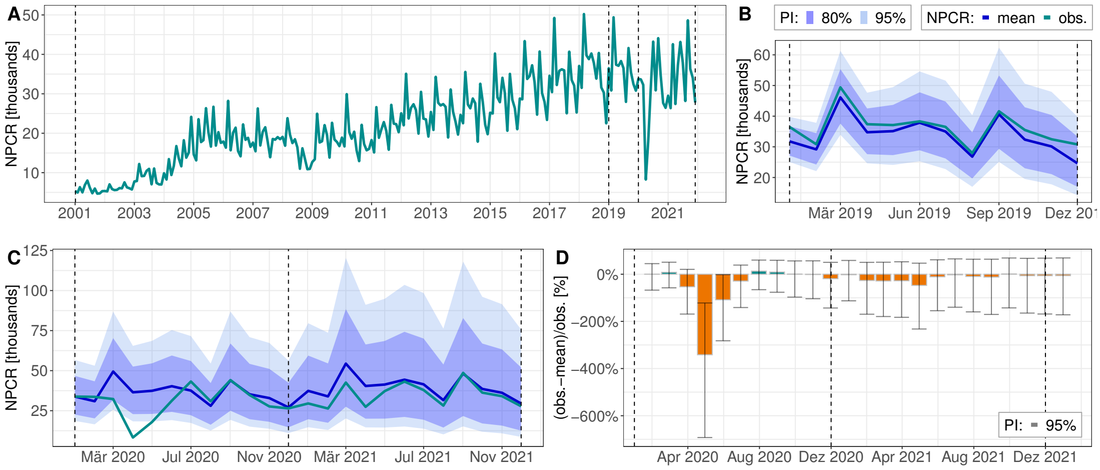
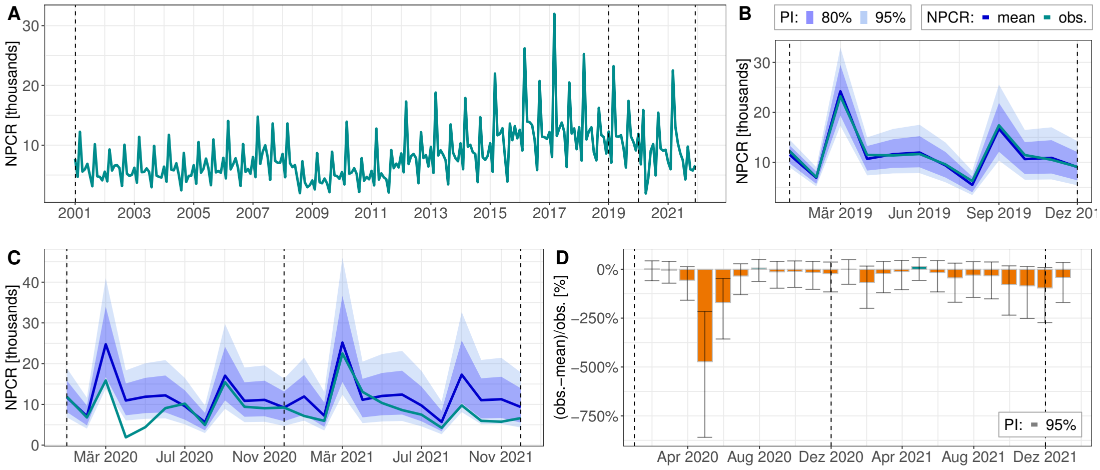
**Kia (Hyundai Group):**

ARIMA(2,1,1)(2,1,1)[12], log, p–value: 0,025, MAPE (2019, panel B): 7,11%, NPCR market share (2021, EU14+EFTA+UK): 4,03%




**Land Rover (Jaguar Land Rover Group):**

ARIMA(2,0,0)(0,1,1)[12] , log, p–value: 0,27, MAPE (2019, panel B): 4,41%, NPCR market share (2021, EU14+EFTA+UK): 1,01%




**Mazda (Mazda):**

ARIMA(4,0,1)(0,1,1)[12], p–value: 0,047, MAPE (2019, panel B): 10,63%, NPCR market share (2021, EU14+EFTA+UK): 1,26%

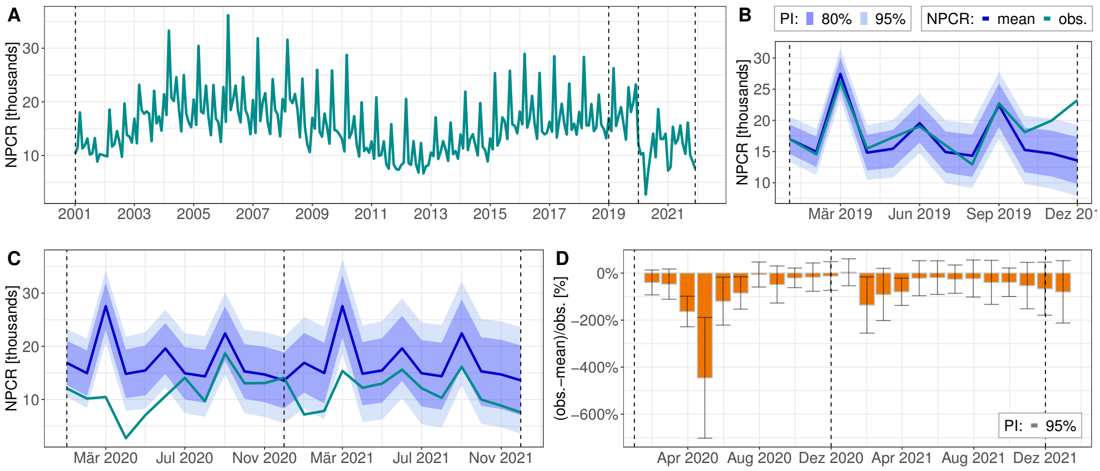



Figure 4.20: Covid-19's Impact on NPCR: Kia, Land Rover, Mazda
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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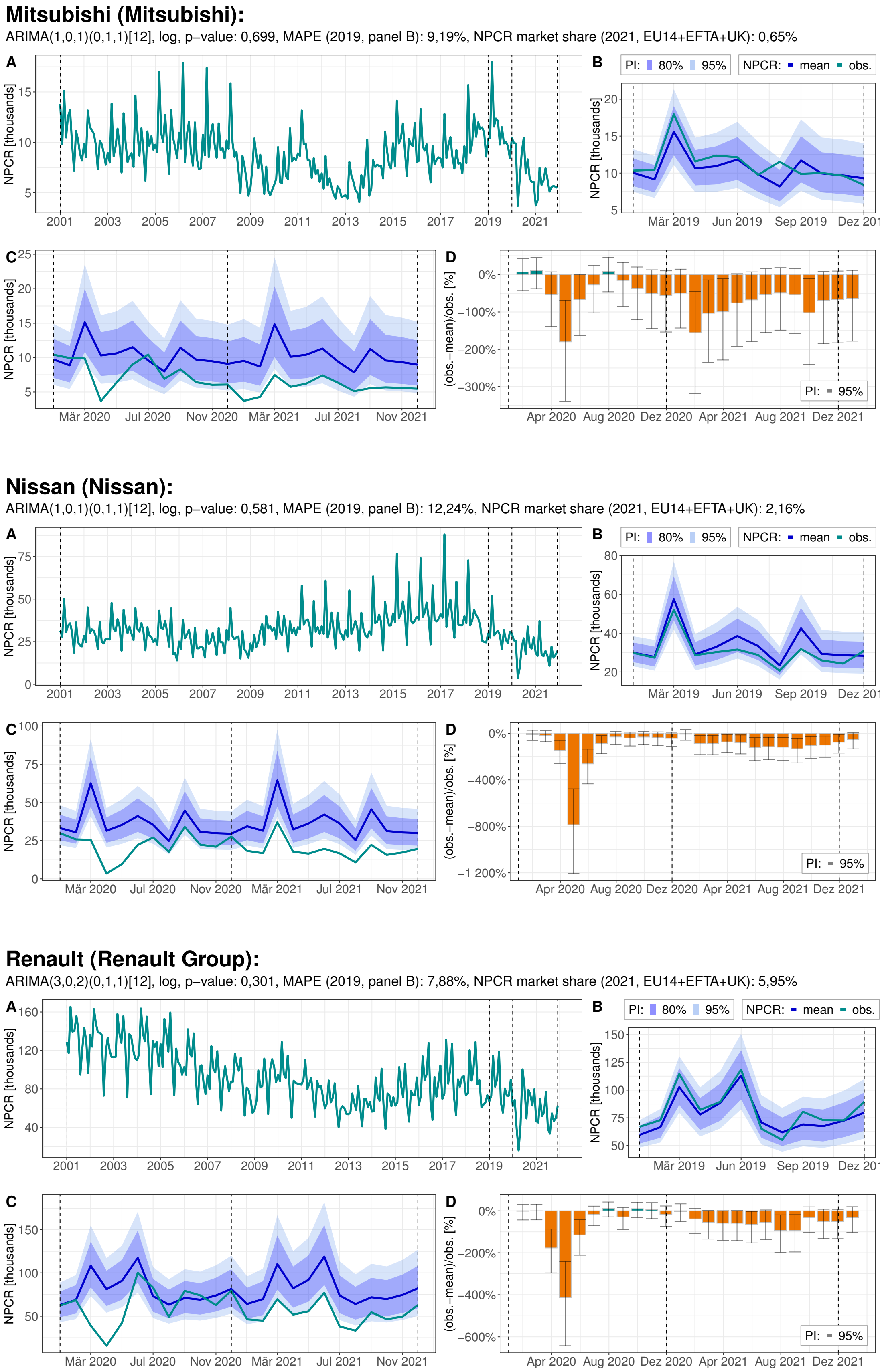


Figure 4.21: Covid-19's Impact on NPCR: Mitsubishi, Nissan, Renault
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)



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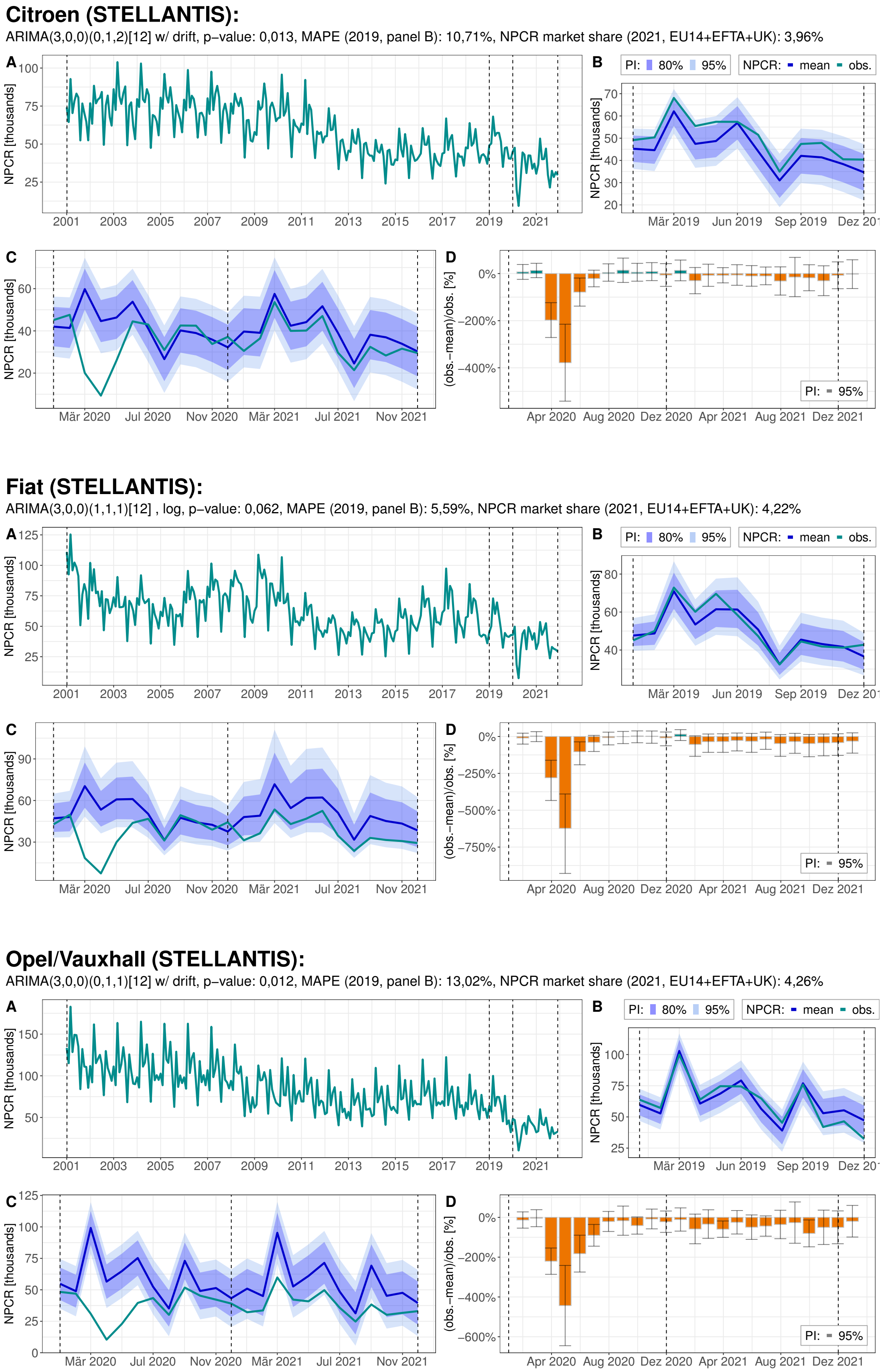


Figure 4.22: Covid-19's Impact on NPCR: Citroen, Fiat, Opel/Vauxhall
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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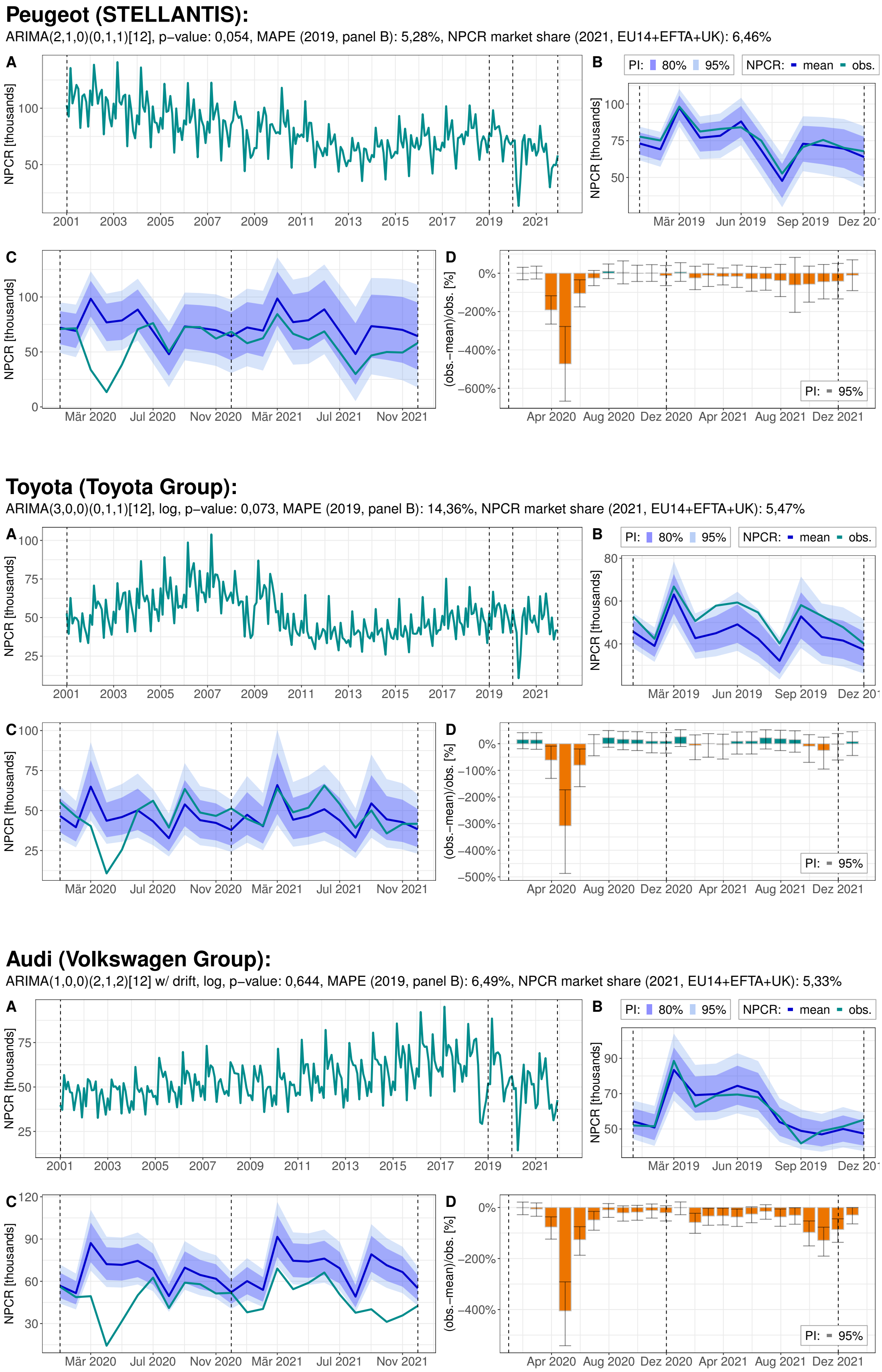


Figure 4.23: Covid-19's Impact on NPCR: Peugeot, Toyota, Audi
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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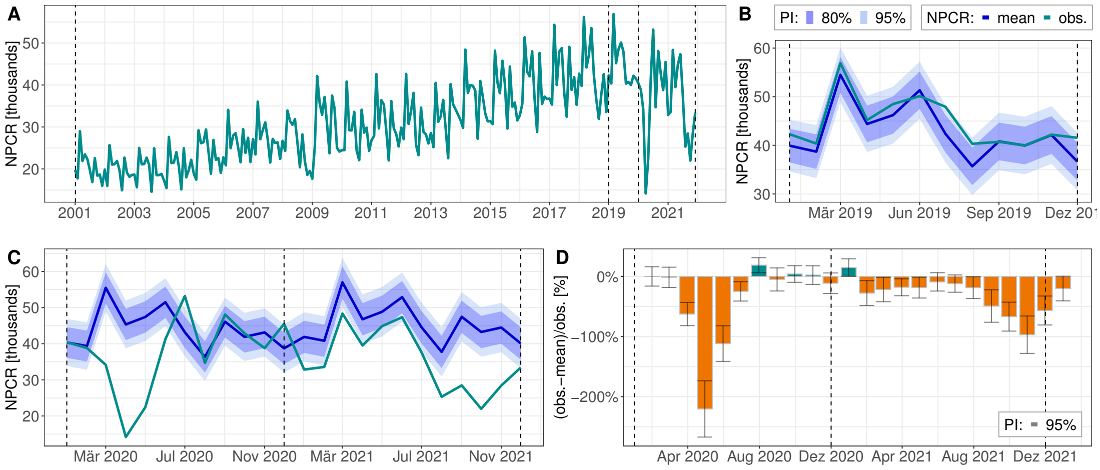
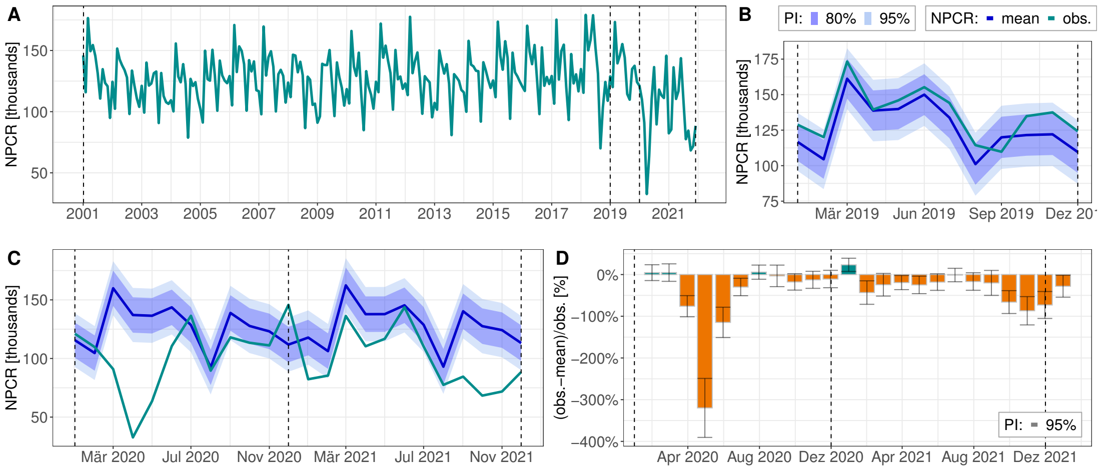
**Skoda (Volkswagen Group):**

ARIMA(3,0,0)(0,1,2)[12] w/ drift, p-value: 0,554, MAPE (2019, panel B): 4,84%, NPCR market share (2021, EU14+EFTA+UK): 3,98%




**Volkswagen (Volkswagen Group):**

ARIMA(1,0,1)(2,1,2)[12], p-value: 0,387, MAPE (2019, panel B): 8,2%, NPCR market share (2021, EU14+EFTA+UK): 11,09%




**Volvo (Volvo):**

ARIMA(3,0,0)(0,1,1)[12], p-value: 0,756, MAPE (2019, panel B): 11,92%, NPCR market share (2021, EU14+EFTA+UK): 2,54%

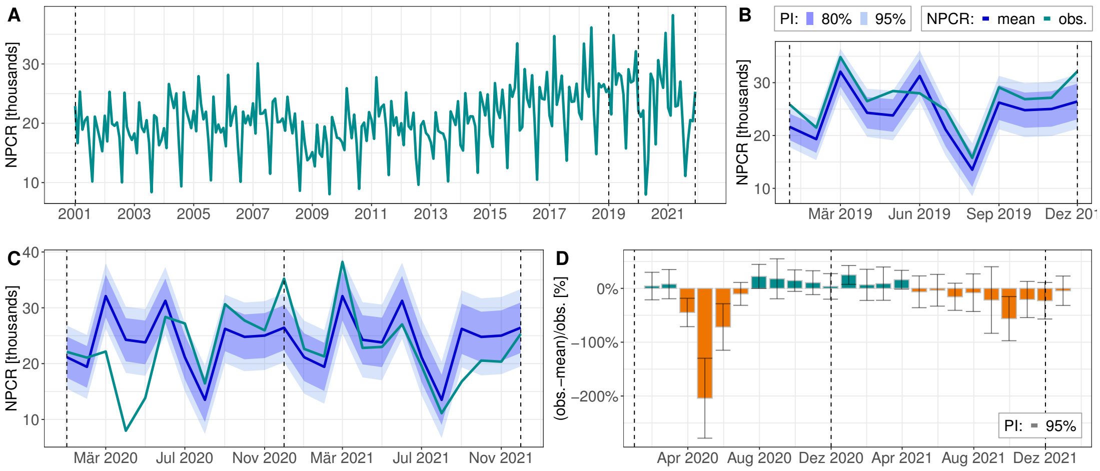



Figure 4.24: Covid-19's Impact on NPCR: Skoda, Volkswagen, Volvo
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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impact on NPCR by countries, it is suggested to consider the impact on NPCR by OEMs in spring 2020 in relation to the Covid-19 induced macro-shock, followed by a recovery phase in the second half of 2020. Beyond that, the NPCR impact in 2021 can be considered with regards to supply chain disruption and related shortages, especially in connection with the semiconductor shortages, which drastically intensified in the second half of 2021 (OECD 2021a, pp.17-20).

### 4.3.3 OEMs: Comparison of Covid-Impact on NPCR

The following section provides a comparison of the results in relation to research question 2, stated in section 1.2, based on the evaluation of the Covid-19 impact on NPCR for each OEM stated in figures 4.18 - 4.24. Hence, the OEMs will be compared in reference to the best and worst months, the number of positive and negative months, and their overall performance in relation to NPCR, measured against pre-Covid-19 time series variability.

#### 4.3.3.1 OEMs: Worst and Best Months 2020 and 2021

Figure 4.25 provides a ranking of the worst and the best months of the 21 considered OEMs in the year 2020 and 2021, in reference to the Covid-19 impact and resulting after-effects on NPCR in the EU14, the EFTA, and the UK, measured by the per. mean difference.[15] Similar to the presented study for the 21 selected European countries in section 4.2.3.1, all 21 OEMs show their deepest Covid-19 impact on NPCR, in relation to pre-Covid-19 time series variability, in April 2020. As illustrated in panel A of figure 4.25, Honda recorded the most severe impact with -902,7% in April 2020, followed by Nissan (04/20, -787,4%), Fiat (04/20, -622,7%), and Hyundai (04/20, -482,5%). The deepest impact, considering NPCR of all 21 OEMs in total, was in April 2020 with -376,0%, in relation to the proposed evaluation approach. Furthermore, BMW (04/20, -210,1%), Volvo (04/20, -204,1%), and Mitsubishi (04/20, -180,0%) are settled in the lower Covid-19 NPCR impact range, in comparison to the other OEMs in the year 2020. The best month in 2020 of each of the 21 OEMs is stated in panel B of figure 4.25. As can be noticed, Toyota ranks first with a per. mean difference of +26,2% in December 2020, followed by Volvo (12/20, +25,0%), Volkswagen (12/20, +23,3%), and BMW (07/20, +21,4%), while the best month, considering all OEMs on an aggregate basis, was December 2020 with a plus of 7,3%. Beyond that, Audi

[15] See section 4.2.2 for an explanation of the per. mean difference. The following descriptions are related to the per. mean difference, however, the corresponding values of the 95% prediction intervals are stated in figure 4.25.

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(12/20, -1,0%), Nissan (12/20, -1,0%), and Opel/Vauxhall (10/20, -1,0%) showed the only negative values in their best month in 2020.

The ranking of the 21 OEMs in reference to their worst month of the year 2021 is depicted in panel C of figure 4.25. As noted earlier in this thesis, the year 2021 was characterized by supply chain disruptions, a variety of shortages, and especially by the semiconductor shortages in the automotive industry, which drastically intensified in the second half of the year 2021(OECD 2021a, pp.17-20). Taking this into account, Honda recorded the worst month in comparison to the other OEMs, as in the year 2020, with a decrease in NPCR of -200,5% in September 2021, in comparison to time series variability, followed by Mitsubishi (01/21, -155,6%) and Mazda (01/21, -135,6%). The worst month for all 21 OEMs in total was September 2021 with a decline in NPCR of -57,28%, in relation to the proposed evaluation approach. Beyond that, BMW (09/21, -49,8%), Kia (04/21, -47,5%), Citroen (07/21, -31,5%), and Toyota (10/21, -24,7%) recorded the lowest NPCR impact in their worst month in reference to the ranking. Finally, the best month of each OEM in the year 2021, in reference to their per./;mean difference of the observed and the forecasted NPCR values, is illustrated in panel D of figure 4.25. As in the year 2020, Toyota and Volvo are again at the top of the ranking, with a plus of 22,6% in June 2021 and 16,0% in March 2020 respectively. Considering all 21 OEMs on an aggregate basis, the best month was in the negative range with -23,7% in December 2021, while Ford (09/21, -40,5%), Mitsubishi (09/21, -48,3%), and Nissan (09/21, -52,5%) recorded the worst results in their best month in comparison to the other OEMs.

#### 4.3.3.2 OEMs: Positive and Negative Months 2020 and 2021

The following study is dedicated to the number of positive and negative months of the 21 OEMs in reference to the proposed Covid-19 NPCR impact evaluation approach described in section 4.1. It must be considered, that the results in figure 4.4 are stated in binary form. Hence, they do not give any information on the size of the per. mean difference, as in the related study with respect to the 21 observed European countries in section 4.2.3.2. A plus in the table marks therefore a general increase in observed NPCR in relation to pre-Covid-19 time series variability, while a minus designates a respective general decrease.

As it can be seen from the top of table 4.4, the Covid-19 effect on NPCR in 2020 is visible for most of the OEMs in March, April, May, and June 2020, except for some OEMs like Audi, Nissan, and Opel/Vauxhall that stayed in the negative range for the whole year. Beyond that , a variety of OEMs recovered at least to



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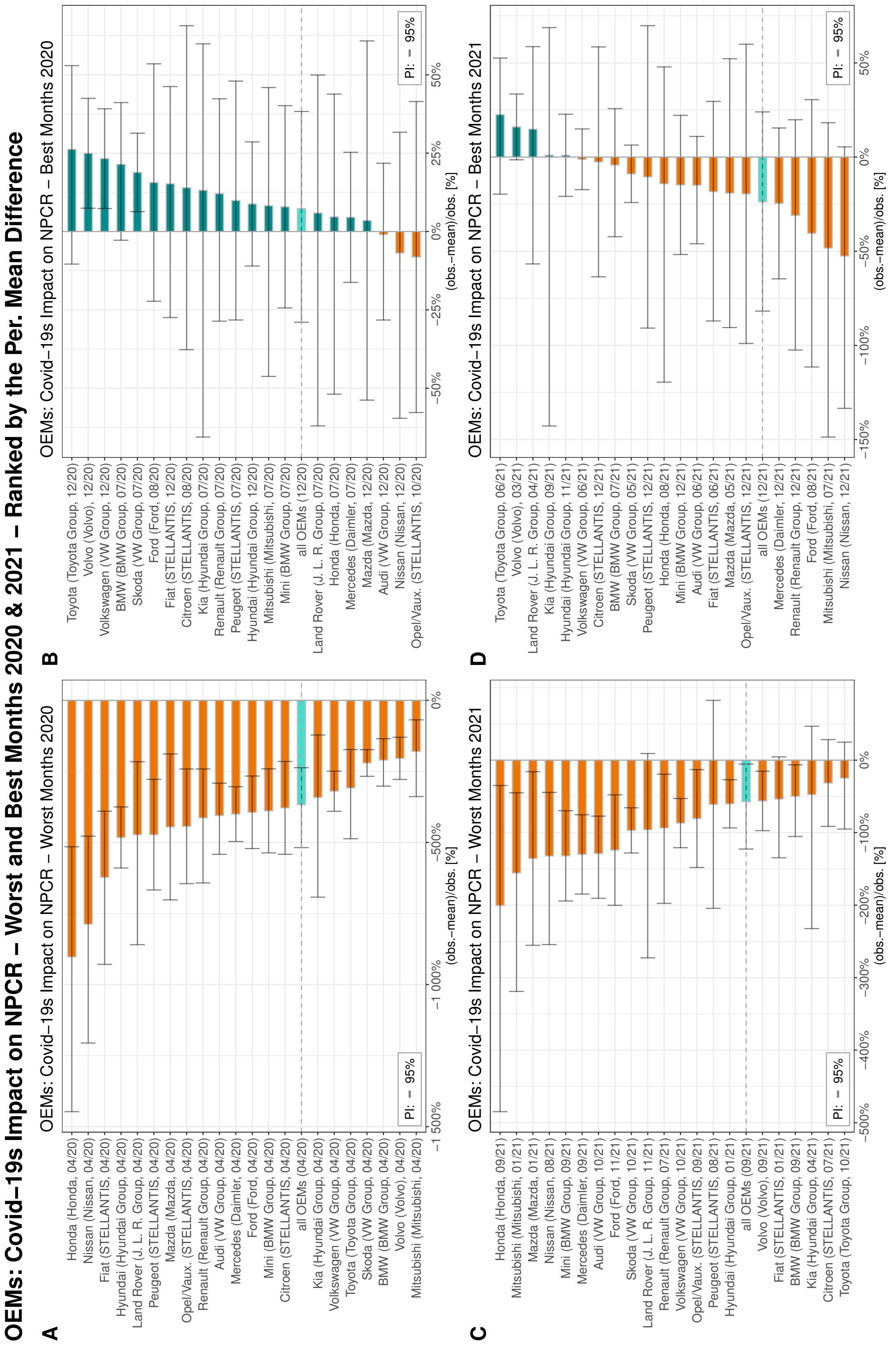


Figure 4.25: OEMs, NPCR: Worst and Best Months, 2020, 2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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| | | | 2020 | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Index | OEM | Group | 01/20 | 02/20 | 03/20 | 04/20 | 05/20 | 06/20 | 07/20 | 08/20 | 09/20 | 10/20 | 11/20 | 12/20 | pos. | neg. |
| 1 | Toyota | Toyota Group | + | + | - | - | - | + | + | + | + | + | + | + | 9 | 3 |
| 2 | Volvo | Volvo | + | + | - | - | - | - | + | + | + | + | + | + | 8 | 4 |
| 3 | Citroen | STELLANTIS | + | + | - | - | - | - | + | + | + | + | - | + | 7 | 5 |
| 4 | BMW | BMW Group | + | + | - | - | - | - | + | + | - | - | - | + | 5 | 7 |
| 5 | Kia | Hyundai Group | + | + | - | - | - | - | + | + | + | - | - | - | 5 | 7 |
| 6 | Peugeot | STELLANTIS | - | + | - | - | - | - | + | + | - | + | - | + | 5 | 7 |
| 7 | Skoda | Volkswagen Group | + | - | - | - | - | - | + | - | + | + | - | + | 5 | 7 |
| 8 | Fiat | STELLANTIS | - | + | - | - | - | - | - | - | + | + | - | + | 4 | 8 |
| 9 | Volkswagen | Volkswagen Group | + | + | - | - | - | - | + | - | - | - | - | + | 4 | 8 |
| 10 | Hyundai | Hyundai Group | - | - | - | - | - | - | + | + | - | - | - | + | 3 | 9 |
| 11 | Land Rover | Jaguar Land Rover Group | + | - | - | - | - | - | + | - | - | - | - | + | 3 | 9 |
| 12 | Mitsubishi | Mitsubishi | + | + | - | - | - | - | + | - | - | - | - | - | 3 | 9 |
| 13 | Renault | Renault Group | - | - | - | - | - | - | + | - | + | + | - | - | 3 | 9 |
| 14 | all OEMs | - | - | + | - | - | - | - | + | - | - | - | - | + | 3 | 9 |
| 15 | Ford | Ford | - | - | - | - | - | - | + | + | - | - | - | - | 2 | 10 |
| 16 | Mercedes | Daimler | - | - | - | - | - | - | + | - | - | - | - | + | 2 | 10 |
| 17 | Honda | Honda | - | - | - | - | - | - | + | - | - | - | - | - | 1 | 11 |
| 18 | Mazda | Mazda | - | - | - | - | - | - | - | - | - | - | - | + | 1 | 11 |
| 19 | Mini | BMW Group | - | - | - | - | - | - | + | - | - | - | - | - | 1 | 11 |
| 20 | Audi | Volkswagen Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 21 | Nissan | Nissan | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 22 | Opel/Vauxhall | STELLANTIS | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |

| | | | 2021 | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Index | OEM | Group | 01/21 | 02/21 | 03/21 | 04/21 | 05/21 | 06/21 | 07/21 | 08/21 | 09/21 | 10/21 | 11/21 | 12/21 | pos. | neg. |
| 1 | Toyota | Toyota Group | - | + | - | + | + | + | + | + | - | - | - | + | 7 | 5 |
| 2 | Hyundai | Hyundai Group | - | - | - | - | - | + | + | - | - | - | + | + | 4 | 8 |
| 3 | Volvo | Volvo | + | + | + | - | - | - | - | - | - | - | - | - | 3 | 9 |
| 4 | Kia | Hyundai Group | - | - | - | - | - | - | - | - | + | - | - | - | 1 | 11 |
| 5 | Land Rover | Jaguar Land Rover Group | - | - | - | + | - | - | - | - | - | - | - | - | 1 | 11 |
| 6 | all OEMs | - | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 7 | Audi | Volkswagen Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 8 | BMW | BMW Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 9 | Citroen | STELLANTIS | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 10 | Fiat | STELLANTIS | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 11 | Ford | Ford | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 12 | Honda | Honda | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 13 | Mazda | Mazda | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 14 | Mercedes | Daimler | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 15 | Mini | BMW Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 16 | Mitsubishi | Mitsubishi | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 17 | Nissan | Nissan | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 18 | Opel/Vauxhall | STELLANTIS | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 19 | Peugeot | STELLANTIS | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 20 | Renault | Renault Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 21 | Skoda | Volkswagen Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |
| 22 | Volkswagen | Volkswagen Group | - | - | - | - | - | - | - | - | - | - | - | - | 0 | 12 |

Table 4.4: OEMs, NPCR: Positive and Negative Months, 2020, 2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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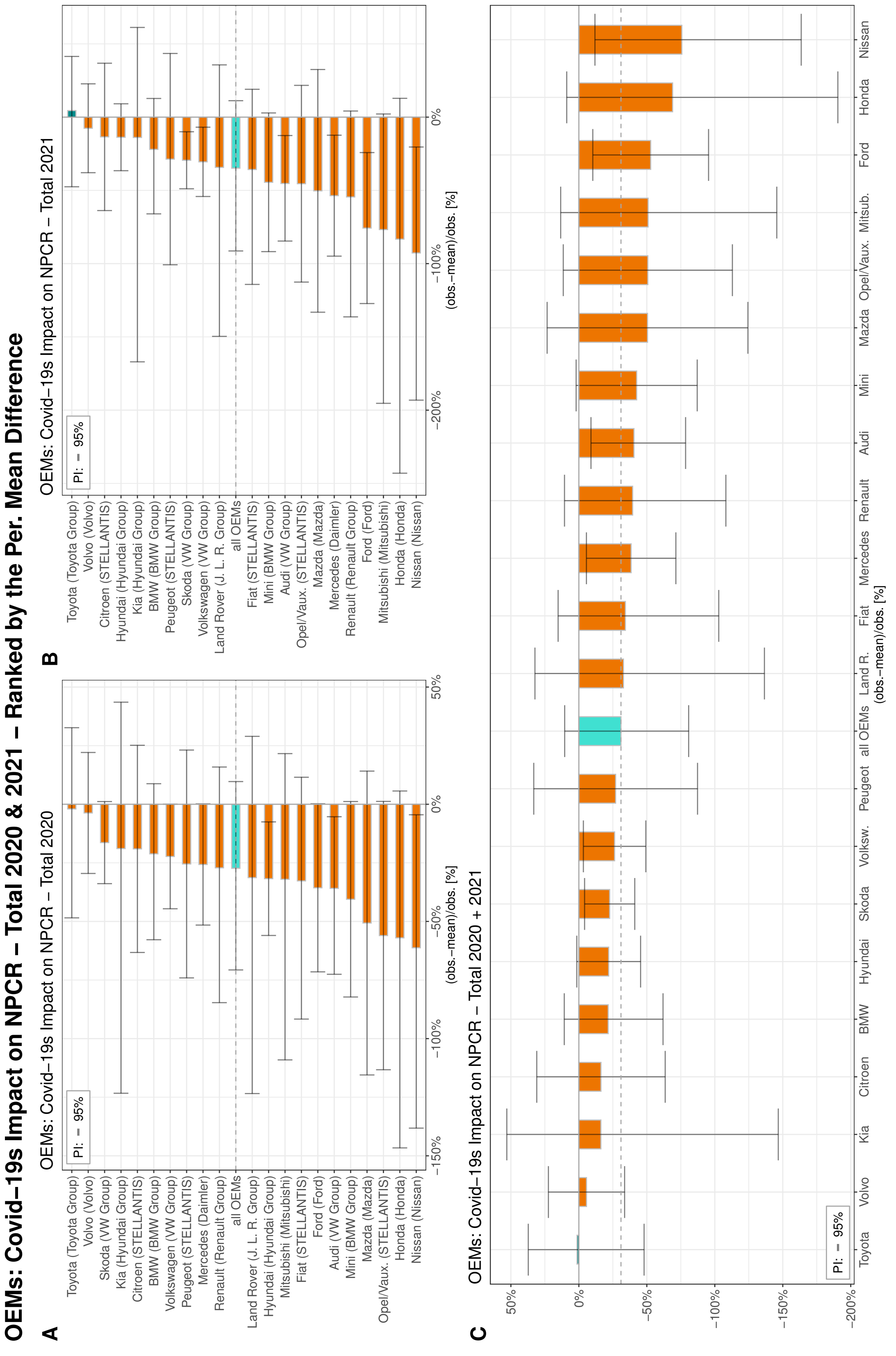


Figure 4.26: OEMs: Covid-19s Impact on NPCR, Grand Total, 2020, 2021
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

some extent in the second half of 2020, while Toyota, Volvo, and Citroen performed best, with 9, 8, and 7 positive months respectively in 2020. Yet, in 2021 almost all OEMs were completely in the negative range, which is basically a result of the supply chain disruptions and especially of the intensifying semiconductors shortages in the automotive industry, as was suggested by the analysis presented in section 2.3. However, contrary to this general pattern, Toyota performed quite well in the year 2021 with 7 positive months, while Hyundai and Volvo recorded at least 4 and 3 positive months respectively.

#### 4.3.3.3 OEMs: Overall Performance 2020 and 2021

As in the related study with respect to the 21 European countries presented in section 4.2.3.3, the 21 considered OEMs will be evaluated concerning their overall performance in 2020, 2021, and over both years, in reference to their per. difference of the observed and forecasted NPCR values, which will be measured by the per. mean difference.[16]

In this context, the performance of each OEM in 2020, ranked by their corresponding per. mean difference, is illustrated in panel A of figure 4.26. As can be noticed, all OEMs are settled in the negative range in the year 2020. Toyota is at the first rank with a decrease of -2,0% in observed NPCR in relation to pre-Covid-19 time series variability, followed by Volvo (-3,7%), Skoda (-16,4%), and Kia (-18,9%). The OEMs with the most severe impact are Mazda (-50,7%), Opel/Vauxhall (-56,0%), Honda (-57,0%), and Nissan (-61,2%) at the last rank, in relation to the proposed evaluation approach. Considering NPCR of all 21 OEMs in the EU14, the EFTA, and the UK in total, a decline of -27,3% was recorded in the year 2020, which amounts to -2'572'054 new passenger car registrations in comparison to pre-Covid-19 time series variability. Panel B of figure 4.26 illustrates the impact of Covid-19 on NPCR in the EU14, the EFTA, and the UK of the 21 OEMs in 2021. As in 2020, Toyota is at the first rank in 2021 with the only increase in the per. mean difference of 4,5%, compared to the other OEMs. Beyond that, Volvo is at rank 2 in 2021 as in the previous year, with a decline of -7,6% in NPCR compared to pre-Covid-19 time series variability, followed by Citroen (-13,5%) and Hyundai (-13,7%). The OEMs with the most severe decline in 2021 in reference to the proposed evaluation approach, were Ford (-75,7%), Mitsubishi (-76,7%), Honda (-83,3%), and Nissan (-92,7%) at the

[16] See section 4.2.2 for an explanation of the per. mean difference The following descriptions are related to the per. mean difference, however, the corresponding values of the 95% prediction intervals are stated in figure 4.26.

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last rank. New passenger car registrations of all 21 OEMs in total accounted for a decline of -34,8% in the year 2021, which demonstrates a respective decrease of 3'126'230 units in comparison to pre-Covid-19 time series variability. As in the study for the 21 observed European countries, stated in section 4.2.3.3, the overall impact on the 21 OEMs in 2021 (-34,8%) was even greater than in 2020 (-27,3%). It is suggested in reference to the analysis of section 2.3 of this thesis, that this is a result of the semiconductor shortages, which drastically intensified in the second half of the year 2021

Finally, Panel C of figure 4.26 shows the overall performance regarding NPCR in the EU14, the EFTA, and the UK, measured by the per. mean difference, of the 21 OEMs over the years 2020 and 2021 in total. As illustrated in panel C, Toyota is the only OEM with an increase (+1,35%) in observed NPCR over the years 2020 and 2021, in comparison to pre-Covid-19 time series variability. Volvo is ranked second, with a per. mean difference of -5,62%, followed by KIA (-16,2%) and Citroen (-16,3%), while Mitsubishi (-50,9%), Ford (-52,8%), Honda (-69,0%), and Nissan (-75,8%) performed worst over the year 2020 and 2021.The aggregate decline in NPCR in the EU14, the EFTA, and the UK of all 21 OEMs in 2020 and 2021, compared to pre-Covid-19 time series variability exhibited in the European Automotive industry, amounts to -5'698'284 units, which constitutes a corresponding per. mean difference of -30,9%.

Based on the quantitative analysis of this chapter, the last chapter of this thesis 5 will state a summary of the main findings, concluding remarks, some speculations on potential causes for differences in the results of the observed countries and OEMs, and an outlook for possible future research.

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# 5 Conclusion

This thesis studied the quantitative impact of Covid-19 and the resulting after-effects on new passenger car registrations (NPCR) in Western Europe. Chapter 2 presented a pre-Covid-19 analysis of the automotive industry and a discussion on Covid-19's impact on the global economy and the automotive industry as a basis for the quantitative analysis. Beyond that, chapter 3 was dedicated to the theory of time series analysis and forecasting with a particular focus on Seasonal ARIMA (SARIMA) models and set the theoretical framework for the numerical studies presented in chapter 4.

It was required to establish a clear baseline for the quantitative evaluation of the impact of Covid-19 and resulting after-effects on European new passenger car registrations. As to establish this baseline SARIMA models have been fitted in R to datasets of the ACEA - for NPCR by country (ACEA 2021e) and by manufacturer (OEM) (ACEA 2021f) in Europe - for a specified pre-Covid time frame (Jan/2003-Dec/2018 for countries, Jan/2001-Dec/2018 for OEMs). Beyond that, an evaluation of the forecast accuracy of the best fitting SARIMA models was conducted in a specified pre-Covid verification time frame (Jan/2019-Dec/2019), which data haven't been used for the fitting process of the models. As a measure for the forecast accuracy, the mean absolute percentage error (MAPE) was used, while a MAPE $< 15\%$ has been considered acceptable. In the next step, the model with the lowest MAPE was selected for forecasting European NPCR of a specific country or OEM respectively in a specified post-Covid-19 time frame (Jan/2020-Dec/2021). Accordingly, the forecasted events can be considered as realizations of NPCR, which neglect the disruptive Covid-19 effects and consider pre-Covid-19 time series variability only, exhibited in the European automotive industry. This approach allowed for an adequate evaluation of the quantitative Covid-19 impact by comparing the observed new passenger car registrations and the forecasted realization in the specified post-Covid time frame. With respect to the results of this approach, the following two sections summarize the main findings of the thesis and provide an outlook on possible future research questions.

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## 5.1 Summary of the Main Findings

In the numerical studies presented in sections 4.2 and 4.3, the Covid-19 impact and the resulting after-effects on new passenger car registrations (NPCR) for 21 countries of the EU27, the EFTA, and the UK, and 21 OEMs concerning NPCR in the EU14, the EFTA, and the UK were analyzed in reference to pre-Covid-19 time series variability exhibited in the European Automotive Industry; the proposed evaluation approach for this purpose has been described in section 4.1. Thereby, the 21 selected countries (see section 4.2.1) cover most of the NPCR in the EU27, the EFTA, and the UK, with an aggregate market share of 94,03% in 2021 (ACEA 2022a), while the 21 selected OEMs (see section 4.3.1) cover the great part of the NPCR in the EU14, the EFTA, and the UK, with an aggregate market share of 84,79% in 2021 (ACEA 2022b).

First, it can be stated that the selected SARIMA models for the 21 countries (see table 4.1) and the 21 OEMs (see table 4.3) were able to reasonably establish the baseline forecast for the evaluation of Covid-19's impact on new passenger car registrations (NPCR), as evidenced by the fairly good fit during the verification time frame (Jan/2019-Dec/2019). In this context, the forecast accuracy (measured by the MAPE) of the aggregated NPCR forecast for the 21 countries and the 21 OEMs, which results from the respective sum of their forecasts from the 21 individual SARIMA models, amounts to 5.53% (21 countries) and 4.82% (21 OEMs) respectively. Beyond that, ranges the MAPE for the selected individual 42 models between 3,85% and 14,63% in the verification year 2019.

By a comparison of the results for the 21 countries (see section 4.2.2) and the 21 OEMs (see section 4.3.2) on an aggregate basis over the considered evaluation time frame (Jan/2020-Dec/2021), a similar pattern was observable. In both studies, it was suggested, that the spread of the virus and related lockdowns and containment measures contributed in March 2020 to a steep drop in NPCR, which reached its trough in April 2020 (21 countries: -372,9%, 21 OEMs: -367,0%). After this severe impact on NPCR, a strong recovery phase could be noticed until July 2020, while the observed NPCR and the forecasted NPCR values stayed more or less at par until the end of 2020. Based on the analysis stated in section 2.3, it was suggested further, that the fast recovery in demand and the slower recovery of production capacities contributed to significant supply-demand mismatches in the global economy and especially in the automotive industry in the year 2021. In this regard, particularly the semiconductor shortages put strong downward pressure again on the automotive industry (OECD 2021a, pp.17-20). Accordingly, the results of both studies showed, that NPCR stayed in the nega-

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tive range in the whole year 2021, compared to time series variability. While the situation was easing slightly in the first half of 2021, the situation deteriorated in the second half of the year, with a maximum drop in NPCR for the 21 countries in October 2021(-51,5%) and the 21 OEMs in September 2021(-57,3%), in reference to the proposed evaluation approach.

In summary, was the year 2020 characterized by a Covid-19 induced deep impact on new passenger car registrations (NPCR) in March and April 2020 and a subsequent strong recovery phase. In contrast, was the effect of the supply chain disruptions and shortages on NPCR in 2021 less severe in a single month but was persisting the whole year. As a result, the overall impact on NPCR in the 21 countries (-31,1%, -3'439'513 NPCR) and in the 21 OEMs (-34,8%, 3'126'230 NPCR) in 2021 was more severe than in 2020 (21 countries: -27,4%, -3'082'185 NPCR; 21 OEMs: -27,3%, -2'572'054 NPCR). In reference to the analysis of chapter 2.3, it is suggested, that this is a result of the semiconductor shortages, which drastically intensified in the second half of the year 2021. Based on the proposed evaluation approach, it is suggested that the impact of Covid-19 and the resulting after-effects on NPCR were quite severe so far. In summary, NPCR decreased for the 21 European countries in total over the observed time frame (Jan/2020-Dec/2021) by -29,2% or -6'521'698 NPCR and for the 21 OEMs concerning NPCR in the EU14, the EFTA, and the UK by -30,9% or -5'698'284 NPCR, in comparison to pre-Covid-19 time series variability exhibited in the European Automotive industry.

Beyond that, the results concerning Covid-19's impact on NPCR for each of the 21 European countries of the EU27, the EFTA, and the UK, and each of the 21 OEMs with respect to NPCR in the EU14, the EFTA, and the UK, were presented in sections 4.2.2 and 4.3.2 and subsequently compared in sections 4.2.3 and 4.3.3. It could be observed, that the results for the individual countries and OEMs showed generally the same pattern in the specified Covid-19 NPCR impact evaluation time frame (Jan/2020-Dec/2021) as the previously described results for the 21 countries and the 21 OEMs in total, yet, with different characteristics in relation to the initial Covid-19 impact in spring 2020, the following recovery phase, and in 2021, which was characterized by the semiconductor shortages. However, the results of some countries and OEMs are particularly noteworthy.

Regarding the deepest Covid-19 impact on NPCR in relation to time series variability, which was recorded in April 2020, Italy (04/20, -3712,4%), the UK (04/20, -3592,4%) and Spain (04/20, -2587,3%) stand out in comparison to the result for all 21 countries (04/20, -372,9%) in total (see figure 4.12). The same

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holds for Honda (04/20, -902,6%), Nissan (04/20, -787,4%) and Fiat (04/20, -622,7%) compared to the aggregate value of all 21 OEMs (04/20, -372,9%) (see figure 4.25). In contrast, Denmark (04/20, -68,9%) and Norway (04/20, -58,8%), BMW (04/20, -210,1%), Volvo (04/20, -204,1%), and Mitsubishi( 04/20, -180,0%) were the countries and OEMs least affected in this respect.

In terms of recovery in 2020 and overall performance in 2020 and 2021, concerning new passenger car registrations (NPCR) in comparison to pre-Covid-19 time series variability, the following main findings emerged. Among the observed countries, Norway (+0.2%) and Denmark (-0.8%) recovered the most and performed the best overall in 2020; Germany (-11.5%) was ranked third, while the United Kingdom (46.4%), Ireland (-50.9%), and Spain (-53.9%) were particularly hit hard in 2020. Of the OEMs observed, Toyota (-2.0%) and Volvo (-3.7%) in particular recovered the most in 2020, while Opel/Vauxhall (-56.0%), Honda (-57.0%), and Nissan (-61.2%) were the OEMs with the heaviest impact on NPCR in 2020 overall. In reference to the provided analysis for 2020, it is worth mentioning that most of the observed countries and OEMs have at least partially recovered in the second half of the year from the deep Covid-19 induced impact on NPCR in spring 2020 (see table 4.2 and 4.4).

In 2021, which was characterized by the semiconductor shortage in the automotive industry, the situation looked different. Except for Norway, Estonia, Ireland, and Denmark, which recorded 8, 7, 4, and 3 positive months in 2021, most other countries stayed completely in the negative range. As in 2020, only Norway showed a plus in NPCR in 2021 compared to pre-Covid-19 time series variability, yet, a significantly higher one than in the previous year with +20,1%. Estonia (-1,7%) and Denmark (-10,7%) ranked second and third while the UK (-44,9%) and Spain (-60,4%) were again in the highest impact range as in 2020; Lithuania (-115,2%) was most affected in 2021. Of the 21 OEMs observed, only Toyota performed quite well in 2021 with 7 positive months, while Hyundai and Volvo recorded at least 4 and 3 positive months. As a result, Toyota (+4,5%) ranked first in 2021, with the only increase in NPCR compared to pre-Covid-19 time series variability. Beyond that, Volvo (-7,6%) performed second best as in 2020, followed by Citroen (-13,5%), and Hyundai (-13,7%). The OEMs with the most severe NPCR decline in 2021, compared to pre-Covid-19 time series variability, were Ford (-75,7%), Mitsubishi (-76,7%), Honda (-83,3%), and Nissan (-92,7%) at the last rank.

Regarding the overall performance in the complete considered post-Covid-19 time frame (Jan/2020-Dec/2021) measured by observed NPCR against pre-Covid-

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19 time series variability, Norway was the only country with a plus of 11,2%. Additionally, countries like Denmark (-5,5%), Estonia (-5,5%), Luxembourg (-14,1%) and Germany (-17,7%) are in the lowest Covid-19 impact range, while countries like Portugal (-45,0%), the UK (-45,6%), Spain (-57,2%), and Lithuania (-66,7%) have been affected most in reference to the proposed evaluation approach (see figure 4.13). Concerning the OEMs, only Toyota recorded an increase (+1,35%) in observed NPCR over 2020 and 2021 compared to pre-Covid-19 time series variability. Volvo (-5,62%) was ranked second, followed by KIA (-16,2%) and Citroen (-16,3%), while Mitsubishi (-50,9%), Ford (-52,8%), Honda (-69,0%), and Nissan (-75,8%) performed worst over the years 2020 and 2021 (see figure 4.26). In this context, the last section of this thesis provides some speculations on potential causes for such differences in the results of the observed countries and OEMs proposed by the analysis and states a related outlook for possible future research topics.

## 5.2 Outlook

In reference to the proposed evaluation methodology, it can be stated that the Covid-19 impact and resulting after-effects on new passenger car registrations (NPCR) for the 21 observed countries of the EU27, the EFTA, and the UK, and the 21 observed OEMs with respect to NPCR in the EU14, the EFTA, and the UK was obvious. However, it was interesting to notice that some countries like Norway or Denmark and some OEMs like Toyota or Volvo have performed quite well regarding NPCR over the specified evaluation time frame (Jan/2020-Dec/2021) in comparison to their peers. Beyond that, some countries like the UK, Spain, and Lithuania and OEMs like Ford, Honda, and Nissan have been hit much harder in reference to NPCR, measured against pre-Covid-19 time series variability. Subsequently, some speculations are made about possible causes for these differences based on the analysis presented. However, scientific evidence for possible causes would have to be investigated in further research projects.

As stated in the introductory chapter in section 2.3.3, the impact of the Covid-19 pandemic on electric vehicles sold was not as strong as for the automotive industry at large. Since 65% of all new car sales in Norway in 2021 were electric vehicles (Klesty 2022), this might have influenced Norway's good results concerning NPCR suggested by the analysis. It was mentioned further in section 2.3.4.2, that Toyota improved its supply chain transparency drastically because of the shortages induced by the earthquake and the tsunami in Japan in 2011 (Hensley et al. 2021, p.2). In the proposed analysis, Toyota was the only OEM that



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performed quite well in the year 2021, which could indicate that Toyota's supply chain and its management were better prepared for the logistical disruptions and the semiconductor shortages in 2021. Volvo is one of the first movers in the field of innovative sales methods, as was stated in section 2.3.5 of this thesis. That could be a sign of Volvo's good performance in 2020. Beyond that, Toyota, which has its headquarters in Japan, and Volvo, part of Geely headquartered in China, may have generally had better access to semiconductors in 2021. Germany is the leading automotive market in Europe, and the automotive industry is one of the largest contributors to GDP in the country (Statista 2021). Therefore, German policymakers are very keen to protect the automotive sector in particular, which could be related to Germany's good recovery concerning NPCR in 2020, as was suggested by the analysis. Furthermore, Italy, Spain, and the UK were particularly hit hard by the first wave of the Covid-19 pandemic in spring 2020 (WHO 2022). Related strict containment measures to prevent the spread of the virus are most probably the cause for their deep drops in NPCR in March and April 2020. However, a part of the generally poor performance of the UK in 2020 and 2021 might also be explainable by its exit from the EU on January 31, 2020 (EU 2022). In addition, Denmark is known for its good Covid-19 crisis management and high vaccination rate in comparison to other countries in Europe (Statista 2022a). That could explain Denmark's good performance concerning NPCR over 2020 and 2021. Hence, such differences in the results of the provided analysis for the 21 observed European countries and the 21 observed OEMs could be investigated in future research projects based on:

(a) Specific car types (fuel-based vehicles, electric vehicles, hybrid vehicles, etc.)

(b) Supply chain resilience, exposure to disruptions and related shortages, etc.

(b) Innovative retail strategies, e.g., online car sales, virtual car showing tools, private car showings, etc.

(d) Governmental automotive policies

(e) Government responses to the pandemic

Another future research question could focus on the interactions of the effects of the prevailing very disruptive environment in the automotive industry and the impact of Covid-19 on new passenger car registration (NPCR). In reference to the pre-Covid-19 analysis of the automotive industry in section 2.1.1, the automotive industry was facing four major disruptive mega-trends - *vehicle electrification, connectivity, autonomous driving, and shared mobility* - even before Covid-19. These disruptive mega-trends are even more present today and will massively



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transform the automotive industry over the next decades (Cornet et al. 2019, p.14). Hence future research projects could be concerned with a separation of the long-term Covid-19 effects on NPCR and the effects attributed to the prevailing highly disruptive environment in the automotive sector. Beyond that, factors like increasing political tensions and trade restrictions, a change in mobility behavior, or one of the other various challenges which the automotive industry is facing today could be considered in this respect.

In this context, the proposed new passenger car registrations (NPCR) impact evaluation approach stated in section 4.1 provides a way to establish the baseline NPCR forecasts to conduct such analyses. The capability of the proposed time series model (SARIMA) forecasts to reasonably establish the pre-Covid-19 systematic patterns (trend, seasonality) of new passenger car registrations and their ability to highlight the Covid-19 impact and the resulting after-effects on NPCR make these forecasts suitable for more disaggregated analyses.

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# Appendix

## Appendix A

### Invertibility of a Moving Average Process

Generally, it is possible to express any stationary finite AR(p) model, which parameters satisfy the stationary constraints, as an infinite MA($\infty$) model. An example, where an AR(1) model is rewritten as an MA($\infty$) model by using repeated substitution is illustrated below (Hyndman and Athanasopoulos 2018, p.237):

$$\begin{aligned} y_t &= \phi_1 y_{t-1} + \varepsilon_t \\ &= \phi_1(\phi_1 y_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \\ &= \phi_1^2 y_{t-2} + \phi_1 \varepsilon_{t-1} + \varepsilon_t \\ &= \phi_1^3 y_{t-2} + \phi_1^2 \varepsilon_{t-2} + \phi_1 \varepsilon_{t-1} + \varepsilon_t \\ & etc. \end{aligned} \tag{.1}$$

Under the stationary condition of the AR(1) model: $-1 < \phi_1 < 1$, the value of $\phi_1^k$ is getting smaller with an increasing value of $k$, which results in an MA($\infty$) process as depicted below in equation .2 (Hyndman and Athanasopoulos 2018, p.237):

$$y_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_1^2 \varepsilon_{t-2} + \phi_1^3 \varepsilon_{t-3} + \ldots \tag{.2}$$

The reverse is only possible with some additional constraints on the MA parameters. In this case, it is said that the MA process is *invertible.*, i.e., that it is possible to express an invertible MA(p) model as an infinite AR($\infty$) model. However, the invertibility constraints are not simply imposed to convert MA processes into AR process, but have additional useful properties, which will be explained with an MA(1) process $y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1}$ in the following. The most recent error of an MA(1) process can be stated in its AR($\infty$) formulation, as a liner function of current and past observations (Hyndman and Athanasopoulos 2018, p.238), as illustrated in equation .3.

$$\varepsilon_t = \sum_{j=0}^{\infty} (-\theta)^j y_{t-j} \tag{.3}$$

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A rational assumption would be that the most recent observations have higher weights than observations from the more distant past, which requires $|\theta| < 1$ and leads to the invertible constraint of the MA(1) process, which is illustrated in equation 3.18 in section 3.4.2 of this thesis. The invertibility constraints for an autoregressive model of an order $q \geq 3$ are more complicated and beyond the scope of this thesis. However, the interested reader can find more information regarding this topic in Chatfield and Xing (2019, pp.51-52)

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# Appendix B

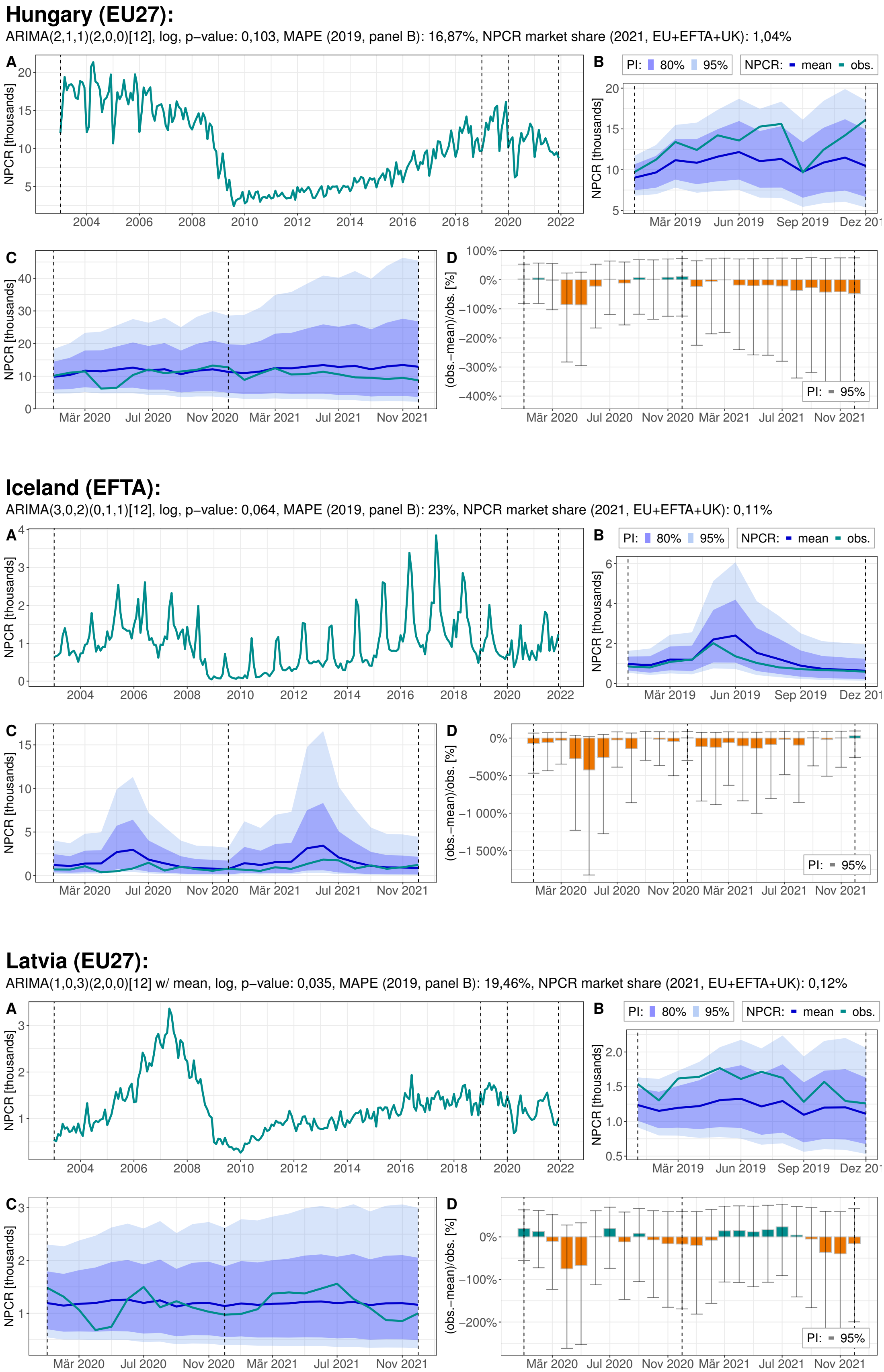


Figure .1: Covid-19's Impact on NPCR: Hungary, Iceland, Latvia
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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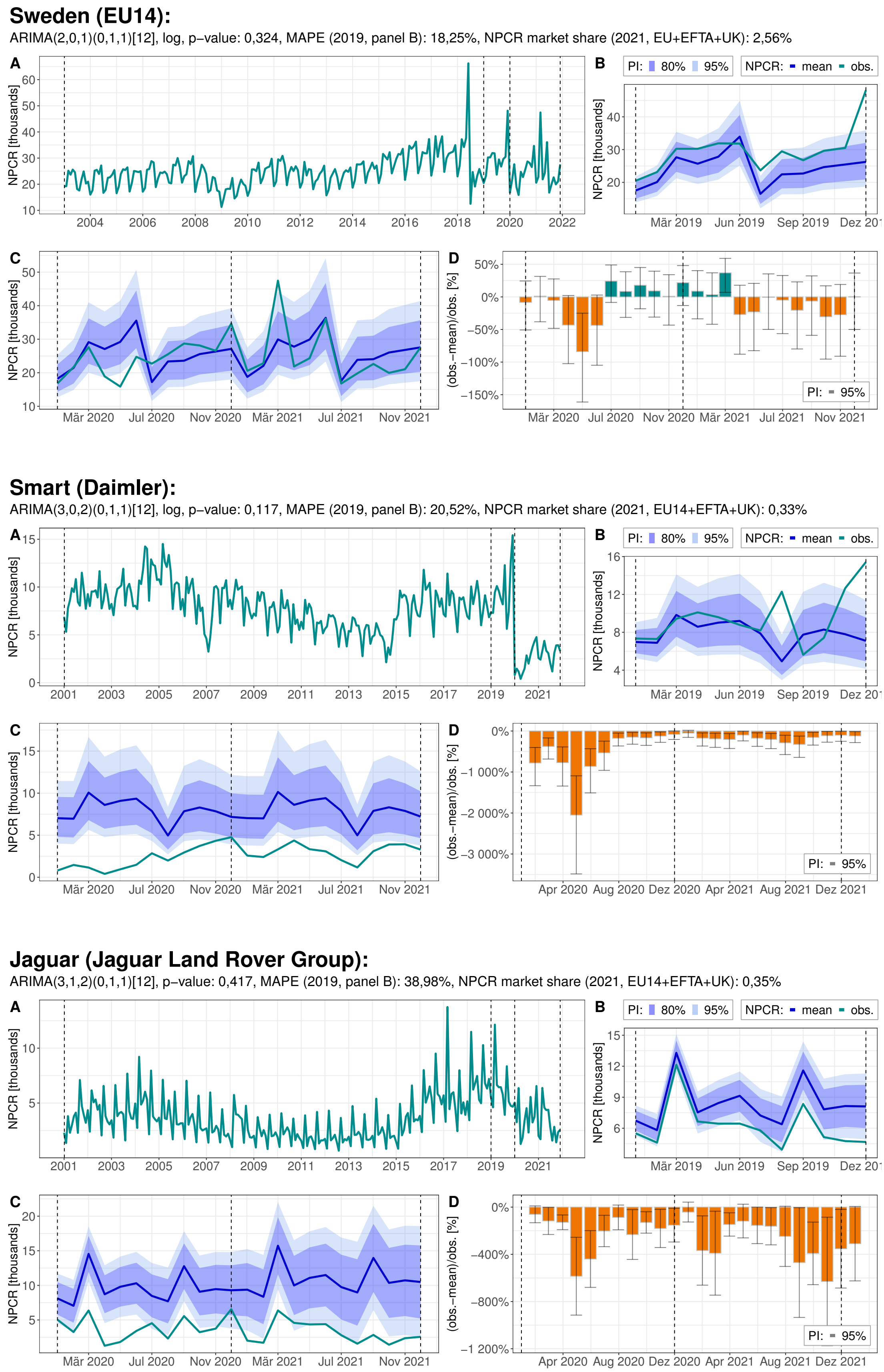


Figure .2: Covid-19's Impact on NPCR: Sweden, Smart, Jaguar
Data Source NPCR observed (obs.): (ACEA 2021e), (ACEA 2022a)

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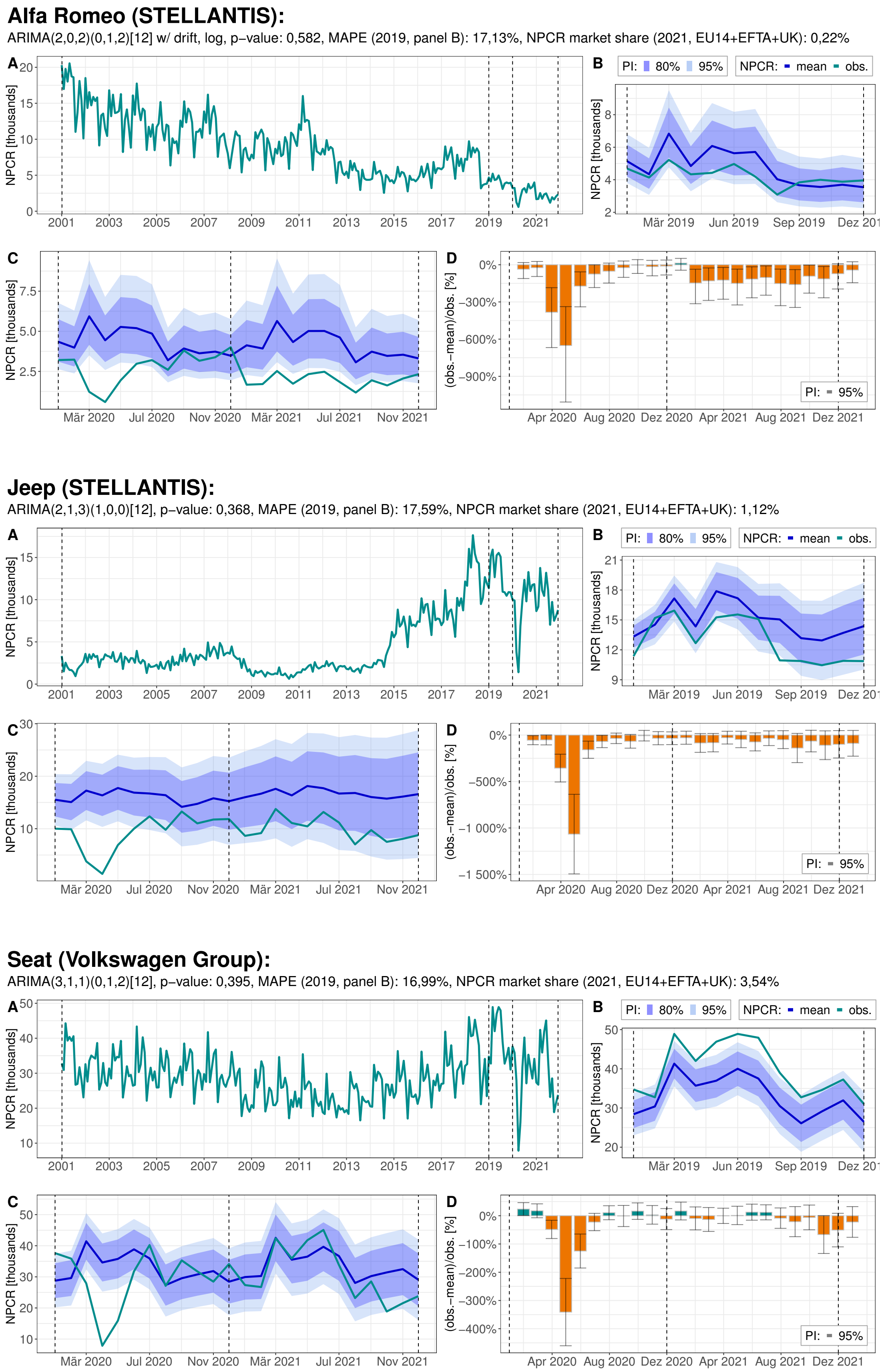


Figure .3: Covid-19's Impact on NPCR: Alfa Romeo, Jeep, Seat
Data Source NPCR observed (obs.): (ACEA 2021f), (ACEA 2022b)

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