Institut für Höhere Studien
Institute for Advanced Studies
Vienna

TU Wien
Continuing Education Center

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Reputation and Certification in Online Shops

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Prof.Rudolf Winter-Ebmer

Mag. Agnes Kügler

0252172

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MSc Economics

Affidavit

I, Agnes Kügler

hereby declare

that I am the sole author of the present Master's Thesis,

Reputation and Certification in Online Shops

34 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and that I have not prior to this date submitted this Master's Thesis as an examination paper in any form in Austria or abroad.

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Abstract

This paper discusses the impact of seals of quality in e-tailing shops on consumer behavior by using data acquired from the online price search engine geizhals.at. This price comparison site covers most of the Austrian e-tailing market. The main question is if the self-organized retailer evaluation mechanism provided by the search engine is sufficient to overcome the intrinsic information inequality experienced by consumers or if other instruments, like seals of quality are needed to provide additional signaling methods for sellers. The demand for a product cannot be measured directly, so the concept of 'Last-Click-Through' is used as a proxy. In total the dataset covers three dimensions, namely time, firms and products, which need to be considered in the modeling process. Therefore fixed effect estimations are performed, also considering the endogeneity problem caused by the nature of demand models.

1 Introduction

Since large online market places like Amazon and eBay emerged at the end of the 90s of the last century, more and more online market places and small, specialized web shops have been founded. As a consequence the need for meta search engines for price comparison became urgent. How should the user know where to find the desired product at the minimum price? On the one hand it is impossible for the consumer to know each adequate shop offering the product that is being searched. On the other hand even if the web shops were known to the user, it would be very time consuming to manually search in all of them. Sometimes, different web shops use different product identifiers for one and the same product. Only by assessing the technical details or the serial numbers of the manufacturers, if they can be found at all, a consumer can guess that two products are actually the same. Therefore price comparison services like http://pricegrabber.com or http://pricewatch.com have been established. In the German speaking world the shopbot http://geizhals.at was developed in 1996 and rapidly became one of the most frequently used price search engines. As a matter of fact in special sectors like the markets for high tech products and electronic goods the market share of these web shops is increasing.

There had been a lot of research done regarding online markets, since never before it has been possible to investigate consumer behavior so thoroughly. Due to the huge amount of data generated by online shopping the analysis of consumers' decision processes and their preferences has become more solid. Many authors concentrated on questions regarding the price setting behavior in online markets. For example, Ellison and Ellison (2009) show that online markets are extremely price sensitive due to high competition. They investigate the usage of obfuscation strategies to generate a less price sensitive market and thus earn higher markups. Clay et al. (2001) study the methods of retailer differentiation and the impact of high competition on price convergence.

A paper about airline ticket offerings of online travel agents has been written by Clemons et al. (1999), concentrating on price discrimination and product differentiation.

Additionally, a lot of work has been done regarding the effects of online feedback mechanisms. Dellarocas (2003) analyses the differences between Internet based feedback mechanisms and traditional word-of-mouth networks. Many studies, including for instance Dewan and Hsu (2004), Bajari and Hortaçu (2003) and Ba and Pavlou (2002), find that positive feedback or a higher net score increase prices, whereas negative feedback does not influence pricing significantly.

What has hardly been looked at is the impact of certification and seals of quality on consumer behavior in online markets. This paper focuses on exactly this aspect of consumers' decision finding.

Since consumers have to be able to trust the retailers having honest intentions, self-organized assessment of retailers by consumers is obviously necessary to reduce efficiency losses. But the question is if an additional layer of credibility by an independent third party is desirable as well. Has the introduction of quality seals like the Euro Label or the WKO seal any effects on consumers?

In the next section some thoughts about the categorization of product attributes are discussed. A detailed description of the database and the sample used in further regressions can be found in section 3. Section 4 provides discussions about the measurement of demand and the estimation procedure. In the last section the estimation results are presented and shortly reconsidered.

2 Theoretical Considerations

Especially in online markets, where the search costs for consumers as well as the entrance costs for sellers are low and thus competition is particularly high, it is essential for sellers to distinguish themselves from their competitors.

To make a difference at a vertical level firms could decide to offer products of higher quality. At the horizontal level sellers choose products with different characteristics in order to address different consumer groups. Of course these two characterizations can not be seen independently from each other when considering products endowed with several attributes. One could think of influencing the horizontal level as well when deciding to sell high quality products only. In most cases the sophistication of the design will go hand in hand with the level of quality.

If the seller has once taken the decision to bet on high quality products, the question remains how to communicate this choice to the consumers.

Categorization Following the categorization of goods by Nelson (1970), the quality signaling problem of firms can be studied more accurately. There are three different kinds of quality attributes available, namely search, experience and credibility attributes.

In most cases information about the price and quality of goods can be achieved by search. The demand for a dress might not only depend on the price but also on the fit when the consumer tries it on. Such search attributes are in most cases physical attributes like color, style, fabric, size, etc.

However, there are also goods for which the quality cannot be evaluated until the consumer has actually bought them. Examples of experience attributes are taste, performance or productivity. Only by experience one can assess the quality of services provided by sellers like one might rate a song only after hearing it.
The third quality attribute is credibility. Sometimes the consumer cannot observe the quality neither before nor after the purchase. Thus they have to rely completely on the credibility of the firm. Examples are environmental impact of the production process or health and safety related issues in the food and drug industry.

Signaling and Hedonic Markets According to the literature (see Nesheim (2006), Ekeland et al. (2004)), in an hedonic market each consumer derives utility from a vector of characteristics $z \in Z_m \subseteq \mathbb{R}^{n_z}$, where the bundle Z_m is the feasible set given current market conditions. The price is given by $p(z)$ and the utility $U(p(z), z, x)$ is decreasing in prices. The consumer is represented by $x \in X \subseteq \mathbb{R}^{n_x}$, where x is a vector of consumer characteristics and X represents the space of all types of consumers. Thus, given $p(z)$, the consumer x chooses the bundle z to maximize her utility. The consumer has to solve the maximization problem

$$max_{\{z \in Z_m\}}\{u(x, z, p(z))\}.$$

The solution to this gives the demand correspondence of consumer type x.
Considering a discrete choice model for deriving individual demand and J elements in Z_m, in the quasilinear case consumer x chooses z_j if and only if $u(x, z_j) - p_j \geq u(x, z_k) - p_k$ for all $k \in \{1, ..., J\}$. Thus beside the prices, only the product characteristics matter. Now let $p = (p_1, ..., p_J)$ and $z = (z_1, ..., z_J)$. Additionally denote the demand of consumer type x for product j, $D_j(p, z, x) \in [0, 1]$, and $f_x(x)$ describes the density of consumers with support X. Then aggregate demand for good j can be written as

$$q_j(p, z) = \int_x D_j(p, z, x) f_x(x) dx.$$

Since in this model the demand of consumer x only depends on observable characteristics, the only way to incorporate unobservable attributes into the decision process is by involving measures of credibility as characteristics of the product.

In particular in the e-tailing markets problems accompanied with asymmetric information are of central importance since consumers do not have the possibility to peer the products' physical form until purchasing them. To reduce this draw-

back and to differentiate from competitors retailers use (a mixture of) different strategies.
Basically sellers of high quality goods or services might utilize four possible signaling strategies to distinguish their products from those of their competitors (see Dewally and Ederington (2006)).

The first strategy and an obvious solution to the problem is certification, which can be offered either by the firm itself or by a third independent party. Of course the turning point here is the credibility of the certification issuing institution which determines the consumers' confidence. Only if the consumer trusts the certification (and the certification issuing institution) this could help to improve the seller's reputation. Naturally such certifications are also useful in the case of experience attributes.
The second strategy could be investing resources to build up a reputation for high quality products or a good price-quality ratio as was analyzed by various authors (see Shapiro (1983), Klein and Leffler (1981)). Actually online markets provide a good framework for a quick reputation building. In meta search engines or online market places, like eBay, consumers are invited to evaluate the seller's service and the quality of the sold product. Thus on the one hand this self-organized assessment helps to establish a reputation and on the other hand it can serve as a mirror of a seller's past performance. As a consequence most empirical studies working with online markets point out the influence of these consumer evaluations on demand, price differentials etc. (see Dewally and Ederington (2006), Dellarocas (2003))
Another strategy would be to offer services like warranties or money back guarantees. This conveys the impression the seller being convinced of the offered product's quality and is thus fully committed to the product.
The fourth strategy would be information disclosure. For example, in eBay auctions it is possible to transmit a picture of the offered product, such that the consumer is at least able to infer from the picture to the quality level. All of these would give a clear signal that the product and service offered is of high grade and the retailer is a good trading partner.

Thus the big advantage of online market places and meta search engines is that measures for credibility are available to a large extent. As already mentioned, one way to measure the credibility is to look at the self-organized consumer evaluation of the retailers and the products they offer. A consumer is only willing to trust a seller before the actual purchase has taken place if other consumers made fair deals with him in the past. In addition one could control the other strategies more or less easily since information about the availability of quality seals or other certifications, warranties and money back guarantees is publicly accessible. The only thing one has to do is to switch on the internet and evaluate the information gained.

3 Data

3.1 The Database

For this study the database of http://geizhals.at[1] is used. This website is a price search engine, which compares products offered by different e-commerce retailers by standardized protocols according to their prices, but also including a more or less detailed description of the product and its characteristics like the amount of shipping costs involved, the availability of the product, consumers' online evaluations, etc. If available, sellers are also allowed to present seals of quality which can be seen by the users immediately after starting the product search and thus should be taken into account in their purchase decision.

On the product level, the observations can be clustered into different subclasses, like Camcorder, Video, DVB Receiver, Beamer and Scanner, Television and sub-subclasses like DVD equipment, SAT-receiver or digital camera. In each of these subclasses the consumer can choose between offers by several suppliers according to the product characteristics described above.
To get a better impression how this meta search engine works, the reader is invited to have a look at figure 1 in the appendix. The figure shows the offered proposals given by http://geizhals.at after having started an arbitrary search for a silver digital camera produced by *CANON*. The offers are ordered according to their prices, which can be seen in the first column. The second column informs the consumer about the company logo and if the seller is endowed with a quality seal. The online feedback as well as the number of consumers, which already have assessed that particular retailer, are shown in the third column. Details of shipping costs, the availability of the product and the geographical location of the retailer can be taken from the fourth column. Product information is given in the fifth column.
Because of the broad market penetration of the geizhals.at, it grasps the whole Austrian online market also capturing e-tailers located abroad, particularly in

[1]The English translation of 'geizhals' is 'nickel nurser'.

Germany, which are interested in the Austrian e-commerce business.
The observations taken into account for this paper range over a period from the 1^{st} of May 2006 till the 30^{th} of December 2008. Weekly data is considered. During this period 50.601.258 observations could have been made. In total 1.553 e-commerce retailers have been observed, offering 35.006 different products.

3.2 The Quality Seals

Currently, there are two e-commerce quality seals used in geizhals.at. On the one hand there is a seal issued by the WKO (Austrian Economic Chamber of Trade, Commerce and Industry)[2]. On the other hand a seal called Euro Label is available, issued by the club 'Verein zur Förderung der kundenfreundlichen Nutzung des Internet'[3].
The information about which e-tailers have entered contracts with one or both of these seal issuing institutions can be found at their webpages. The data about the quality seals includes not only the fact that an e-commerce retailer has such a certification, but also the date of grant, as well as the revoking date[4].

In total 1209 quality seals of the two firms have been awarded. In the observation period 166 firms are equipped with at least one quality seal. 8 e-tailers actually have the WKO seal as well as the Euro Label. Out of the sample 90 suppliers have the Euro Label and 84 suppliers are able to disclose the WKO seal. During the observed time the WKO seal was revoked from two retailers only and the Euro Label had never been revoked from suppliers in the sample.
The development of retailers with quality seal(s) in the sample can be seen in figure 2. During the observation period the number of sellers entitled with a quality seal increased more or less steadily. Between the 50^{th} week (April 9, 2007) and the 100^{th} week (March 24, 2008) both seals seemed to be given to roughly the same amount of firms. After the 100^{th} week, the increase of the number of retailers endowed with the WKO is slightly less than the increase of the number of firms entitled with the Euro Label.
Altogether at this moment in total the Euro Label Austria and the Euro Label Germany have been awarded to 639 retailers. The WKO seal to 570 companies. There are different reasons why this data only matches with 166 retailers of the

[2]http://portal.wko.at/wk/dok_detail_html.wk?AngID=1&DocID=312182
[3]http://www.euro-label.com
[4]For matching the quality seals with the data available from geizhals.at a Perl code including a phonetic search was written, which can be obtained on request from the author.

geizhals.at-data in total.
At first 199 companies of the Euro Label and 60 companies of the WKO seal have been awarded after the end of the observation period. In addition there is no information about the granting date of the WKO seal in 14 cases and thus these retailers are not considered in the analysis. Therefore one is left with 241 retailers with an Euro Label and 496 with a WKO seal.
Secondly some of the suppliers are not in business anymore and their internet domains have disappeared. This fact makes it impossible to retrace the correct matches.
At third there are a lot of companies awarded with a quality seal which are not acting in the market sector of interest. E.g. the companies 'Bambino World Handels GmbH', 'Austrian Airlines AG' or 'Robert Chlebec Reisen GmbH' are definitely not trading with products belonging to classes like Television, SAT-Receiver or Camcorder.

3.3 The Data Sample

Due to computational restrictions it was not possible to consider the whole data sample in this study. Rather than that a smaller subsample was chosen to get first impressions.
As already mentioned above, the dataset can be divided into several subclasses. In this paper one of theses classes, namely the subclass 'fotos', was chosen. Within this subclass I am concentrating on the offers of digital cameras.

From May 1, 2006 till the December 30, 2008 in total 4.369.332 observations (product-firm-time combinations) have been made. 929 retailers are actively offering 2.669 different products in this subsubclass.
Out of these a total number of 113 retailers are awarded with either the WKO seal or the Euro Label. Within this sample 54 different retailers endowed with an Euro Label and 64 retailers endowed with the WKO seal have been observed. As can be seen from figure 3, at the maximum, in one week 47 sellers with an Euro Label and 43 retailers with a WKO seal were listed at http://geizhals.at. Within this subsample over the whole observation period more retailers are entitled with an Euro Label than with a WKO seal. One explanation of this structure could be found in the composition of the retailers' location. The total number of retailers in this sample, 929, is made up of only 302 Austrian sellers, an overwhelming number of 624 German retailers and two suppliers from the Netherlands. Since the WKO seal is a quality seal issued by an Austrian lobby, whereas the Euro Label has locations in Austria and Germany as well, most German suppliers will

be endowed with an Euro Label rather than a WKO seal.

4 Empirical Analysis

For the estimation of the demand for retailer j's product i the following model is considered.

$$y_{ijt} = \alpha_i + \theta_j + \mu_t + \beta x_{ijt} + \gamma w_{jt} + \epsilon_{ijt} \quad (1)$$

Where products are indexed $i = 1, ..., N_j$, offered by retailer $j = 1, ..., J_t$ and they are observed within period $t = 1, ..., T_{ij}$. Note that we have an unbalanced panel since each product can be offered by different retailers at different time points. α_i, θ_j and μ_t represent the fixed effects which may be correlated with any of the observable covariates. x_{ijt} are vectors of covariates. w_{jt} are vectors of observable j-level covariates.
For the moment, assume that $\mathbb{E}\left[\epsilon|X\right] = 0$ and $\mathbb{E}\left[\epsilon_{ijt}^4\right] < \infty$. In the following estimations w_{jt} includes the two indicator variables for the WKO seal and the Euro Label[5] as well as the self-organized assessment of the retailers[6]. Note that w_{jt} do not vary over products i. x_{ijt} includes the price of product i of retailer j relative to the best-price offered for this product, the self-organized product assessment[7], the availability of the product i of retailer j, which was valid for the longest time period within the week under observation and shipping costs. y_{ijt} is a measure for consumer demand.

4.1 Consumer demand

There are two possible ways to measure the consumers' demand for product i of retailer j. On the one hand it could be measured by referral requests, i.e. by the total clicks of consumers at geizhals.at on a link to the product i of retailer j. However, referral rates should be rather seen as an instrument to measure the attention different retailers get.
On the other hand consumers' demand could be approximated with the concept of 'Last-Click-Through' (LCT). Unfortunately the actual purchase decision is un-

[5]The dummies are 1 if the retailer has a quality seal and 0 else.

[6]Consumers are able to evaluate retailers and give them grades ranging from 1 to 5 where 1 is the best grade.

[7]Similar to retailers, consumers are able to evaluate products as well, where the best grade is 5 and the worst is 1.

known since this act happens at the e-commerce retailers' own website and the data at hand only covers actions taking place at geizhals.at. But one could argue that the last click to a shop offering the demanded product after a thorough online-search for this product can be identified as the click related to the highest purchase probability (see Hackl et al. (2009), Smith and Brynjolfsson (2009)). Here the last-click-through is the dependent variable y_{ijt}.

4.1.1 How is the LCT calculated?

I follow Dulleck et al. (2009) in calculating the LCT and use their results. The authors suggest two approaches:

1. Calculating a dendrogram is the official clustering procedure which establishes hierarchical clusters by using the nearest neighbor principle.

   By using this procedure the clicks are grouped into search intervals. As a prerequisite one has to place some minimal requirements for the definition of a search period in a first step. Such a requirement could be to define the end of a search period as the interspace of one week without clicks and the resulting period has to contain at least 3 clicks. (An alternative could be to specify a minimum length of one month and a minimum amount of clicks of 5 clicks.)

   In a next step one has to check whether the calculated intervals meet the minimum requirements. Is the time span between the intervals at least a week? If not, then this interval is pooled with the nearest neighbor. If it is at least one week then one should check whether the interval contains at least three clicks. If the answer is no, pool it with the nearest neighbor. If yes, then this is a self-contained interval.

2. The alternative to calculating a dendrogram would be using the Grubbs test for outliers in the gaps between the clicks. The Grubbs test is a test to search for outliers taking into account the standard deviation of the sample. One basic assumption of this test is the normal distribution of the sample. Since a search requires the comparison of several alternatives, even a search period of one hour would have outliers. Therefore the minimal requirements described above are needed to be introduced as well.

Dulleck et al. showed that both methods lead to very similar outcomes, where the advantage of the Grubbs test is the easy implementation. The choice of the significance level is related to different levels of the dendrogram. This results in an identical grouping of the clicks in searching intervals as when using the official clustering method.

4.2 Data Description

Table 1 shows the descriptive summary statistics of the used variables. The variable $Time$ covers 139 observation weeks. $Firms$ and $Prods$ describe the total number of firms acting in the subsubclass 'digital cameras' offering different products.

The last-click-through, LCT, has a maximum of 544 clicks, a minimum of 0 and a mean value of 1.008. The variable RBP stands for the relative best price and is calculated by dividing the price of retailer j's product i by the lowest price offered for this product (='best price'). Its maximum and minimum value is 1 and 4.991, respectively, where observations more or equal to 5 times larger than the best price have been excluded from the analysis[8]. The variable EL is 1 if the retailer at time point t is entitled with the Euro Label and 0 otherwise. The same holds for the WKO seal, represented by the variable WKO. *Avail* describes the availability of the product. If the seller had not specified this attribute, *Avail* has value -1. The values 0, 1 and 2 stands for 'the product is not available', it is 'available at short notice' or just 'available', respectively. In the subsequent regressions dummy variables has been introduced representing the different characteristics of this variable. The variables *Austrian*, *Germany* and $Netherlands$ are 1 if the retailer is located in this country and 0 otherwise.

In http://geizhals.at different forms of shipping costs are reported. Thus one can distinguish between costs related to cash in advance, payment by credit card or cash on delivery. We only consider shipping costs for cash in advance transactions. Since there are a lot of missing values for this and the following variables, table 1 shows the number of observations available separately. The variable *Product Assessment* represents the ratio of the number of positive recommendations to the total number of evaluations within a month. Thus it ranges between 0 and 1 and its mean lies at 0.713. $Firm\ Assessment$ describes the average of the firm evaluations made by consumers of the last month. Its mean value is 1.767 and the variable ranges between 1 and 5, where 1 is the best grade a consumer can give.

Additionally in all subsequently presented estimations missing flags are included which account for the missing values in the variables *Avail*, *Product Assessment*, $Firm\ Assessment$ and *Shipping Costs*.

[8] In total 695 observations have been deleted.

The variable $ARBP$ is used later as an instrument and has a maximum at 3.752 and a minimum at 1. It represents the average relative best price of all products i except the product i offered by retailer j.

4.3 Estimation Procedure

Note that in the above presented model setup some pitfalls can be encountered. At first it is a three-way fixed effect model (FE-model) to be dealt with, since the dataset is three dimensional. Secondly the dataset is very large such that one is confronted with severe computational problems. Therefore time and memory saving methods of solving linear equation systems are required. The fact that there are different levels of observations and thus the data being clustered is another issue to think about. In particular for any testing procedure this should be borne in mind. The fourth complication arises by the estimation of a demand model. As usual in such a case, one is confronted with endogeneity problems. Consequently the introduction of an instrumental variable should be considered. In the following these problems and possible solutions are shortly discussed.

Assume that the unobserved time component μ_t is to be treated as fixed and estimated directly by using time dummies. Subsume these time dummies into one of the vectors of observed covariates.
The new two-way model is

$$y_{ijt} = \alpha_i + \theta_j + x_{ijt}\beta + w_{jt}\gamma + \epsilon_{ijt}, \tag{2}$$

or in matrix notation

$$y = F\alpha + D\theta + X\beta + \epsilon, \tag{3}$$

where $X(N^* \times K)$ is the design matrix of time varying characteristics, $F(N^* \times J)$ is the design matrix for the firm effects and $D(N^* \times N)$ is the design matrix for the product effects[9]. N^* is the number of year-product-firm combinations in the dataset.
It can be easily seen that a very large dataset is used. The dataset is of dimension $(T \times N \times J) \times K$, which is a row-dimension of several millions.[10] Thus a technical problem arises regarding the memory capacity of the computer used.

[9] For the sake of brevity in the following the subindices of J, N and T are skipped. But bear in mind that we are dealing with an unbalanced panel of three dimensions.

[10] In total 139 observation weeks, over 900 different retailers and more than 2.000 products are in the sample.

4.3.1 Spell Fixed Effects

If one is not interested in the estimates of α_i and θ_j and the sole aim is to control for unobserved heterogeneity, consistent estimates of β and γ can be obtained by taking differences or by demeaning within each product-retailer combination (or 'spell'). This is because for each spell of a product within a retailer neither α_i nor θ_j vary.
Defining $\lambda_s \equiv \alpha_i + \theta_j$ as spell-level heterogeneity, which drops out after subtracting averages at the spell-level, both α_i and θ_j have disappeared:

$$y_{ijt} - \overline{y_s} = \beta(x_{ijt} - \overline{x_s}) + \gamma(w_{jt} - \overline{w_s}) + (\epsilon_{ijt} - \overline{\epsilon_s}) \tag{4}$$

Any variable x_{ijt} or w_{jt} which is constant within a spell will not be identified. Thus one ends up with a two-dimensional panel and after sweeping out the spell-fixed effects only the time dummies are left for estimation[11].

4.3.2 Matrix Decomposition

Consider again equation (3). Another common way to handle this problem is to include one effect as a dummy variable and sweep out the other effect (here product effect) by the within transformation, i.e. by subtracting the group mean for all observations (see Andrews et al. (2006)). The transformed model is

$$\widetilde{y} = \widetilde{F}\alpha + \widetilde{X}\beta + \widetilde{\epsilon} \tag{5}$$

with the normal equation

$$\underbrace{\begin{pmatrix} \widetilde{X}'\widetilde{X} & \widetilde{X}'\widetilde{F} \\ \widetilde{F}'\widetilde{X} & \widetilde{F}'\widetilde{F} \end{pmatrix}}_{G} \begin{pmatrix} \beta \\ \alpha \end{pmatrix} = \underbrace{\begin{pmatrix} \widetilde{X}'\widetilde{y} \\ \widetilde{F}'\widetilde{y} \end{pmatrix}}_{H}$$

When applying this method by directly constructing the demeaned firm dummy variables, the matrix $(\widetilde{X}, \widetilde{F})$ has to be stored. But here the problem occurs since far too much memory would be needed. The estimation of product and firm effects would be impossible with restricted memory. To find a solution consider the matrices G and H. Unlike the matrix $(\widetilde{X}, \widetilde{F})$, which is of dimension $(N^* \times (K+J))$, the cross product matrices G and H are of dimensions $((K+J)\times(K+J))$ and $((K+J)\times 1)$ only.

[11] This procedure was implemented using the statistical package 'stata' and the command 'xtreg,fe'.

How should G and H be computed for very large datasets? Cornelissen (2006) suggests a decomposition using the fact that each element of G and H is a cross product sum of no more than two regressors. Thus for computing one element of G or H only two regressors need to be stored. Note that the X-part is raised by a dataset, but the F-part of the cross-product matrix can be created during the estimation without actually generating all the dummy variables. The information is compressed into the group identifiers.

Based on the fact that F is a sparse matrix, only certain parts of F are needed to be used and memorized. The cross-product matrices G and H can be represented as a sum of matrices G_i/H_i for each product:

$$G = \sum_i G_i = \sum_i \begin{pmatrix} \widetilde{X_i}'\widetilde{X_i} & \widetilde{X_i}'\widetilde{F_i} \\ \widetilde{F_i}'\widetilde{X_i} & \widetilde{F_i}'\widetilde{F_i} \end{pmatrix}$$

and

$$H = \sum_i H_i = \sum_i \begin{pmatrix} \widetilde{X_i}'\widetilde{y_i} \\ \widetilde{F_i}'\widetilde{y_i} \end{pmatrix} .$$

Now consider the decomposition for only those parts, where the F matrix is included. One gets

$$G = \begin{pmatrix} \widetilde{X}'\widetilde{X} & 0 \\ 0 & 0 \end{pmatrix} + \sum_i \begin{pmatrix} 0 & \widetilde{X_i}'\widetilde{F_i} \\ \widetilde{F_i}'\widetilde{X_i} & \widetilde{F_i}'\widetilde{F_i} \end{pmatrix} \tag{6}$$

and

$$H = \begin{pmatrix} \widetilde{X}'\widetilde{y} \\ 0 \end{pmatrix} + \sum_i \begin{pmatrix} 0 \\ \widetilde{F_i}'\widetilde{y_i} \end{pmatrix} . \tag{7}$$

The idea of the next step comes from Labor Economics. Literature often distinguishes between 'movers' and 'stayers' (see Abowd et al. (2002)), where movers are workers who change the employer at least once during the time of observation and stayers never change the employer. The $\widetilde{F}$ matrix has a different structure for stayers and movers. As stayers never change their employers, the demeaned firm dummies are zero. Applied to the current problem, i.e. that if products are always supplied by the same retailer and never by others sellers, $\widetilde{F}$ is a null matrix. Therefore equations (6) and (7) can be written as

$$G \;=\; \begin{pmatrix} \widetilde{X}'\widetilde{X} & 0 \\ 0 & 0 \end{pmatrix} \;+\; \sum\nolimits_{i \in Movers} \begin{pmatrix} 0 & \widetilde{X_i}'\widetilde{F_i} \\ \widetilde{F_i}'\widetilde{X_i} & \widetilde{F_i}'\widetilde{F_i} \end{pmatrix} \tag{8}$$

and

$$H \;=\; \begin{pmatrix} \widetilde{X}'\widetilde{y} \\ 0 \end{pmatrix} \;+\; \sum\nolimits_{i \in Movers} \begin{pmatrix} 0 \\ \widetilde{F_i}'\widetilde{y_i} \end{pmatrix}. \tag{9}$$

The same applies for the current problem. Only for movers the cross-product sub matrices $\widetilde{X}'\widetilde{F}$, $\widetilde{F}'\widetilde{F}$ and $\widetilde{F}'\widetilde{y}$ need to be computed. As the matrices can be computed product by product, the $\widetilde{F}$ matrix does not have to exist completely at any point in time.

If a product is never offered by certain firms, these columns of the $\widetilde{F_i}$ matrix will contain only zeros. Thus for each product i some columns of the cross-product including $\widetilde{F_i}$ will be equal to zero and one can treat these matrices as sparse. In a next step the zero columns are left out and the new matrix $\widetilde{F_i^L}$, which is $(T_i \times L)$, where $L \subseteq J$ is the number of firms offering product i. Now $(\widetilde{X_i}'\widetilde{F_i^L})$, $(\widetilde{F_i^L}'\widetilde{F_i^L})$ and $(\widetilde{F_i^L}'\widetilde{y_i})$ are computed instead of $(\widetilde{X_i}'\widetilde{F_i})$, $(\widetilde{F_i}'\widetilde{F_i})$ and $(\widetilde{F_i}'\widetilde{y_i})$.

4.3.3 Clustering

In the past the need to account for any within-group dependence in estimating standard errors has been ignored by many researchers. One reason may be that many statistical packages do not estimate robust standard errors in FE-models. But disregarding the presence of clustering can lead to severe bias in the standard error estimates and thus has an undesirable effect on testing (see Moulton (1990) and Moulton (1986)).

In addition Kezdi (2003) shows for a two-way FE-model that there is no need to fear bad finite sample properties even for small samples. By using a Monte Carlo study he concludes that the properties of the standard error estimators rather depend on the total sample size $N \times T$ and particularly on N itself, but not that much on the relative size of T to N. Anyway, for the purpose of this paper any fear regarding the sample size is negligible because of the large size of the cross-sectional data.

The robust variance matrix estimator for a simple FE-model (see Cameron et al. (2006), Cameron and Miller (2010), Arrelano (1987), Stock and Watson (2008)) is

$$\left(\frac{1}{N}\sum_{i=1}^{N}\widetilde{x_i}'\widetilde{x_i}\right)^{-1}\underbrace{\left(\frac{1}{N}\sum_{i=1}^{N}\widetilde{x_i}'\widehat{u_i}\widehat{u_i}'\widetilde{x_i}\right)}_{\widehat{B}}\left(\frac{1}{N}\sum_{i=1}^{N}\widetilde{x_i}'\widetilde{x_i}\right)^{-1} \tag{10}$$

with $\widehat{u_i} = \overline{y_i} - \widetilde{x_i}\widehat{\beta}_{FE}$.

But the model at hand has more than just one cross-sectional dimension. For each retailer and each product one observation is available at one point in time. Therefore consider a model where the observations fall into more than one group. Suppose each observation belongs to a group $i \in \{1, 2, \cdots, N\}$ and to a group $j \in \{1, 2, \cdots, J\}$. Now write the model as

$$y_{ijt} = x'_{ijt}\beta + u_{ijt},$$

where it is assumed that for $t \neq s$ and if $i \neq i'$ and $j \neq j'$

$$\mathbb{E}\left[u_{ijt}u_{i'j't}|x_{ijt}, x_{i'j't}\right] = 0.$$

When errors belong to the same group there might be an arbitrary correlation structure. The variance $\Omega = V(u|X)$ can no longer be written as a block diagonal matrix.
Instead of keeping only elements of $\widehat{u}\widehat{u}'$ belonging to the same cluster in one dimension, all elements belonging the same cluster in any dimension are kept.

$$\widehat{B} = \widetilde{X}'(\widehat{u}\widehat{u}'.*S^{NJ})\widetilde{X}, \tag{11}$$

where S^{NJ} represents an indicator matrix where the $q^{th}r^{th}$ element equals one if the q^{th} and r^{th} observation share any group and equal zero otherwise. $.*$ represents elementwise multiplication.
Consider three $(N^* \times N^*)$ matrices. Denote S^N a matrix with the $q^{th}r^{th}$ entry equals one if the q^{th} and r^{th} observation belong to the same group $i \in \{1, 2, \cdots, N\}$. Let S^J be a matrix with the $q^{th}r^{th}$ element equals one if the q^{th} and r^{th} observation belong to the same cluster $j \in \{1, 2, \cdots, J\}$. Denote $S^{N\cap J}$ with the $q^{th}r^{th}$ entry equals one if the q^{th} and r^{th} observation belong to group i as well as to group j.
Then

$$S^{NJ} = S^N + S^J - S^{N\cap J}.$$

It follows that $\widehat{B}$ can be written as

$$\widehat{B} = X'(\widehat{u}\widehat{u}'.*S^N)X + X'(\widehat{u}\widehat{u}'.*S^J)X - X'(\widehat{u}\widehat{u}'.*S^{N\cap J})X.$$

Then the three components can be computed by

1. Compute the variance matrix using clustering on $i \in \{1, 2, \cdots, N\}$ by performing an OLS regression of y on X.

2. Compute the variance matrix using clustering on $j \in \{1, 2, \cdots, J\}$ by OLS.

3. Compute the variance matrix using clustering on $(i, j) \in \{(1, 1), \cdots, (N, J)\}$ by OLS.

Then $\widehat{V}(\widehat{\beta})$ is computed by summing up the first two and subtracting the last variance matrix.
Similar to the one-way clustering also in the two-way version a small sample correction is usually done. Just use the formula for one-way clustering throughout all computations. Then $c_1 = \frac{N}{N-1}\frac{N^*}{N^*-K}$, $c_2 = \frac{J}{J-1}\frac{N^*}{N^*-K}$ and $c_3 = \frac{S}{S-1}\frac{N^*}{N^*-K}$, where S is number of unique groups provided by the intersection of the N and J groups[12].

4.3.4 Endogeneity

So far it was assumed that all explanatory variables are exogenous. Apparently this is not the case with the variable RBP. The price can be seen as endogenous as retailers change their prices in response to the quantity demanded and as well as consumers' actions depend on the price setting behavior of the suppliers. Thus also the price relative to the price-leader cannot be seen as exogenous.
As a consequence one might consider to introduce an instrument and perform a Two-Stage-Least-Square (2SLS) estimation instead.
A possible instrument could be the average relative best price of all products i except the product i offered by retailer j. Call this variable $ARBP$. It is calculated by

$$ARBP_{ijt} = \frac{\sum_{k \neq j} RBP_{i,k,t}}{I_t - \#Products_{i,j,t}}$$

for $k \in \{1, \cdots, J_t\}$, $i \in \{1, \cdots, N_j\}$, $t \in \{1, \cdots, T_{ij}\}$. I_t is the total number of product i offered by all retailers j at time t and $\#Products_{i,j,t}$ is the number of

[12] Due to numerical instabilities it was not possible to accomplish this method within the framework of this study. In the following estimations rather a one-way clustering on product-level was performed.

products i of retailer j at time t.

To perform a 2SLS estimation firstly estimate

$$RBP_{ijt} = \alpha_i + \theta_j + ARBP\varphi + x_{ijt}\lambda + \epsilon_{ijt} \tag{12}$$

with the procedure described above, where x_{ijt} includes all regressor variables but RBP. Then save the predicted values, $\widehat{x_{ijt}}$, from the first stage regression. In a second step estimate the model

$$y_{ijt} = \alpha_i + \theta_j + \widehat{x_{ijt}}\beta + \epsilon_{ijt} \tag{13}$$

to get the estimated coefficient vector $\widehat{\beta}$ and the estimates for the fixed effects.

5 Results

Table 2 contains the results of both, a product specific fixed effect estimation and the 2-way fixed effect estimation on the firm and the product level. Standard errors are given in brackets and the stars are indicating statistical significance at 1%-, 5%- and 10%-levels.
The first, the 4^{th} and the 6^{th} columns contain the output of estimations without having a firm specific fixed effect, but rather only a product-FE. The second column shows the changes when including product-clustered standard errors. As can be easily checked the differences between column (1) and (2) are relatively small. The third, the 5^{th} and the 7^{th} columns show the the results from estimations including a firm-FE as well[13].

The main conclusion from looking at table 2 is that the introduction of quality seals in the demand model seems to matter. In columns (4) and (5) one quality seal, namely the WKO seal, has been added in the regressions. Surprisingly, having a WKO seal has a negative and significant effect on LCTs. After the introduction of the firm-FE the sign changes, but the coefficient is nearly equal to zero.
Having a glance on columns (6) and (7) a similar pattern can be observed. The highly significant but negative coefficient of the WKO seal turns into a positive coefficient, which is hardly different from zero when adding the firm-FE. Thus the results regarding the WKO seals do not seem to be robust and are not very

[13] When thinking about the significance of the coefficients the reader should always bear in mind that for better accuracy two-way clustered standard errors should have been calculated.

convincing. In contrast the coefficient of the Euro Label has the expected positive sign in both specifications and is also significant at a 1%-level. Interpreting column (6) we find that having an Euro Label is connected with an increase of LCTs of 0.533 units, which is remarkable remembering the mean LCT being around one.

The coefficient of the self organized firm assessment is significant at a 1%-level in all estimations with fixed effects at the product level, but not including firm-FE. In accordance with theory the sign of the coefficient is here negative. Since 1 is the best grade a consumer could give, the lower the firm assessment the better the reputation of the retailer and the higher the demand. Note that after introducing the firm-FE, the absolute value of the coefficient of $Firm\ Assessment$ drops to nearly zero and became only significant at a 10%-level. As expected the effect of the firm evaluations is transmitted to the firm-FE as the variable $Firm\ Assessment$ is not varying much in time and constant over products.

When examining the control variables the coefficient of the price relative to the price leader is negative and highly significant. A one unit increase in the price in relation to the best price leads to a reduction of LCTs of around 3.4 units. This effect is smaller when firm-FEs are considered. The self organized product assessment has a positive impact on the measure of consumer demand and is significant throughout the estimations. An increase in product evaluations of about one unit would result in an increase of demand of around 0.2 units, which is worth mentioning when considering the mean of LCT. The variable $Shipping\ Costs$ has no significant effect on LCT in estimations. Being located in Austria or Germany is important when firm specific effects are not considered. Then having the store located in Germany seems to have a negative impact on demand. This result is significant different from zero throughout the estimations. It is noticeable that including the WKO seal, which is issued by an Austrian lobby, the coefficient for being located in Austria becomes significant and increases. When including both seals, the fact that a retailer has her shop in Austria increases demand by about one-third. In contrast a retailer settled in Germany has to expect a negative effect on demand. The coefficient for being located in Germany is quite robust through all estimations and significant at a 1%-level.

In line with theory, a product which is marked as 'not available' attracts less last clicks and the product characteristic 'available' has a positive impact on the demand measure.

Table 3 shows the 2SLS estimations. The first and third columns contain the estimation results of a regression without a firm specific effect and without clus-

tered standard errors. The second and 4^{th} columns contain the results when also clustered standard errors on the product level have been calculated.
In general no drastic changes can be detected after using instrumental variables. Both seals, the WKO seal and the Euro Label, are again significant at a 1%-level. As already noticed in table 2 the WKO seal has an unexpected negative sign, whereas the Euro Label is positive. Having an Euro Label increases the measure of demand by nearly 0.5 last clicks, half the amount of a retailer gets on average. The coefficients for firm evaluations are quite similar to the estimations without instruments. Also when incorporating the clustered standard errors on the product level the coefficients stay statistically significant. A better evaluation by one grade would lead to an 10% increase in demand. Unfortunately due to computational problems it was not possible to provide the IV-estimation results including firm specific fixed effects in the framework of this study. I expect that when including a firm-FE in the estimation a similar change to table 2 will take place and the significance of the coefficient might drop.
Examining the control variables, the huge decrease of the impact of the relative prices is ostentatious. If a retailer is 10% more expensive than the price leader, the demand will go down by 0.9 clicks. Bearing in mind that the mean of LCT lies at 1.008 this suggests a quite price sensitive market structure. In comparison with table 2 the impact of product evaluations increased a little bit, but the changes are not remarkable. The same holds for the effect of a product being not available. The importance of the availability of the product has shrunken by about one third, but remains significant in these estimations. It is questionable whether it stays significant when including a firm specific effect. When looking at the IV-estimations it can be seen that the dummy for being located in Austria has no significant effect any more. In contrast the coefficient for being settled in Germany stays highly significant and negative. Again having her shop in Germany reduces a retailer's number of last clicks by about 1.2 clicks. Consumers are able to use the feedback mechanism and have the possibility to choose retailers featured with a quality seals. But perhaps this is not enough to make the location of a seller unimportant. It might be that consumers would like to keep the option to go to the shop and complain about possible defects. Since http://geizhals.at is mostly used by Austrian users, this might explain the distinct negative effect of a German settlement.

6 Conclusions

In particular in online markets it is essential for retailers to establish mutual trust. On the one hand competition is high and thus it is necessary to communicate the offered product quality confidentially. Since consumers are not able to examine the good in its physical form and to build rapport to the retailer it is important to offer enough information to countervail the intrinsic information inequalities. On the other hand especially in the electronic sector most online shoppers buy sporadically, which makes it even more difficult for retailers to reduce their signaling problem. Thus appropriate feedback mechanisms or other instruments to reduce the information asymmetries, like certification by a third party, are needed. Literature has long been focusing on self-organized evaluation done by consumers, which has a remarkable effect on the consumption decision in online markets. This paper tries to study the question if these firm assessments are sufficient to bypass the lack of information experienced by consumers or if there is still the need for additional reassurances represented by special seals of quality.

Based on regression analysis of click data from the Austrian price search engine http://geizhals.at it is tried to examine the impact of quality seals on demand. At the moment two quality seals are represented at http://geizhals.at, the so called WKO seal and the Euro Label. Consumer demand is approximated by the concept of 'Last-Click-Through' (LCT). A particular challenge is given by the three-dimensionality of the dataset, including products, firms and time, and is discussed in detail, as well as by the huge size of the data set. Several model specification are considered including time, firm and product fixed effects. In addition an instrumental variable (IV) estimation is considered as a consequence of the endogeneity problems of the demand model.

The main result of this paper is that quality seals have an impact on consumer demand. At least for the positive effect on demand induced by the Euro Label strong empirical evidence is presented. The WKO seal seems to be less robust with respect to different model specifications and is not significant anymore when including firm fixed effects. The firm evaluations are statistically significant and provide a strong effect on LCT, but lose its significance when introducing firm fixed effects. This is not surprising because consumers' feedback hardly varies over time and remains constant over products.

In general consumers try to reduce their lack of information and in parallel several instruments are used to reach this target. In fact even when a consumer-organized evaluation mechanism is offered, the impact of quality seals should not be missed.

Actually, looking at the strong influence of the location of a retailer on consumers' decisions, it stands to reason if even both together, the evaluations and the quality seals, have the capacity to overcome consumers' fears.

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A Appendix

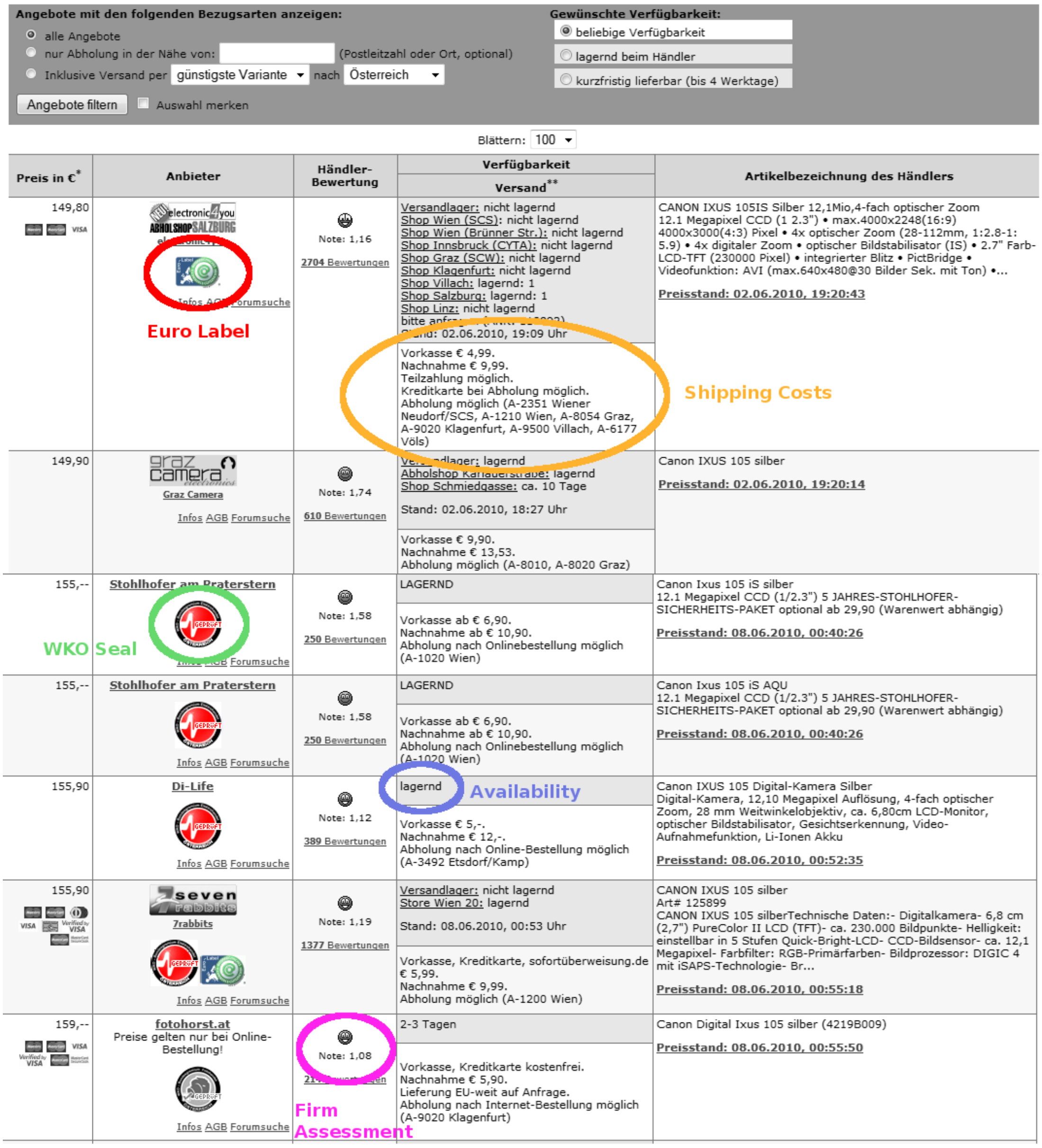

Figure 1: Outcome of an arbitrary product search at http://geizhals.at.

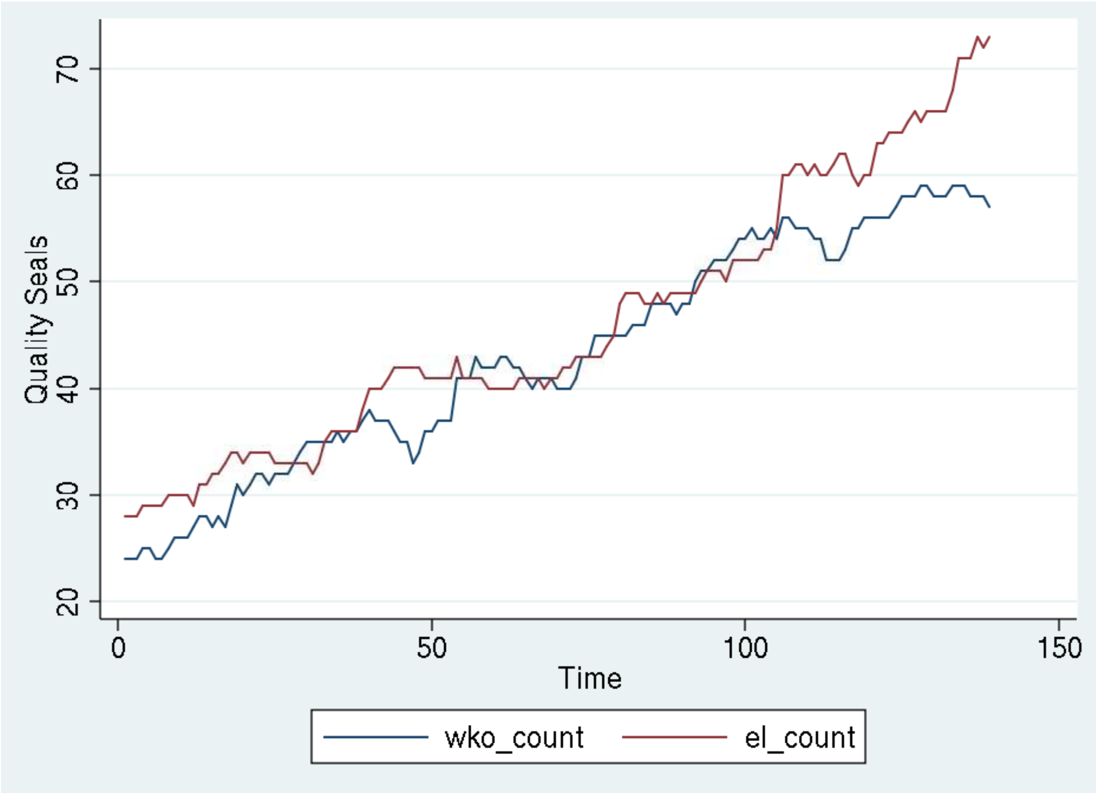

Figure 2: Number of retailers with WKO and Euro Label

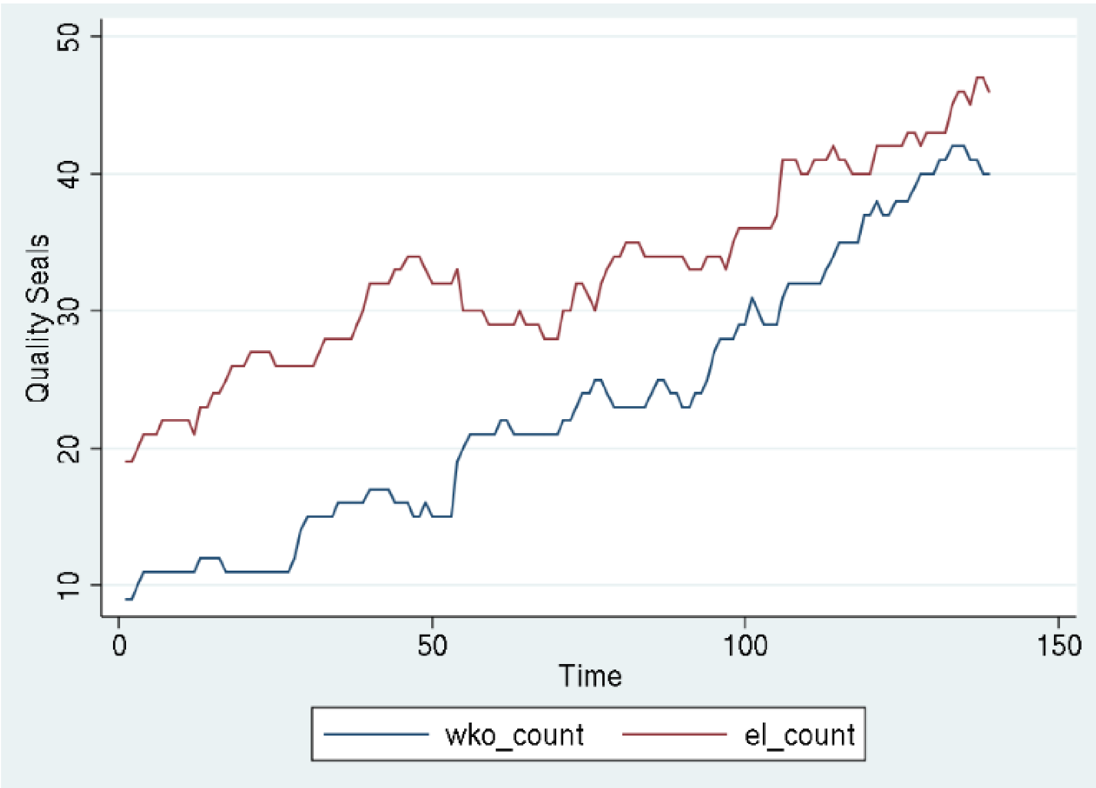

Figure 3: WKO and EL (Digital Cameras)

Table 1: Summary Statistics

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**Number of Obs.**
Time	78.644	(39.738)	1	139	
Firms	440.379	(267.513)	1	929	
Prods	1347.095	(534.555)	1	2669	
LCT	1.008	(4.944)	0	544	
RBP	1.214	(0.183)	1	4.991	
EL	0.108	(0.31)	0	1	
WKO	0.048	(0.214)	0	1	
Avial	0.779	(0.982)	-1	2	
Austrian	0.348	(0.476)	0	1	
Germany	0.652	(0.476)	0	1	
Netherlands	0	(0.019)	0	1	4369332
Shipping Costs	103562.57	(833368.3)	0	48635278.367	160933
Product Assessment	0.713	(0.307)	0	1	2607872
Firm Assessment	1.767	(0.779)	1	5	3220031
ARBP	1.214	(0.09)	1	3.752	4365908

Table 2: Regression Results without IV:

	LCT	LCT	LCT	LCT	LCT	LCT	LCT
	(1)	(2) [a]	(3)	(4)	(5)	(6)	(7)
Relative Price	-3.460	-3.460	-1.996	-3.435	-1.997	-3.407	-1.997
	(.014)***	(.267)***	(.014)***	(0.014)***	(.014)***	(.014)***	(.014)***
Firm Assessment	-.111	-.111	.006	-.112	.006	-.107	.007
	(.003)***	(.013)***	(.004)*	(.003)***	(.004)*	(.003)***	(.004)*
Product Assessment	.196	.196	.200	.198	.2	.198	.200
	(.016)***	(.089)**	(.015)***	(.016)***	(.015)***	(.016)***	(.015)***
Shipping Costs	-2.97e-09	-2.97e-09	1.12e-08	-2.11e-09	1.12e-08	-1.66e-09	1.15e-08
	(1.37e-08)	(7.72e-09)	(1.28e-08)	(1.37e-08)	(1.28e-08)	(1.36e-08)	(1.28e-08)
Not Available [b]	-.219	-.219	-.328	-.213	-.327	-.231	-.280
	(.006)***	(.027)***	(.014)***	(.006)***	(.014)***	(.008)***	(.007)***
Available	.435	.435	-.021	.447	-.021	.452	.027
	(.006)***	(.049)***	(.014)	(.006)***	(.014)	(.009)***	(.007)***
AT	.219	.219		.346		.336	
	(.121)*	(.167)		(.121) ***		(.121)***	
DE	-.788	-.788		-.758		-.782	
	(.121)***	(.167)***		(.121)***		(.121)***	
WKO				-.722	.042	-.791	.017
				(.011)***	(.025)*	(.011)***	(.025)
EL						.533	.183
						(.007)***	(.023)***
N	4369332	4369332	4369332	4369332	4369332	4369332	4369332
R^2	.047	.047		.048		.05	
F	1449.522	7.659	320.96	1469.93	319.66	1497.889	318.07
Product FE	Yes	Yes		Yes		Yes	
Firm & Product FE			Yes		Yes		Yes
139 Time Dummies are included.							

[a] Clustered on Product Level.

[b] The base for the different characteristics of availability is 'Available at Short Hand'.

Table 3: IV-Regression Results:

	LCT	LCT	LCT	LCT
	(1)	(2) [a]	(3)	(4) [b]
Relative Price	-9.240	-9.240	-9.008	-9.008
	(.033)***	(.282)***	(.033)***	(.272)***
Firm Assessment	-.099	-.099	-.097	-.097
	(.003)***	(.014)***	(.003)***	(.014)***
Product Assessment	.250	.250	.250	.250
	(.016)***	(.130)**	(.016)***	(.129)**
Shipping Costs	-5.84e-10	-5.84e-10	4.38e-10	4.38e-10
	(1.39e-08)	(1.23e-08)	(1.39e-08)	(1.28e-08)
Not Available[c]	-.174	-.174	-.202	-.202
	(.006)***	(.020)***	(.006)***	(.016)***
Available	.272	.272	.275	.275
	(.006)***	(.032)***	(.006)***	(.031)***
AT	.120	.120	.219	.219
	(.123)	(1.77)	(.123)*	(.173)
DE	-1.213	-1.213	-1.194	-1.194
	(.123)***	(.138)***	(.123)***	(.133)***
WKO			-.657	-.657
			(.011)***	(.027)***
EL			.453	.453
			(.007)***	(.048)***
N	4365908	4365908	4365908	4365908
R^2	.01	.01	.01	.01
Chi^2	433239.08		441962.35	
Product FE	Yes	Yes	Yes	Yes
139 Time Dummies are included.				

[a] Clustered on Product Level.
[b] Clustered on Product Level.
[c] The base for the different characteristics of availability is 'Available at Short Hand'.