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JEL Classification: L81, L10

Keywords: E-commerce, online trade, business strategies, Retailing

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Successful retailer strategies in price comparison platforms*

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1 Introduction

As price dispersion is a widespread phenomenon in the B2C e-commerce business[1] consumers shopping online use internet platforms (such as eBay, Amazon[2], AliExpress or price search engines) to compare prices of different retailers. Hence these platforms are central players in the information procurement of customers. For this reason, the communicated information about the web-shops' offers on these platforms is of central importance for the success of online retailers. This study identifies and investigates the strategic options of online stores on these platforms.

The set of strategic options is strongly determined by the platform design: Due to technical restrictions and the need for a clear presentation, these platforms only offer standardized interfaces (variables) for the communication between retailers and customers. Analyzing these interfaces, it turns out that there is only a rather limited set of variables retailers can unilaterally decide about. To sell products online, e-commerce retailers can typically determine which products to list (already from the start of the product life cycle or later on), how to price the products over time, whether to make the products available immediately (to put them in stock) or offer longer delivery times (and order from the wholesaler after the order receipt from the customer), and how much to charge for shipping.

We define an e-commerce retailer's strategy as a specific combination of these four variables. Specifically, the retailer decides on the i) listing of a product, ii) its price path over time, iii) its availability and iv) the shipping cost. These four components form the core of an e-tailer's strategy and are communicated to customers via online platforms. Note that these four items are also of central importance in practically all information portals in e-commerce (Amazon, eBay, various price search engines). All four components can be directly influenced by the e-tailer, in contrast to other indicators such as the price rank on the price-comparison site, which can only be influenced by the e-tailer indirectly. E-commerce retailers may also apply different strategies for different products because of different product environments. We use a random sample of about 5,000 products offered by 780 retailers that were introduced on the Austrian price comparison platform

[1]For the relevance of price dispersion in e-commerce see for instance Baye et al. (2004), or more recently Gorodnichenko et al. (2018) or Böheim et al. (2019).

[2]Note, that Amazon is very successful in pursuing the strategy to become a prominent platform for online retailers under the brand name "Amazon Marketplace".

geizhals.at[3]. Using k-means clustering, we find evidence for the existence of clearly distinguishable strategy clusters. By analyzing the frequency of the different strategies applied, it is also possible to identify different company types.

Another important dimension of a firm's strategy is service quality of a shop which is typically captured by customer evaluations (Hackl and Winter-Ebmer, 2019). As we observe firms several times offering different products we can control for service quality as well as other firm characteristics by using firm fixed effects.

As the choice of the correct strategy can be crucial for the survival of online stores in the B2C-e-commerce business, we present evidence on the effectiveness of different e-commerce strategies on success variables, as measured by clicks (revenues), market shares, and firm survival. Hence, we investigate the firms' success in their pricing and listing strategies in online platforms, in which all the relevant strategic choices of e-tailers in their search for customer attention are communicated via a dominant online platform.[4]

Note that in markets which are characterized by a strong competition for the attention of customers, clicks on an offer are important indicators for the success of web-shops[5]. Although, we will have our focus on price search engines, our results can be transferred to all other kinds of standardized platforms which juxtapose offers from different retailers.

E-commerce is mainly driven by Bertrand competition. For most of the traded products, however, consumers usually have to incur search costs due to firm heterogeneity. In this case, the theoretical literature on search has shown that some firms are able to increase prices relative to the competition, as discussed by Stahl (1989) and in the survey by Ellison (2016). The purpose of price comparison sites is to make prices highly visible and almost completely eliminate consumers' search costs.[6] To avoid this market situation, firms may react with non-price competition, such as competition on availability policies

[3] Johnson et al. (2004) show that consumers do not search much on individual e-commerce sites. A price-comparison site may thus cover a substantial amount of e-commerce. Geizhals.at is a perfect example for such a market as it is the most important local price search engine. Practically all Austrian online retailers have to list at this price search engine in order to be able to enter the online business at all.

[4] We speak from dominant platforms if the viability of retailers depends on the referral of customers via the platform and the platform can enforce identical information on the web-shops homepage and the comparison platform. See, for instance, the MFN-clause of Amazon with publishers in the e-book market as very extreme form of dominance which even resulted in the EU case law 'CASE AT.40153 E-book MFNs and related matters (Amazon)'.

[5] Clicks (=referral requests to the retailers web-site) are *the* prerequisite for actual sales. Conversion rates are one of the important key figures in e-commerce and measure the percentage, how many clicks will lead to actual sales (Park, 2017).

[6] E.g. Baye et al. (2009) find that a firm enjoys a 60% jump in its clicks when it offers the lowest price at a price-comparison site. Tang et al. (2010) show that, in general, the introduction of price-comparison sites reduced book prices.

and shipping costs, and obfuscation (Ellison and Ellison (2009), Wilson (2010) or Gabaix and Laibson (2006)) by taking actions to make price search more costly.

Note that the assumption that web-shops can freely decide on listing, price path, availability and shipping cost may not hold for all products and/or firms due to exogenous constraints: Manufacturers and wholesalers might follow special supply policies (e.g. not to deliver those shops which offer below the manufacturer's recommended retail price). Different kinds of vertical restraints might have influence on the listing and price decisions (e.g. resale price maintenance, exclusive dealing, ...). Although, these constraints might be relevant for some products and firms, the competition law of many countries prohibits a systematic restriction of the entrepreneurial activity of retailers by an excessive market power of producers and wholesalers.[7] For this reason, we assume that these constraints are the exception rather than the rule, and that our assumption, that retailers can unilaterally decide on their offer, is legitimate.

As there is practically no systematic scientific analysis on the optimal retailer strategies in online platforms beyond pure pricing strategies - neither theoretically nor empirically - we have chosen the following data driven research design: (i) By applying k-means clustering based on the broad range of product offers by various retailers we want to find out, whether clearly distinguishable strategies can be identified at all in the e-commerce business. As different strategies might be applied for different products, we want to answer this question at the offer level. (ii) By using clicks, last-click-throughs and market shares as dependent variables in regression analysis we identify which strategies are more successful than others. We tackle potential endogeneity problems of the choice of a strategy by using an instrumental variables idea: strategy choice in the case of predecessor goods as an instrument. (iii) As some firms apply certain strategies at the product level more often than others, it is possible to assign shops to different firm types each focusing on different strategies. (iv) Regression analysis allows us to differentiate between firm types which are successful from other firm types which show a high probability that they will not survive in the e-commerce business.

One advantage of such a data-driven approach is that it comes up with stylized facts on web-shops' behavior which can also serve as a starting point for a more rigorous theoretical

[7] In Austria, for instance, the competition authority tracks a series of complaints about discriminating delivery policies in e-commerce.

approach. It is, for instance, an interesting fact, that the most frequent applied strategy is the worst performing managerial practice.

The results of the cluster analysis show that e-tailers apply three different sets of strategies for offering products. We call the major strategy cluster *In-Stock-Offers*, *Permanent-Offers*, and *Long-Shot-Offers*[8]. *In-Stock-Offers* are listed for a short period of time, but the products are made immediately available at that time. They are sold at low prices with low shipping costs and low variability. *Permanent-Offers* are listed for a long time, but the products are not immediately available and are sold at intermediate prices and shipping costs. The price variability is low, but once prices are changed, the changes are large. *Long-Shot-Offers* are not listed for a long time, nor are the products immediately available. These offers are characterized by the highest prices and shipping costs. Their prices are changed frequently but only by small amounts. According to our firm success measures *In-Stock-Offers* are the most successful bids, followed by *Permanent-Offers*. *Permanent-Offers*, however, perform better than *In-Stock-Offers* in terms of the survival of firms. *Long-Shot-Offers* perform worst among all our performance measures.

Our analysis provides the following strengths: (i) We are using a large-scale dataset from a dominant price search engine covering essentially the entire national e-commerce market in Austria. (ii) Using original and complete data[9] from this website we can observe all potential strategic options of the relevant e-tailers. (iii) We can follow firms' strategic behavior over the complete life-cycle of products. (iv) We provide causal evidence for the effectiveness of these strategies. (v) Although we show results for Austrian e-tailers only, the external validity of this study is much larger. As e-tailing is becoming increasingly important in many sectors of the economy, evaluating the strategies of e-tailers in price-comparison environments is important as well. Increased competition in Bertrand market structures forces firms to expand their strategies outside of simple price comparisons.

2 Relation to the Literature

Our analysis provides empirical evidence for e-tailers' strategies in online platforms. There is hardly theoretical or empirical literature which has a broader focus on the effectiveness of

[8] "Long-Shot" refers to a bet in which the chances of winning are small but the possible gains are large.

[9] Unlike in other taxonomies of retailers' strategies (e.g. Tokman et al. (2016) or Homburg et al. (2008)) we do not use survey questions but rely on the actual information on the price-comparison site.

different e-commerce strategies in online platforms taking into account the whole universe of strategic options of online retailers. Most of the contributions are dealing with particular aspects of the e-commerce trade. This section addresses the existing literature.

Gorodnichenko and Talavera (2017) or Gorodnichenko et al. (2018) conduct investigations of strategies of firms in price-comparison sites, which concentrate on pricing itself. Bauer and Jannach (2018) propose a machine-learning based framework for estimating optimal prices in e-commerce. See also Schlosser et al. (2006) on the impact of web-site design investments on consumers' trusting beliefs and online purchase intentions. However, given the existence of price dispersion in e-commerce Ellison and Fisher-Ellison (2005) conclude that consumers are heterogeneously informed on the markets' price structure. Hence, in consumer decision-making, not only the cheapest price but also a number of other factors play a role.

As described in more detail by Ellison (2016) and Ellison and Ellison (2018), firms offering products online have an incentive to obfuscate when consumers bear search costs and price comparison platforms explicitly reduce these search costs. Firms intend to increase consumers' search costs through, for example, add-on prices and, thus, charge prices higher than those under Bertrand competition.[10]

A related study to our analysis is that of Ellison and Snyder (2014). They investigate competition among firms participating in an online market and empirically assess the factors that drive firms to change prices. The analysis provides evidence for differences in pricing decisions across firms. The authors embed their results in a framework for simulating counterfactual market settings, and use the simulations to examine counterfactuals involving different mixes of firms based on pricing strategies. Whereas Ellison and Snyder (2014) concentrate on firms' pricing strategies in selling a commodity-type memory module, we extend the analysis to more products and further aspects beyond pricing, that is, listing decisions, availability and shipping costs. Additionally, we investigate which strategies are more successful.

Based on data from price comparison web sites Cao et al. (2003) show that e-tailers can set higher prices and will have higher overall customer ratings if they provide a satisfactory ordering process. On the other hand, reducing prices does not positively affect satisfaction

[10]See McDonald and Wren (2018) for a discussion of an online search obfuscation effort by firms using multiple brands.

with the fulfillment process. Hence, the authors conclude that price competition alone is not a viable long-term strategy for on-line retailers.

Haynes and Thompson (2014) investigate sellers' entry behavior using data on digital cameras from Nextag.com. They analyze whether sellers employ hit-and-run strategies in line with the theoretical notion of the contestability of markets. Hit-and-run strategies correspond to shorter forays into the market at lower entry prices. They show that sellers with poor reputation as well as smaller sellers are more likely to favor a hit-and-run strategy than larger sellers with better reputations. They also find that former entrants induce a much larger price response from low reputation incumbents. This finding reflects the more intense competition for price-sensitive consumers who do not care about retailer reputation.

A key aspect of our analysis is listing decisions regarding new products. When, for example, Pauwels et al. (2004) investigate the effects of new products and sales promotions on firm value in the automobile industry, they rely on financial performance indicators such as revenue, firm income, and stock market performance. We do not use these measures of success, as most of our retailers are not listed on the stock market, and thus, data on financial performance is not available. Instead, we measure the effectiveness of firms' strategies using revenue, clicks, market share and survival.

Frischmann et al. (2012) investigate the use of shipping costs as a strategic variable in e-commerce and distinguish between sellers charging no shipping costs and those charging relatively high shipping costs. These strategies are meant to target different consumer segments, particularly those with biased perceptions of price awareness.

Dinerstein et al. (2018) argue that the design of the platform has implications on sellers' and buyers' behavior. They argue that a direct comparison of seller listings for a given product reduced prices by 5-15 percent. Although their analysis is focused on situations where products vary only in price and quality, they conclude that "similar forces would be at play for other product attributes that can be changed in the short run".

Our analysis extends the existing literature by combining different policies on entry, listing decisions and pricing by looking at short-term and long-term success of these firms – looking at a random sample of online products.

3 Empirical approach

For our analysis, we use comprehensive data from Austria's largest price comparison portal, geizhals.at, covering the following product groups: IT-hardware, software, games, video and photo devices and TV, phones, audio/hi-fi systems, films, household appliances, sporting goods, and drugstore items. According to information provided on geizhals.at, about 1,000 retailers utilize the price comparison portal to offer 1,392,241 products for delivery in Austria (excluding Amazon Marketplace). According to the business model of geizhals.at, each retailer must pay a small fee each time an interested customer clicks on a link on the price search engine's webpage to access the e-tailer's webpage (= referral request). It is important to note that geizhals.at is the dominant price search engine in Austria. If an online-shop wishes to enter the e-commerce business in Austria in one of the above mentioned product groups, it is practically impossible to avoid listing its offers on the geizhals.at website. Thus, it is reasonable to assume that our data cover essentially the entire online Austrian market for most of these product groups.

3.1 Identification of e-commerce strategies

E-commerce retailers may apply different strategies depending on the product offered. We define an e-commerce strategy as the set of choices that each retailer has to make for each product, and we will define the "offer level" as the observational unit of the strategy of retailer j for product i. An e-commerce strategy can consist of all decision parameters a firm can use during the life cycle of a product, provided that the strategy is also communicated to the consumer via the price-comparison site.

Figure 1 shows a snapshot of an arbitrary hardware product offered by the price search engine. Analyzing this information shows that the set of strategic choices boils down to four essential categories: *A) the listing decision* (whether the product should be added to the retailer's assortment at all); *B) the price decision* (the pricing of the product over its life cycle and the target price rank on price comparison portals); *C) the availability decision* (whether the product is held in storage even before orders arrive or ordered from a wholesaler after a customer places an order); and *D) the shipping cost decision* (the pricing of shipping and whether this pricing implies a possible obfuscation strategy). These four categories are the foundation for our strategic variables. To characterize e-commerce strategies, we focus only on strategic variables that can be directly influenced by the retailer and directly communicated to the customer via the price comparison portal geizhals.at. No other category of strategic variables can be influenced directly by the retailer and varies across products. In that sense, we cover the entire universe of strategic decisions that a retailer must make in offering a product on geizhals.at.[11]

In order to identify e-commerce strategies, we use a k-means clustering algorithm based on the four strategic categories of listing, availability, pricing, and shipping cost decisions. The k-means clustering algorithm results in a set of meaningful and clearly distinguishable strategy groups.

The success of these different e-commerce strategies is measured with variables that were previously used in e-commerce to measure the success of a product or firm (Smith and Brynjolfsson (2001), Dulleck et al. (2011), or Hackl et al. (2014a)). (i) *Number of clicks* is an indicator of customers' attention or the demand created by the offer. (ii) *Number of last-click-throughs (LCT)* (Smith and Brynjolfsson (2001), Bai and Luo (2011) or Park (2017)) is typically seen as a better indicator of an actual sale because it identifies the last firm that a searching customer clicked on during a search on geizhals.at.[12] (iii) *Revenues by Clicks* are calculated as the offered price times the number of clicks. (iv) Finally, *Revenues by LCTs* give the offered price times the number of LCTs. Note, that in price comparison platforms, in which online shops compete for the attention of consumers, clicks (=referral requests to the retailers web-shop) are a key parameter for success.

The choice of a particular strategy by a firm may be endogenous to expected sales or be determined by other – unknown – characteristics of the firm or the market. We offer thus an instrumental variables strategy to identify the causal impact of the choice of such a strategy on firm success: we use the strategy choice for predecessor goods, which have been listed by the same firm and which finished their product life cycle before the market launch of the products in our inflow sample as instrument.

[11]The retailer rating, which is also given on the geizhals.at website, is determined by the customers' evaluation and, thus, can be a long-term strategic element for firms. It is fixed for different products of one firm and, thus, cannot be used for product level regressions, but we will control for firm ratings when we consider success at the firm level.

[12]As we can distinguish different customers at www.geizhals.at using a cookie identifier, we can determine each customers' search episode(s) as a sequence of clicks (=referral requests) from a specific cookie to different e-tailers. A single consumer can have multiple search episodes. We define the LCT as the last click within each search episode, and we assume that it is more probable that the customer made a purchase at this last shop than at any other shop. LCTs are better proxies for actual sales, but they are not perfect (e.g., a cookie identifier may correspond to more than one person, a cookie identifier may be blocked, or a consumer may not make a purchase at the last referral request).

Our strategies are defined at the product level. Hence, firms might apply different strategies for different products. As the firm behavior is quite heterogeneous in the usage of different strategies, we can identify specific types of firms (*firm pools*) which differ in their strategy usage. We find evidence for the existence of both clear-cut and mixed retailer strategies. Switching to the firm level has the advantage that we can use firm survival as outcome variable. Being obviously an ultimate success measure, it is even more important for such short-lived e-commerce markets: In our sample after two years about 30% of all companies were no longer listed on the price comparison platform.

3.2 Data

We use data for new products in Geizhals.at to understand firm strategies over the full life cycle of products. We restrict our data to a random sample of about five percent of all products introduced in 2010.[13] The following criteria have been applied in the composition of the dataset: (i) Although geizhals.at is available in other countries as well (e.g Germany, the UK, and Poland), we only consider the Austrian market. The website geizhals.at has a dominant position in e-commerce only in Austria. Moreover, the default view of the website shows only the Austrian market. This restriction leads to a representative sample of Austria's e-commerce. (ii) We use an inflow sample, only taking into account products that were introduced during 2010. The usage of an inflow sample prevents biased results in favor of long-running products. We use a full year of inflow to prevent biases caused by seasonal effects. (iii) The year 2010 guarantees a sample of new products for which we can observe e-commerce strategies over the *entire* product life-cycle. (iv) Products must have been introduced in Austria first. We do not want to bias our findings by considering products already introduced in other geographical markets. (v) Products in the sample must have a minimum of 50 clicks (for Austrian retailers) and a minimum product life-cycle of 100 days. (vi) Each product must be offered by at least two Austrian retailers. (vii) Furthermore, we eliminate outliers at the offer-level: Offers exceeding five times the median price of a product, offers exceeding five times the median shipping costs of a product, and offers with shipping costs above 1,000 euros are excluded. In doing so, we eliminate clear input typos.

[13] 101,906 products were introduced on geizhals.at throughout 2010.

After applying these restrictions, we obtain 149,862 observations at the offer level, covering 4,888 products offered by 780 retailers. Thus, each product is offered by 30 retailers on average. The first section of Table 2 provides descriptive statistics for the variables that are used for the k-means clustering. Moreover, Table 2 includes success variables, which are used to evaluate the absolute and relative success of different e-commerce strategies at the product level.

The start of a product's life cycle is easy to define, but the end may be less clear because firms may still offer the product even though demand (clicks) has already disappeared. Thus, we define the end of the life cycle as the point when the 97th percentile of clicks on the product has been reached. For products with very high demand[14], we set a maximum of 500 clicks as the cut off to determine the end of the product life cycle.

4 Description of e-commerce strategies

4.1 Clustering method

To identify different strategies at the offer level we use a clustering approach. The k-means clustering method partitions a dataset into k partitions such that the sum of squared deviations from the cluster means (J) is minimal (Lloyd, 1982):

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} ||x_j - \mu_i||^2$$

using data points x_j with means μ_i of clusters S_i. This Euclidian distance operation assigns each data point to the next cluster mean. We use normalized data points between zero and one.

Data points are variables which describe an e-commerce strategy and which, therefore all can be attributed to listing, availability, price, and shipping cost decisions. The selection process of variables takes into account the following considerations.

(i) We use variables that can be determined by the offering retailer itself and, thus, are not driven by rivals' actions. (ii) We avoid variables with high multicollinearity. (iii) We prioritize variables that are immediately observable by customers.

[14]We define a product as being "in very high demand" if the number of clicks in the last three percentiles of its life cycle exceeds 500.

This resulted in the following list of variables: *Listing Percentage* is the percentage of the product life cycle that the product was on offer. *Beginning of Offer* and *End of Offer* are also used to characterize the listing decision within the clustering procedure. *Average Planned Price Rank* serves as an indicator of the firms' target price rank and is defined as the rank a product would have had after a change in the price keeping all other prices constant.[15] *Number of Daily Price Changes* is an indicator of a retailer's price-activity, and *Coefficient of Variation of Absolute Price* is an indicator of the extent to which prices have changed. These three variables are used to represent the pricing decision. The availability of the product is captured by the percentage of listing days that a product is in stock (*Availability Percentage*). Finally, the shipping cost decision is covered by *Absolute Shipping Costs.*[16]

The k-means clustering algorithm requires an ex ante definition of the number of clustered groups k. We use the following statistical measures to determine the optimal number of groups k. (i) The kink in the within-sum-of-squares is a measure of the within–group variation and declines for each additional group added. (ii) The proportional-reduction-of-error shows how the within-group variation is reduced by using k groups instead of $k-1$ groups. (iii) The Calinski-Harabasz pseudo-F is another measure of the quality of clustering. Figure 2 shows that the results for all three measures uniquely indicate that k=*3* is optimal. As a result, we obtain three e-commerce strategy groups at the offer level by applying k-means clustering with k=3.

4.2 Clustering outcomes

Using k-means clustering, we obtain three clusters, which we call *In-Stock-Offers*, *Permanent-Offers*, and *Long-Shot-Offers*. We deduce the descriptions of these groups from the major clustering variables[17].

The *In-Stock-Offers* cluster comprises around 22% of all offers. These offers are available for 87% of the listing time. Although they are only offered for about one-third of the entire product life-cycle, once they are listed, they remain in stock. This high availability is in stark contrast to that in the other clusters, which show availability of less than five

[15] We refrain from using the actual observed price rank because this indicator is determined by market behavior.

[16] The robustness checks in Section 6 show that the clustering results do not change if different compositions of the clustering variables are used.

[17] For descriptive statistics related to the three resulting groups, see Table 2.

percent. Moreover, prices and shipping costs are lowest in this cluster, and the variability of prices is low as well. It may be that these firms order products in larger quantities and offer them steadily and cheaply from their shelf.

We call the second cluster *Permanent-Offers*; this cluster comprises around 29% of all offers. The main determinant of these offers is long listing behavior; a product is listed most of the time, but it is not kept in stock. Moreover, this cluster has intermediate prices and shipping costs. Prices are not changed often, but by large amounts. These offers may be seen as firms wanting to list a product without intending to keep it in stock or seeing a necessity for frequent price changes.

Finally, we call the third cluster *Long-Shot-Offers*. Almost 50% of all offers belong to this group. These offers are characterized by the highest prices and shipping costs. The products are generally neither held in stock nor listed for a long time. Prices are changed frequently but only by small amounts. Rent-skimming behavior (Varian, 1980) might explain these offers. E-tailers assume that their client base comprises informed and uninformed customers. Informed customers have low search costs and buy from the cheapest website. Offers in the Long-Shot-Offers cluster, however, are addressed towards uninformed customers with higher search cost, who buy both via the referral request at the geizhals.at web-site as well as directly from the firms' websites without contacting a price search engine.[18]

Figure 3 gives a schematic presentation of the main components of these three strategies. Additional information, particularly information on outcomes and market-determined characteristics of these clusters, is given in Table 13.

The standardized discrimination function loadings show that the listing decision and availability make the largest contribution to the offer clusters.

5 Success of e-commerce strategies

We next consider the profitability of the e-commerce strategies identified by our cluster analysis. We analyze the success of these strategies in two steps. First, we concentrate on the offer level and proxy success using demand and revenue. Second, we aggregate our data at the firm level and measure success using firm survival.

[18]Legal contracts between e-tailers and geizhals.at commit retailers to list identical prices in the price search engine and on their websites.

5.1 Offer level

Our first analysis checks which of the three strategies are most successful at the offer level. Unfortunately, we cannot directly measure the profitability of a strategy, as the costs of specific strategies and actual purchases are not directly measurable. Instead, we use (see also the Section 3) (i) *Number of clicks*, (ii) *Number of last-click-throughs (LCT)*, (iii) *Revenues by Clicks*, and finally (iv) *Revenues by LCTs*. While we do not observe profit as such, it is important to know how to attract demand and generate revenue. Hence, from the perspective of a web-shop click-related success variables are extremely important key parameters. Additionally, e-tailer and product fixed effects help us account for time-invariant unobserved factors that influence cost and demand in our regressions.

Table 3 shows the results of ordinary least squares and fixed effects regressions for each of the success variables. For the e-commerce strategy clusters, we use dummy variables equal to one if the offer belongs to the respective cluster and zero otherwise. The *In-Stock Offers* act as the base group for all regressions. Column (1) shows the results without any specific controls. Column (2) uses e-tailer fixed effects to control for unobserved heterogeneity among the offering retailers. Finally, Column (3) adds product fixed effects to control for product-specific heterogeneity. The last specification with e-tailer and product fixed effects is the most appropriate specification, because we are interested in the success of different strategies for the same e-tailer and product, accounting for time-invariant cost and demand heterogeneity.

The results in Table 3 show the strategy ranking in terms of demand and revenue. With respect to demand (i.e., number of clicks and LCT), we find that the *In-Stock-Offers* are always the most successful, followed by *Permanent-Offers*, and *Long-Shot-Offers*, which is the least successful cluster. When considering revenues, we no longer find statistical differences between *Permanent-Offers* and *In-Stock-Offers* when we control for unobserved firm and product heterogeneity. This pattern can be explained by the fact that the *Permanent-Offers* cluster predominantly consists of more expensive products (mean price of 393 euros vs. 342 euros). Thus, Column (2) implies a positive, revenue-increasing effect of *Permanent-Offers*. In any case, the *Long-Shot-Offers* cluster performs the worst.

The quantitative effect of using a different strategy is non-negligible. Looking at our preferred specification with e-tailer and product fixed effects (Column (3)), switching from an *In-Stock-Offer* to a *Long-Shot-Offer* reduces the number of clicks by 51%, and the amount of LCTs by 48%; revenues drop by 37%.[19] Choosing a different e-tailing strategy has far-reaching consequences on customer attention to products, and, to the extent that this attention is also converted into actual purchase, the consequences may even be larger.

As robustness check we show in subsection 6.1 that IV-regressions controlling for potential endogeneity strongly confirm the causal interpretation of our results.

5.2 Firm level

Success of e-commerce strategies: In the second step of our analysis, we consider firms. We aggregate the data at the firm level and construct firms' shares of *In-Stock-Offers*, *Permanent-Offers*, and *Long-Shot-Offers*. These variables are related to firms' survival in 2012, which we again interpret as a measure of profitability. We use the dummy variable *Still Alive in 2012* as an indicator for success. Both in Austria and globally, e-commerce is characterized by a high number of market entries and exits. Of the 780 retailers in our dataset that we observe from 2010 onwards, only 535 are still active in 2012. This indicator is important as it allows for conclusions about the profitability of these retailers. Whereas the other success variables relate to revenues or induced demand, the indicator of firm survival allows more direct inference regarding the profits of firms. We augment these regressions with additional explanatory variables at the firm level, such as pick-up possibilities, product mixes, firm ratings, and the number of products offered by firms.

Our results are given in Columns (1) and (2) of Table 5. We find that firms with high shares of *Permanent-Offers* are more likely to stay alive than firms with high shares of *In-Stock-Offers*. This strategy ranking differs from our earlier results on product-specific offers related to demand or attention. The ranking may have changed for two reasons. First, *Permanent-Offers* are more often used for expensive products with possibly higher mark-ups. Second, firms in the cluster *Permanent-Offers* rarely hold inventory, but rather sell their products directly via a wholesale firm. We saw the importance of selling more expensive products in Table 3: revenues between *Permanent-Offers* and *In-Stock-Offers* are equal. Higher inventory costs may make *In-Stock-Offers* less profitable – leading to our results in Table 5.

As before, firms with high shares of *Long-Shot-Offers* perform worst. As firm survival is related to business coming via referral requests from the price-comparison site geizhals.at,

[19] Percentage values are based on the average number of clicks, LCTs and revenues of the base group, which is *In-Stock-Offers*. See Table 2 for the corresponding values.

as well as demand from customers, who do not use a price comparison website, this survival analysis is also informative with respect to the rent-skimming strategy mentioned above: As survival at geizhals.at is correlated to actual survival of the firm, rent-skimming by addressing customers going directly to the high-priced web-shop of the firm (without comparing prices at geizhals.at first) does not seem to pay off – these firms go out of business earlier.

Our control variables perform according to expectations. Larger firms (with more products) live longer, as do those with better consumer ratings. The distribution of the product mix is not important for survival, whereas firms with no pick-up possibility (i.e., firms with no brick-and-mortar stores) live longer.

Defining firm pools: Thus far, we have characterized firms based on the percentages of strategies chosen. However, firms may choose specific e-commerce strategies for specific products. A more nuanced picture emerges if we take these strategic elements into account when characterizing firm types.

Thus, we implemented the following algorithm to assign retailers to firm-strategy pools. (a) Assign a retailer to the pool F1, F2, or F3 if more than 70% of offers fall in the respective cluster (e.g. *F1: In-Stock-Firms* make more than 70% of their offers as *In-Stock--Offers*). (b) If two strategies combine to make up more than 70% of offers, we assign firms to the strategy pools F4, F5, and F6, accordingly: F4 is *In-Stock-Offers* and *Permanent-Offers*, F5 is *In-Stock-Offers* and *Long-Shot-Offers*, and F6 is *Permanent-Offers* and *Long-Shot-Offers*.[20] (c) The remaining retailers are assigned to firm strategy pool F7, which reflects firms with mixed e-commerce strategies.[21]

Looking at the number of retailers assigned to each group, we see that *F1: In-Stock-Firms* (with 230 retailers), *F3: Long-Shot-Firms* (with 224 retailers), and *F6: Large-Department-Stores* (with 117 retailers) are of particular importance. Although the mass of *In-Stock-Offers* is concentrated in the F1 firm pool and that of *Long-Shot-Offers* is concentrated in the F3 pool, we observe the highest number of *Permanent-Offers* in the F6 pool. Pools F1, F3, and F6 account for 73% of all retailers and cover 85% of all offers.

[20]Changing the percentage limit to 60 or 80 percent does not substantially change the assignment of retailers to firm pools or the corresponding success rates of firms discussed later in the text. The results can be found in Tables B.2 and B.3 in the (Web-)Appendix.

[21] Using additional information – not used in the clustering – we try to characterize these firms and give them appropriate names. (Table 4). Subsection A.2 in the (Web-)Appendix contains a detailed characterization of the the firm pools.

Table B.4 in the (Web-)Appendix gives an overview of the distribution of offers over the firm pools.

Columns (3) and (4) in Table 5 use these firm pools as explanatory dummy variables.[22] The firm pool *F1: In-Stock-Firms* acts as the base group for all regressions. Starting with the comparison of the large firm pools F1, F3, and F6, we confirm our results at the offer level. We do not observe significant differences between the success of firm pools *F1: In-Stock Firms* (with mainly *In-Stock-Offers*) and *F6: Large-Department-Store* (in which *Permanent-Offers* are predominant). In comparison to the cheap and immediately available products of *F1: In-Stock Firms*, the broad product assortment and loss leader strategies might attract consumers to *F6: Large-Department Stores*. In this case, loss leaders (or complementary) products are not especially cheap but are hard to obtain elsewhere. Customers accept these offers, as they can typically save on shipping costs and only have to deal with one store. In contrast to the results for pools F1 and F6, we do not find any empirical evidence that *F3: Long-Shot-Firms* use a successful e-commerce strategy. The same finding applies to the considerably smaller group of *F5: Short-Term-Suppliers*, which is a mixture of F1 and F3 firms. F5 retailers perform worse than F1 retailers, but better than F3 retailers, which is due to the mixture of the two strategies.

There are two small firm pools that account for neither the mass of offers nor a large number of retailers but perform better than the successful firm pools F1 and F6. These two firm pools are *F2: Specialized-Suppliers* (53 retailers) and *F4: Power-Sellers* (only 59 out of 780 retailers). These two small firm pools perform better than the pools F1, F3, F5, and F6. A detailed inspection of the characteristics of *F4: Power-Sellers* shows that these retailers are similar to F1 retailers. Clearly, these *F4: Power-Sellers* utilize special managerial skills with regard to assortment composition and selective warehousing, which are highly attractive for consumers. The most successful firm pool, however, is *F2: Specialized-Suppliers*. These are shops that identify highly profitable niches of special products that are only occupied by a few other retailers. The final group, *F7: Mixed-Strategy-Type*, also exhibits a high probability of survival. However, as this group consists of only seven firms, we refrain from a characterization of firm strategies.

[22] Table B.5 in (Web-)Appendix shows the success of different firm pools with regard to the number of clicks, revenues, click shares, and the number of LCTs.

6 Robustness

We perform the following robustness checks. (i) We bring causal evidence for the effects of strategy clusters on our success variables. (ii) We check the stability of our results with respect to different product groups, and (iii) we demonstrate that changing our clustering variables does not change the assignment of offers to our clustering categories. (iv) The assessment of different clustering strategies presented so far rests on the relative performances of several success indicators at the product level. However, one might argue, success in absolute terms is the decisive variable, and, thus, we also demonstrate the robustness of our results using absolute measures for success defined at the firm level. (v) Finally, one might speculate whether e-commerce strategies might change over the product life cycle. We demonstrate that only a small share of offers change e-commerce strategy types over the life cycle of the products.

6.1 Causal evidence at the offer level

A firm may choose a particular strategy because of expected sales; such a choice may also be correlated with other unobservable characteristics of the e-tailer. We tackle this endogeneity problem with the help of an instrumental variables strategy: For a given firm we use the cluster variables from a predecessor good offered by the same firm as instrument. Here, we use only products in the same sub-sub-category of the ordered www.geizhals.at product scheme. Our instrument takes advantage of the fact that corporate strategy decisions always have a certain temporal persistence. A particular strategy for a predecessor product should have no impact on sales of the successor product, because there is no overlap in the product cycle among these two products: the exclusion restriction should, thus, be satisfied.[23]

Predecessor products of good i and firm j have been selected in the following way (see also Figure B.2 in the (Web-)Appendix): (i) Predecessors must have their market launch at least 365 days before the market launch of product i. (ii) The end of the predecessors' product life cycle must not lie after the market launch of i (otherwise the exclusive restriction might be violated). (iii) They must be offered by firm j. (iv) Predecessors must

[23]Note, that we use a frequently used instrumentation strategy. We look at market participants' behavior in other markets at earlier times when the realization of the outcome variable was in no way foreseeable. In that sense our approach is for instance similar to the shift-share approach common in the migration literature (see, for instance, Card (2001)).

have clicks to calculate a product life cycle with a begin and end time. From potentially 353,494 available candidates for predecessors with a valid market launch date we lose (i) 15,403 products because they have no clicks, (ii) 163,131 products because the ends of their product life cycles lie after the "birth date" of the products in our dataset, (iii) 131,716 products as they were not offered by the respective firm, (iv) 8887 products due to missing data. Hence from the original sample size of 149,862 we have only instruments for 34,357 offers.

First stage results can be found in Table B.1. We chose the values of *Daily Price Changes*, *Listing Percentage*, *Availability Percentage* and *Absolute Shipping Cost* of the predecessor good as instruments as these variables have the highest contribution in the k-means clustering procedure. The Cragg-Donald Wald F-statistics are 240.5 without fixed effects and 22.3 controlling additionally with product and etailer fixed effect. As these values are well above 10 we can reject the hypothesis of weak instruments.

Our IV-regression results can be seen in Table 6. Columns (1) and (4) replicate OLS regressions from Table 3. For comparison reasons columns (2) and (5) show OLS results for the reduced sample for which instruments are available. Finally, columns (3) and (6) depicts the 2SLS regressions. Note, that our IV regressions controlling for potential endogeneity strongly confirm the result of Table 3. Compared to *In-Stock-Offers*, *Permanent-Offers* tend to be less successful (only for the smaller IV sample including all the etailer and product fixed effects we have an insignificant coefficient for *Number of Clicks* and *Number of Last-Click-Throughs*). Long-Shot-Offers are again the worst strategy.

Given these causal results we continue to argue with the OLS coefficients of our full sample for the following reasons: (i) As the IV-sample only comprises 23% of the full sample, we prevent a substantial reduction of our sample size. (ii) As the coefficients of our IV-regressions are typically larger than our OLS estimates in the full sample, this corresponds to a conservative approach, which understates our result rather than exaggerating them.

6.2 Usage of e-commerce strategies across product groups

Here, we analyze whether the usage of e-commerce strategies differs across product groups. Particular strategies may be seen as reactions to consumers' search profiles. Consumers may search differently for more durable goods, such as TVs, than for more short-lived products, such as games.

Table 7 shows the results of a multi-nominal logit model with the choice of e-commerce strategy as the dependent variable and product categories as explanatory variables. In addition to product group fixed effects, we also include explanatory variables, such as the median absolute price and the number of firms that offer the product. Table 7 shows the results with the base group of *In-Stock-Offers*. We note that the product group effects are significantly different from zero and reflect the picture of Figure 4. Additionally, we find that higher prices increase the probability of using more *Permanent-Offers*. Furthermore, if there are more firms in the market, we observe more *Permanent-Offers*.

Next, we evaluate whether these strategies have different success rates in different groups. We calculate success measures comparable to those in Column (3) of Table 3 for each of our product groups. For a better comparison across groups, in Table 8, we show relative changes in the success outcomes when switching from *In-Stock-Offers* to another strategy. We find notable group-specific differences, especially for information goods like software or movies, for which the statistical difference between *Permanent-Offers* and *Long-Shot-Offers* nearly vanishes. Moreover, *Permanent-Offers* is the most successful strategy for selling phones.[24] Although we see some group-specific differences, our main results on the success of different e-commerce strategies hold for most of the product categories. *In-Stock-Offers* are more successful than *Permanent-Offers*, while *Long-Shot-Offers* perform worst. The corresponding coefficients for Table 8 can be found in Table B.6 in the (Web-)Appendix.

6.3 Clustering using variables determined by competition

Thus far, all our clustering variables can be unanimously determined by the retailer and do not reflect consumer reactions. In this subsection, we present the results of a robustness check, in which the clustering procedure includes additional variables that are typically considered to be important, but are determined by the actions of rivals. These variables are *Bestprice Percentage*, *Losses until Reaction*, and *Coefficient of Variation of Relative Rank*. *Bestprice Percentage* is the percentage of time that a given offer by a retailer was the best price among all retailers; *Losses until Reaction* measures the time between

[24] It should be mentioned that cell phones are very often bundled with a contract from a mobile phone providers.

dropping by at least one rank in the price ranking and changing the price of an offer for a given product. Whereas *Bestprice Percentage* is a proxy for the aspired price rank, the other two variables are proxies for the effort to maintain this rank. Note that in all three cases, the effort of a retailer can be thwarted by a competitor setting its price accordingly.

Table 9 shows that using this new clustering procedure does not imply any changes in the classification system. The columns in Table 9 show the original assignment of offers to clusters in the base version, and the rows depict the offer allocation using our new extended clustering procedure. This new scheme is very robust: of all classifications, only 0.66% of cases change cluster. Both the descriptive statistics as well as the results of our success analysis do not change if we add additional competition variables.[25]

6.4 Clustering and the product life cycle

Some studies (Spann et al., 2015) suggest that firms may use different strategies in different phases of the life cycle of a product (PLC) and that such price dynamics may matter substantially in the sales process.

As the PLCs of our products are quite different, with a mean of 895 days, a minimum duration of 101 days, and a maximum of 1,475 days, we construct a relative PLC with three phases based on the average number of offering firms, as follows: The growth phase covers 20 percent of the PLC, the maturity phase extends from the 20th percentile to the 60th percentile, and the declining phase lasts from the 60th percentile until the end of the PLC. This definition of phases is designed according to the development of the number of firms in a market that follows a distinctive inverted U-shaped pattern. Figure B.1 in the Web-Appendix shows the empirical distribution of offering retailers and clicks based on our data for each percentile of the PLC.

Separately, for each of these three phases of the PLC, we can observe our strategy variables that were used in the clustering process depicted in Table 2. With the exception of two variables, we use exactly the same variables for a k-means clustering procedure calculated separately for each of the three phases.[26] Interestingly, comparing the descriptive statistics of the resulting clusters between the phases does not indicate noteworthy

[25]Descriptive statistics (means) of the clusters generated using the extended set of variables can be found in Table B.7. In Table B.8, we show estimations results for success using clusters based on the extended set of variables. Note that the means of the respective clusters and our success rate regressions essentially coincide.

[26]Including *End of offer* and *Beginning of offer* would not make sense in different phases of the PLC.

changes.[27] The different clusters in the respective phases exhibit more or less identical descriptive features as the cluster groups for the entire PLC in Table 2.[28]

Based on the descriptive statistics, we find little evidence that firms switch their e-commerce strategies over the PLC. This result is also depicted in Table 10, which shows the distribution of the original cluster assignment from Table 2 over the clusters of the respective phases of the PLC (e.g., of the original *In-Stock-Offers*, 84.27% remain in this cluster in the growth phase. Only 8.8% of the offers move to the *Permanent-Offers* cluster, and 6.9% switch to the *Long-Shot-Offers* cluster). Analyzing Table 10, we observe that the assignment of offers to their respective clusters largely does not change. The bold figures show values above 50% for each phase of the PLC and indicate that most of the offers remain in the same cluster.

The exceptions are that 37.95% of offers in the original *Long-Shot-Offers* cluster move to the *Permanent-Offers* cluster in the growth phase, and 35.24% of offers in the original *Permanent-Offers* cluster are assigned to the *Long-Shot-Offers* cluster in the declining phase of the PLC. At least for these two relatively small groups, we find confirmation that retailers switch their e-commerce strategies throughout the PLC. Therefore, it is interesting to examine the characteristics and market outcomes of these two product groups in comparison to the non-switching offers.

Columns (1) and (2) of Table 11 compare offers that were assigned as *Long-Shot-Offers* over the whole PLC. Some of them (Column (1)) were identified as *Permanent-Offers* in the growth phase. Columns (3) and (4) refer to *Permanent-Offers* that are or are not identified as *Long-Shot-Offers* in the declining phase, respectively. We find better outcomes for those offers assigned to the *Permanent-Offers* cluster as compared to those assigned to the *Long-Shot-Offers*, even if the strategy is carried out in only one phase of the PLC, as in Column (1). On the other hand, offers moving from the *Permanent-Offer* cluster to the *Long-Shot-Offer* cluster in the declining phase of the PLC perform worse than offers remaining in the *Permanent-Offer* cluster even at the end of the PLC. Thus,

[27] Table B.9 shows the descriptive results for the respective clustering analysis in each of the three phases of the PLC.

[28] The descriptive statistics of the clusters remain their relative positions in the maturity and decline phases over all clusters and variables. We observe only one reasonable shift in relative positions in the growth phase; in contrast to our results in Table 2, *Permanent-Offers* indicate the lowest *Planned Price Rank*. This is not surprising, as *Permanent-Offers* enter the market much earlier in the PLC, when only few retailers are present in the market. Due to the low number of retailers, we observe consequently lower aspired price ranks for this cluster in the growth phase of the PLC.

it seems that some unobservable cost factors related to *Permanent-Offers* force retailers to switch strategies for some of their products to the supposedly cheaper *Long-Shot-Offer* strategy during the PLC.

In the context of robustness checks, however, it is important to note that both groups of strategy switchers are relatively small. For most of the offers, we do not observe a change of strategies over the PLC, and, for this large majority of offers, our results based on using one cluster procedure for the whole PLC hold.

7 Conclusions

Following the advent of online price comparison platforms (e.g. various price-search engines, Amazon, eBay) price-competition has increased enormously for B2C e-commerce firms. As prices are highly visible and entry into such markets is relatively easy, a Bertrand paradox can easily arise in which prices fall to marginal costs even in markets with a limited number of firms. In this situation, firms might resort to non-price competition and obfuscation (Ellison and Ellison, 2009) in their efforts of being listed in online platforms. Firms have a large number of strategy options in such "unfriendly" environments, including listing and stocking decisions, price development over time, auxiliary options for shipping costs, and so on.

Using data from an Austrian price-comparison site, we statistically identify three distinct strategies that firms use for specific products (*In-Stock-Offers*, *Permanent-Offers*, and *Long-Shot-Offers*) and causally identify their impact on firm success. Whereas the first two strategies are reasonably successful in terms of attention, clicks, and revenues, the third one is not. In addition to looking at strategies for individual products, we can also characterize firms by their combinations of products and strategies. Here, we investigate the survival of these e-commerce firms in the market.

From these results, we can draw the following managerial conclusions for the behavior of online-shops in price comparison platforms:

- One successful e-commerce strategy is ordering a large quantity, selling from the shelf relative cheaply, and removing the listing once the stock is sold (*In-Stock-Offer*).
- An alternative strategy is to list the product most of the time without holding it in stock (*Permanent-Offer*).

- Mixtures of these strategies (i.e., neither listing a product for a long time nor holding the product in stock) do not seem to be very successful.

- Looking at the firm level, a couple of specific strategies might pay off. *Power-Sellers* refers to firms including specifically successful products in their portfolios (i.e., high price and high demand products). *Specialized-Suppliers* refers to firms that concentrate on a few product categories with less severe competition.

- As expected, firms with better consumer-assessed quality ratings and those with generally larger product portfolios survive longer; the opposite is true for firms that incur higher costs by having a separate brick-and-mortar store.

- These results hold true for most product groups.

From a broader point of view, our results can also be interpreted with regard to obfuscation strategies. If consumers differ with respect to their search costs, firms may use mixed strategies for a product and randomize prices. A price comparison platform takes away this advantage. Thus, firms have an incentive to obfuscate using add-on pricing, such as shipping costs, and availability. This is, however, not what we observe empirically: We find the lowest relative price, the lowest absolute shipping and the highest availability rates for *In-Stock-Offers*. In contrast to that, *Long-Shot-Offers* have the highest relative product prices combined with high shipping cost and lowest rates of availability. The cluster of *Permanent-Offers* positions itself between the other two. Hence, we do not find a distinct and clear-cut pattern of obfuscation. Our results rather suggests a strategy in which firms specializing in *Long-Shot-Offers* try to skim off rents from uninformed customers in a rather clumsy and – as our empirical results about firm survival confirm – unsuccessful way. On the other hand, firms with *In-Stock-Offers* cater to consumers with lower search costs and charge lower prices as well as low shipping costs.

Although the almost perfectly competitive market[29] for B2C e-commerce firms in a price-search engine environment seems to make marketing endeavors obsolete, firms' carefully chosen strategies can make a difference.

[29] See (Hackl et al., 2014b) for the effect of the number of firms on markups in e-commerce.

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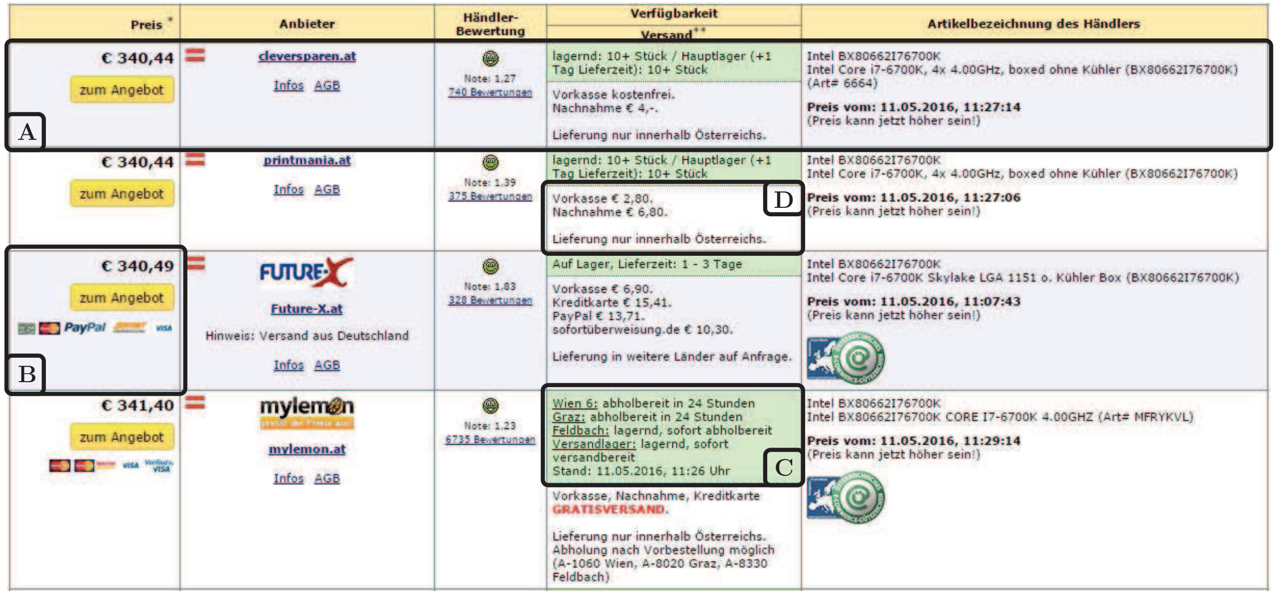
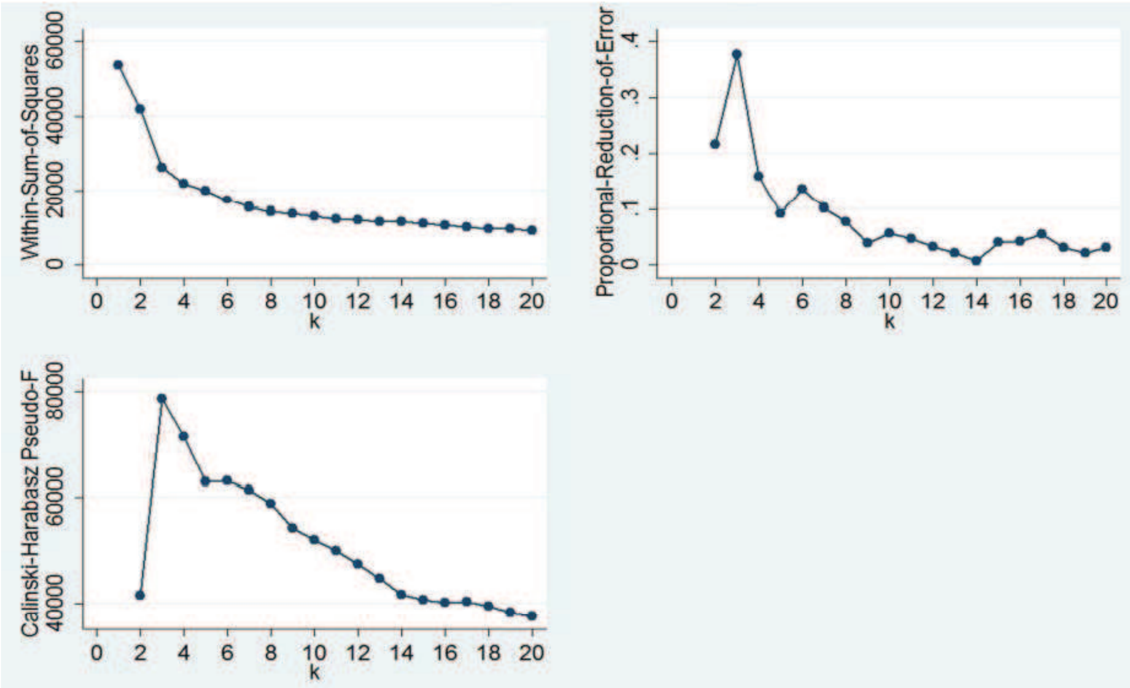
Figures and Tables

Figure 1: Snapshot of the geizhals.at Website



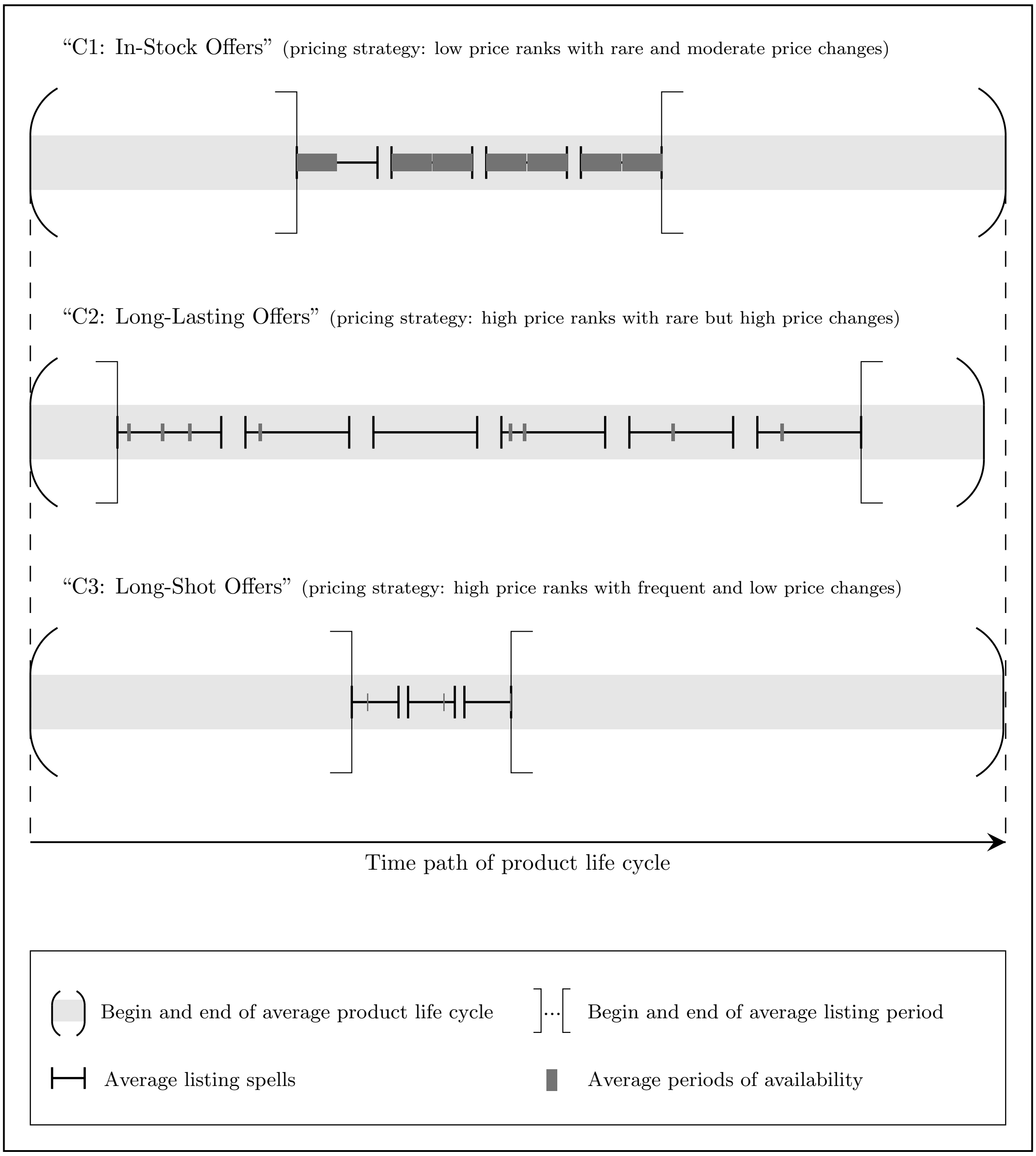
Note: The figure shows a snapshot from the geizhals.at website. Note that the strategic choices, which can be determined solely by the offering firms, reduces to four aspects only: A) to list the product at all, B) the price level, C) whether products are immediately available at the shop (e.g. to have them in stock), and D) the amount of shipping cost. Variables based on these four aspects will be used in the clustering procedure.

Figure 2: Quality measures for the Clustering



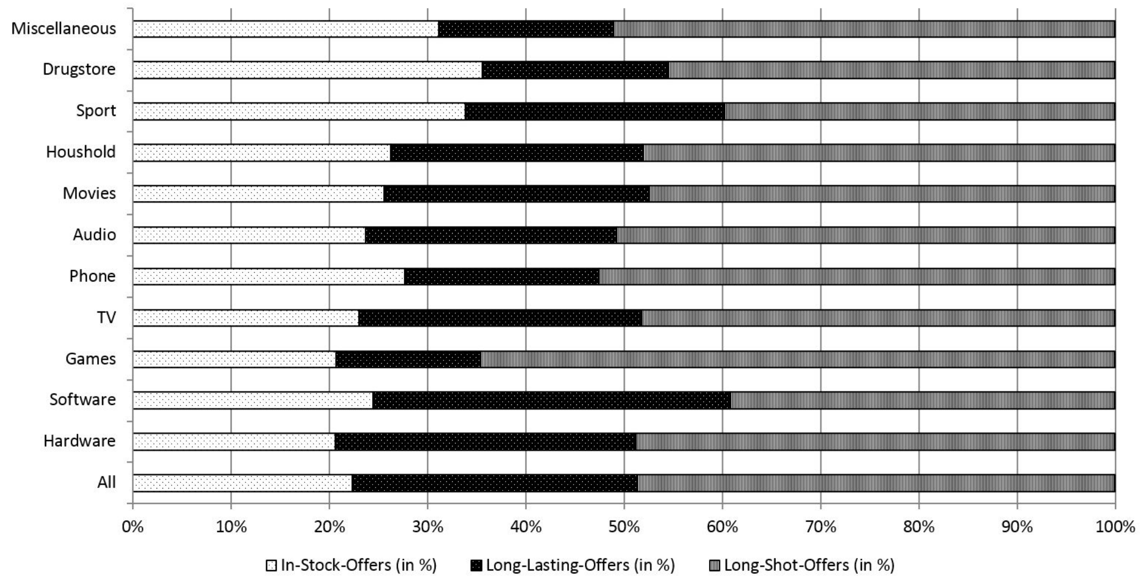
Note: Different quality indicators für the k-means clustering procedure are depicted. The variable k on the abscissa refers to the potential number of clusters. Note, the kink in the within-sum-of-squares and the maximum in the Calinski-Harabasz pseudo-F as well as the proportional-reduction-of-errors for the amount of three clusters.

Figure 3: Schematic representation of cluster descriptives



Note: The figure shows schematic representations of descriptives from Table 2 for the clusters In-Stock-Offers, Permanent-Offers and Long-Shot-Offers. The illustration of the variables is depicted in proportio to their true means.

Figure 4: Cluster shares across product groups



Note: The figure shows the shares of our strategy clusters (In-Stock-Offers, Permanent-Offers and Windfall Offers) across different product groups.

Table 1: Description of Variables

Clustering Variables	
Availability Percentage	Number of days product is in stock of retailer (relative to the number of days product is offered by the retailer).
Beginning of Offer	Time when retailer offered a product for the first time. Measured in days after the first occurrence of the product on geizhals.at. (in days from start of PLC)
End of Offer	Time when retailer removes product from the offered assortment. Measured in days before the product disappears from geizhals.at because no retailer is offering the product anymore. (in days till end of PLC)
Listing Percentage	Time product offered by the retailer relative to the duration of the whole product life cycle.
Daily Price Changes	Number of total price changes relative to the number of days the product is offered by the retailer. Price changes are observed at a daily base, so maximum number of daily price changes is 1. A change of the listing decision for a product (offering or not offering the product) by a retailer is treated like a price change, too.
Planned Price Rank	Average listing rank after a price change.
Coefficient of Variation of absolute Price	Coefficient of variation of the absolute price of the offer.
Absolute Shipping Costs	Average shipping costs for the offer using payment before shipping.
Success Variables	
Click Share	Number of clicks on the retailer's offer relative to the total number of clicks on the product. (in %)
Number of Clicks	Number of clicks on the retailer's offer.
Number of LCT	Number of Last-Click-Through clicks on the retailer's offer.
Revenue by Clicks	Revenue in terms of clicks. Number of clicks times the average price offered by the retailer.
Revenue by LCT	Revenue in terms of Last-Click-Through. Number of LCT-clicks times the average price offered by the retailer.
Firm Characteristics	
Pick-Up Possibility	Retailer offers the possibility to pick-up products in a store.
Product Mix (HHI)	Indicator for the concentration of the product range of a retailer based on spread of offers among different product categories. High value means concentrated assortment while low value indicates a wide range of product types offered.
Firm Rating	Rating of the retailer by users of geizhals.at. 1 means very good while 5 means not very poor performance of the retailer.
Total Clicks on Firm	Total number of clicks on retailer during the year 2010.
No. of Products Offered	Total number of products offered by the retailer during the year 2010.
Average Relative Price	Average relative price (compared to the average product price) of all offers by the retailer.
Product Characteristics	
Median Absolute Price	Median price of all offers of the product.
PLC Duration	Full duration of the product life cycle of a product in days.
No. of Offering Firms	Average number of retailers, offering the product.
Price Density	Density of prices for one product. Calculated as (maximum price - minimum price) / number of offering retailers.
Total Clicks on Product	Total number of clicks on the product during the whole product life cycle.

Table 2: Descriptives (Means) for the Strategy Clusters

	ALL	In-Stock-Offers	Permanent-Offers	Long-Shot-Offers
Clustering Variables				
Availability Percentage	21.8	**86.9**	4.6	*2.1*
End of Offer (in days till end of PLC)	324.0	316.6	*113.0*	**453.0**
Listing Percentage	33.3	33.1	**65.3**	*14.4*
Beginning of Offer (in days from start of PLC)	222.0	245.2	*80.2*	**295.8**
Daily Price Changes	0.153	0.139	*0.138*	**0.168**
Planned Price Rank	11.810	*11.070*	11.600	**12.270**
Coef. of Variation of abs. Price	0.085	0.080	**0.121**	*0.066*
Absolute Shipping Costs	7.745	*7.496*	7.768	**7.845**
Success Variables				
Click Share (in %)	3.180	**7.056**	4.097	*0.857*
Number of Clicks	17.240	**45.530**	18.660	*3.423*
Number of LCT	1.247	**3.153**	1.429	*0.264*
Revenue	6,060	**12,781**	8,269	*1,662*
Observations	149,862	33,479	43,414	72,969
in percent	100.0	22.3	29.0	48.7

Note: The observational unit is the firm-product-level. Highest(Lowest) values are marked bold (italics)!

Table 3: Success of Different Clusters at the Offer Level

	(1)	(2)	(3)
Number of Clicks			
Permanent-Offers	-26.87***	-14.84***	-13.35***
	(0.716)	(1.008)	(1.018)
Long-Shot-Offers	-42.11***	-24.72***	-23.35***
	(0.650)	(0.939)	(0.943)
Constant	45.53***	33.58***	102.0***
	(0.538)	(0.748)	(4.755)
R^2	0.027	0.144	0.234
Number of Last-Click-Throughs			
Permanent-Offers	-1.724***	-0.823***	-0.787***
	(0.0568)	(0.0809)	(0.0818)
Long-Shot-Offers	-2.889***	-1.623***	-1.511***
	(0.0515)	(0.0753)	(0.0758)
Constant	3.153***	2.275***	8.924***
	(0.0426)	(0.0600)	(0.382)
R-squared	0.021	0.117	0.208
Revenues by Clicks			
Permanent-Offers	-4,511***	1,548***	362.9
	(308.9)	(440.2)	(428.1)
Long-Shot-Offers	-11,119***	-3,192***	-4,756***
	(280.4)	(410.1)	(396.8)
Constant	12,781***	7,166***	31,221***
	(232.1)	(326.7)	(2,000)
R-squared	0.011	0.108	0.260
Revenues by Last-Click-Throughs			
Permanent-Offers	-340.9***	100.4**	-6.995
	(27.08)	(39.03)	(37.99)
Long-Shot-Offers	-881.5***	-297.9***	-385.5***
	(24.57)	(36.36)	(35.21)
Constant	1,022***	610.3***	3,300***
	(20.34)	(28.97)	(177.5)
R-squared	0.010	0.085	0.240
Observations	149,862	149,862	149,862
Etailer Fixed-Effects		X	X
Number of Retailers		780	780
Product Fixed-Effects			X
Number of Products			4,888

Note: In all regressions In-Stock-Offers represent the base scenario. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Description of Firm Types

Name +Definition: > 70%	# of e-tailers	Description and Interpretation
F1: In-Stock-Firms In-Stock-Offers	230	high percentage of immediately available offers; most products in stock; low offered price with small dispersion and low price rank; low shipping cost; number of products offered is low; specialized on few product categories; products are long-living goods; high number of clicks;
F2: Specialized-Suppliers Permanent-Offers	53	offer products only in a few product categories; offered over a long period of the product life-cycle; do not put many of the offered products into storage; few price changes; if they adjust prices the magnitude of the change is quite high; products offered are only offered by a few other retailers; offer products with highest absolute price level; high relative price; low number of clicks; good rating;
F3: Long-Shot-Firms Long-Shot-Offers	224	products offered are not in stock; offers are only listed for a very short time of the product life-cycle; prices are often changed; relative price level is high; observed shipping costs are beyond the average; no pick-up possibility; offer many products in many product categories; low number of clicks;
F4: Power-Sellers In-Stock + Permanent-Offers	59	offer high expensive products; relative low median price; low shipping cost; high number of clicks; if listed, it is offered for more than half of the product life-cycle; high availability; few price changes; offer a small number of products; assortment is not concentrated on certain product categories; good retailer rating; a majority of firms operate brick and mortar facilities;
F5: Short-Term-Suppliers In-Stock + Long-Shot-Offers	87	offer products only for a short time of the product life-cycle; availability of the products is high; many price changes; variation of price is low; high shipping costs; planned price rank is below the average; wide product portfolio; rather badly rated by customers; products with a short product life-cycle; high number of clicks;
F6: Large-Department-Stores Permanent + Long-Shot-Offers	117	highest number of offers; high number of clicks; wide product portfolio; combined with brick and mortar facilities; high average price; high shipping costs; do not aim at best-price rankings; low availability; products are listed almost half of the product life-cycle; number of price changes is at an average level; if prices are changed, the variation is quite high; products offered are more expensive than the average product; have a shorter product life-cycle than the average;
F7: Mixed-Strategy-Type remaining	10	low shipping cost; very good rating; low pick-up possibilities; offer only few products; on markets with few competitors; relatively low price;

Table 5: Success on Firm Level: Using Strategy Shares and Firm Types

	(1)	(2)	(3)	(4)
		Still Alive 2012		
Share Permanent-Offers	0.295***	0.240***		
	(0.0520)	(0.0533)		
Share Long-Shot-Offers	-0.229***	-0.239***		
	(0.0478)	(0.0464)		
F2: Specialized Suppliers			0.265***	0.202***
			(0.0569)	(0.0611)
F3: Long-Shot Firms			-0.185***	-0.201***
			(0.0502)	(0.0484)
F4: Power Sellers			0.148***	0.134**
			(0.0554)	(0.0570)
F5: Short-Term Suppliers			-0.123**	-0.105*
			(0.0555)	(0.0539)
F6: Large-Department-Stores			0.0273	0.0112
			(0.0503)	(0.0494)
F7: Mixed-Strategy-Type			0.203***	0.221***
			(0.0533)	(0.0554)
Pick-Up Possibility	-0.105***	-0.0851***	-0.103***	-0.0837***
	(0.0323)	(0.0322)	(0.0325)	(0.0321)
Product Mix (HHI/100000)	0.476	0.972	0.767	1.321
	(0.782)	(0.796)	(0.790)	(0.806)
Firm Rating	-0.0486*	-0.0321	-0.0435*	-0.0260
	(0.0259)	(0.0264)	(0.0260)	(0.0266)
No. of Products Offerd by Firm /100000	0.138***	0.234***	0.146**	0.244***
	(0.0513)	(0.0691)	(0.0601)	(0.0802)
Constant	0.882***	0.915***	0.853***	0.880***
	(0.0556)	(0.108)	(0.0587)	(0.111)
Product Category Fixed-Effects		X		X
R^2	0.134	0.190	0.131	0.193
Observations	774	774	774	774

Note: Dependant Variable: Still Alive 2012. Estimation method: Linear probability model. ‘Share In-Stock-Offers’ and firm type ‘F1: In-Stock-Firms’ represents the base group. A dummy for imputed firm ratings is included. The product fixed effects refer to the product categories used by geizhals.at to which the respective product range of a company predominantly belongs. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Causal Evidence: Success of Instrumented Clusters at the Offer Level

	NO FIXED EFFECTS			FIXED EFFEFCTS		
	OLS	OLS	IV	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Clicks					
Permanent-Offers	-26.87***	-95.13***	-46.94***	-13.35***	-39.80***	-46.32
	(0.716)	(2.570)	(6.848)	(1.018)	(3.977)	(68.14)
Long-Shot-Offers	-42.11***	-110.8***	-75.16***	-23.35***	-49.14***	-147.5**
	(0.650)	(2.635)	(9.683)	(0.943)	(3.968)	(60.62)
Constant	45.53***	115.2***	79.01***	102.0***	99.14***	128.2***
	(0.538)	(2.239)	(5.184)	(4.755)	(16.88)	(47.66)
R-squared	0.027	0.051	0.041	0.234	0.267	0.226
	Number of Last-Click-Throughs					
Permanent-Offers	-1.724***	-6.846***	-3.654***	-0.787***	-2.553***	-3.876
	(0.0568)	(0.204)	(0.544)	(0.0818)	(0.320)	(5.511)
Long-Shot-Offers	-2.889***	-8.119***	-6.881***	-1.511***	-3.308***	-12.43**
	(0.0515)	(0.209)	(0.769)	(0.0758)	(0.320)	(4.902)
Constant	3.153***	8.508***	6.542***	8.924***	10.42***	12.01***
	(0.0426)	(0.178)	(0.412)	(0.382)	(1.359)	(3.854)
R-squared	0.021	0.043	0.035	0.208	0.241	0.192
	Revenue by Clicks					
Permanent-Offers	-4,511***	-22,642***	-10,958***	362.9	-2,929**	-51,977**
	(308.9)	(945.2)	(2,518)	(428.1)	(1,459)	(24,967)
Long-Shot-Offers	-11,119***	-28,948***	-28,920***	-4,756***	-8,505***	-68,924***
	(280.4)	(969.0)	(3,560)	(396.8)	(1,455)	(22,210)
Constant	12,781***	31,013***	25,551***	31,221***	28,042***	38,196**
	(232.1)	(823.3)	(1,906)	(2,000)	(6,191)	(17,463)
R-squared	0.011	0.026	0.016	0.260	0.251	0.211
	Revenues by Last-Click-Throughs					
Permanent-Offers	-340.9***	-1,852***	-801.1***	-6.995	-246.6*	-5,452**
	(27.08)	(85.28)	(227.9)	(37.99)	(132.0)	(2,291)
Long-Shot-Offers	-881.5***	-2,412***	-2,797***	-385.5***	-711.8***	-7,494***
	(24.57)	(87.43)	(322.2)	(35.21)	(131.7)	(2,038)
Constant	1,022***	2,610***	2,268***	3,300***	3,499***	4,442***
	(20.34)	(74.28)	(172.5)	(177.5)	(560.3)	(1,603)
R-squared	0.010	0.022	0.006	0.240	0.244	0.180
Product Fixed-Effects				X	X	X
Etailer Fixed-Effects				X	X	X
Observations	149,862	34,357	34,357	149,862	34,357	34,357
Number of Retailers	780	241	241	780	241	241
Number of Products	4,888	2,024	2,024	4,888	2,024	2,024
F-Stat (Cragg-Donald)			240.498			22.349

Note: In all regressions In-Stock-Offers represent the base scenario. Columns (1) and (4) should facilitate the comparison and can also be found in columns (1) and (3) of Table 3. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Which E-commerce Strategy is Used for which Product?

	Permanent-Offers	Long-Shot-Offers	Permanent-Offers	Long-Shot-Offers
	(1)	(2)	(3)	(4)
Category Hardware	0.232***	0.262***	0.260***	0.400***
	(0.0377)	(0.0330)	(0.0386)	(0.0334)
Category Software	0.224***	-0.117**	0.139**	0.116**
	(0.0543)	(0.0506)	(0.0557)	(0.0516)
Category Games	-0.545***	0.511***	-0.296***	0.429***
	(0.0629)	(0.0492)	(0.0640)	(0.0500)
Category TV	0.0581	0.139***	0.0607	0.208***
	(0.0392)	(0.0345)	(0.0402)	(0.0348)
Category Phone	-0.501***	0.0377	-0.287***	-0.0442
	(0.0496)	(0.0414)	(0.0504)	(0.0419)
Category Audio	-0.145***	0.0720**	0.0923**	0.0125
	(0.0351)	(0.0307)	(0.0358)	(0.0312)
Category Movies	-0.113*	-0.127**	-0.156**	-0.195***
	(0.0655)	(0.0584)	(0.0665)	(0.0589)
Category Household	-0.205***	0.00232	0.206***	-0.236***
	(0.0431)	(0.0376)	(0.0445)	(0.0386)
Category Sport	-0.329***	-0.387***	0.0122	-0.729***
	(0.0816)	(0.0726)	(0.0826)	(0.0737)
Category Drugstore	-0.784***	-0.316***	-0.354***	-0.450***
	(0.0728)	(0.0589)	(0.0738)	(0.0597)
Category Miscellaneous	-0.734***	-0.0935	-0.322	-0.390*
	(0.259)	(0.199)	(0.260)	(0.199)
P Brand Strength (/10000)			-0.154***	0.00703
			(0.0128)	(0.0116)
P Median Absolute Price (/1000)			0.166***	0.157***
			(0.0125)	(0.0122)
P No. of Offering Firms (/100)			1.024***	-2.939***
			(0.0767)	(0.0711)
P Product life cycle Duration (/100)			-0.102***	0.0308***
			(0.00246)	(0.00226)
Constant	0.174***	0.590***	0.811***	0.691***
	(0.0382)	(0.0334)	(0.0470)	(0.0417)
Observations	149,862	149,862	149,862	149,862

Note: Multinomial logit model; "In-Stock-Offers" are the base category. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Success of Different Clusters across Product Groups

	All	Hardware	Software	Games	TV	Phone	Audio	Movies	Household	Sport	Drugstore
Number of Clicks											
Permanent-Offers	-29.32%	-50.72%	-99.14%	-59.07%	-19.24%	28.96%	-23.88%	-29.08%	-13.74%	-22.90% +	10.33%
Long-Shot-Offers	-51.28%	-67.43%	-103.45%	-58.67%	-32.12%	-13.56% +	-30.61%	-29.26%	-51.91%	-47.57%	-19.15% +
Number of Last-Click-Throughs											
Permanent-Offers	-24.96%	-44.19%	-116.48%	-56.62%	-19.76%	40.10%	-17.90%	-27.13%	-12.02%	-18.79%	-2.89%
Long-Shot-Offers	-47.92%	-64.54%	-112.09%	-62.51%	-30.78%	-7.96% +	-22.35%	-20.78% +	-44.79%	-44.91%	-25.44% +
Revenues by Clicks											
Permanent-Offers	2.84% +	4.53% +	428.09%	-76.99%	3.58% +	61.27%	-18.96%	-13.52% +	4.30% +	-45.61% +	-2.35% +
Long-Shot-Offers	-37.21%	-41.18%	188.24%	-70.10%	-21.12%	3.26% +	-31.94%	-10.90% +	-61.19%	-115.06%	-23.53% +
Revenues by Last-Click-Throughs											
Permanent-Offers	-0.68% +	-0.33% +	46.89% +	-72.36%	-5.31% +	61.50%	-4.04% +	-8.38% +	4.73% +	17.94% +	-13.45% +
Long-Shot-Offers	-37.72%	-46.87%	-17.58% +	-71.90%	-24.41%	3.76% +	-13.09% +	0.17% +	-52.78%	-96.45%	-28.82% +
Means of Base Group (In-Stock-Offers) for Each Product Group											
Number of Clicks	45.53	29.2	16.23	85.87	76.18	74.68	65.23	83.84	59.8	66.45	54.1
Number of Last-Click-Throughs	3.153	2.005	1.183	5.044	6.078	6.027	4.323	7.335	3.146	3.124	2.697
Revenues	12,781	6,851	1,769	16,265	32,475	12,343	14,917	25,332	17,354	14,756	5,809
Revenues by Last-Click-Throughs	1,022	593.6	122	929.1	2,821	1,090	1,042	2,402	954.8	766	329.2

Note: Percentages represent the change in the success variable resulting from a switch from an *In-Stock-Offer* to another strategy at the product level. As reference value we use the mean of our success variables for *In-Stock-offers* neglecting the product and etailer fixed effects. These values are shown in the undermost panel. The negligence of product and etailer fixed effects in the reference value is the reason for percentage values below 100%. + means that the coefficients are not significant.

Table 9: Comparison of Base Clustering with Competition Influenced Clustering

		Clustering Base Version			
		In-Stock-Offers	Permanent-Offers	Long-Shot-Offers	Total
Clustering with Competition Variables	In-Stock-Offers	22.26%	0.08%	0.06%	22.40%
	Permanent-Offers	0.03%	28.76%	0.30%	29.08%
	Long-Shot-Offers	0.05%	0.14%	48.33%	48.51%
	Total	22.34%	28.97%	48.69%	100.00%

Note: Columns depict the original assignment to clusters in the base version. Rows indicate the assignment of clusters if additional competition variables are considered in the clustering procedure. Note, that a variation of clustering variables does not change the assignment of offers to clusters.

Table 10: Comparison of Base Clustering with Phases of PLC Clustering

Original Assignment	Growth Phase	Maturity Phase	Declining Phase	**Phase Assignment**
	84.27%	**92.46%**	**93.32%**	In-Stock-Offers
In-Stock-Offers	8.80%	2.65%	2.30%	Permanent-Offers
	6.93%	4.89%	4.38%	Rent-Skimming-Offers
	3.96%	3.27%	4.24%	In-Stock-Offers
Permanent-Offers	**71.46%**	**84.41%**	**60.53%**	Permanent-Offers
	24.58%	12.32%	35.24%	Long-Shot-Offers
	2.12%	1.16%	0.67%	In-Stock-Offers
Long-Shot-Offers	37.95%	12.45%	12.84%	Permanent-Offers
	59.93%	**86.38%**	**86.48%**	Long-Shot-Offers

Note: The table shows how different offers can be assigned to different e-commerce strategies (clusters) over different phases of the product life cycle. Note, that the assignment over the product life cycle remains by and large relatively stable.

Table 11: Comparison of Switching and Non-Switching offers in the growth and declining phase of the PLC

	Growth Phase		Declining Phase	
Original Assignment:	Long-Shot-Offer	Long-Shot-Offer	Permanent-Offer	Permanent-Offer
Phase Assignment:	Permanent-Offer	Long-Shot-Offer	Permanent-Offer	Long-Shot-Offer
Clustering Variables				
C Availabilty Percentage	**0.0218**	0.0137	**0.0219**	0.00690
C Listing Percentage	**0.796**	0.222	**0.822**	0.276
C Daily Price Changes	0.145	**0.248**	0.126	**0.188**
C Planned Price Rank	11.92	**12.34**	10.95	**11.80**
C Coef. of Variation of abs. Price	**0.0550**	0.0298	**0.106**	0.0547
C Absolut Shipping Costs	**7.606**	7.465	**7.503**	6.972
Success Variables				
S Click Share	**1.923**	0.668	**4.374**	2.562
S Number of Clicks	**5.964**	2.954	**17.93**	12.53
S Number of LCT	**0.574**	0.272	**1.194**	1.083
S Revenue	**2,853**	1,465	**7,489**	5,015

The table highlights those offers/products which switch their e-commerce strategy over time. The values indicate means of various descriptives for different groups of offers. The first two columns compare offers which were identified originally as Long-Shot-Offer in the growth phase but switch to Permanent-Offer over the remaining PLC with those offers which have been assigned stably to the Long-Shot-Offer over the complete product life cycle. Similarily, the last two columns compare offers stably assigned to Permanent-Offers over the complete PLC with those offers which switch from Permanent-Offers' to Long-Shot-Offers in the declining phase of the PLC. Higher values are marked bold.

Table 12: Description of Further Variables

Further Descriptives	
Availability at First Offering Day	Indicator for the availability of the offer at the first offering day.
Number of Availability Changes	Indicates how often one retailer changes the availability-state of an offer.
Number of Days Offered	Number of days the retailer is offering the product.
No. of Listing Changes	Indicator for how often a retailer is changing the listing decision for the product offered.
Bestprice Percentage	Percentage of time in which offer is listed as offer with the lowest price of all offers.
Loses Until Reaction	Difference between lowest price rank before a price change and the actual price rank when price change is happening.
No. of Price Changes	Total number of price changes during the time offered.
Rank at First Offering Day	Rank of the offer at the first offering day by the retailer.
Average Relative Price	Average relative price of the offer compared to all other offers for the product.
Relative Price at First Day	Relative Price of the offer at the first offering day by the retailer.
Relative Price at Last Day	Relative Price of the offer at the last offering day by the retailer.
Average Relative Price Rank	Relative Price Rank calculated by actual rank relative to the number of offering firms.
Top-10 Percentage	Number of days offer is listed on rank 1 to rank 10 relative to the number of days product offered.
Coefficient of Variation of relative Price	Indicator for the stability of the offered price.
Coefficient of Variation of relative Rank	Indicator for the stability of the rank of the offer.

Table 13: Further Descriptives (Means) for the E-commerce Strategy Clusters

	ALL	In-Stock-Offers	Permanent-Offers	Long-Shot-Offers
Further Descriptives				
O Availability at First Offering Day	0.166	**0.635**	*0.030*	0.032
O No. of Availability Changes	10.220	12.900	**16.240**	*5.417*
O No. of Days Offered	290.000	306.700	**541.600**	*132.600*
O No. of Listing Changes	8.512	7.853	**12.600**	*6.380*
O Bestprice Percentage	0.082	**0.129**	0.070	*0.068*
O Loses Until Reaction	3.565	3.461	*2.473*	**4.263**
O No. of Price Changes	38.240	34.900	**70.060**	*16.660*
O Rank at First Offering Day	10.590	10.340	*9.021*	**11.650**
O Average Relative Price	1.011	*0.988*	1.005	**1.026**
O Relative Price at First Day	1.017	*1.005*	*1.005*	**1.029**
O Relative Price at Last Day	1.015	*0.984*	1.013	**1.031**
O Average Relative Price Rank	0.563	*0.515*	0.549	**0.592**
O Top-10 Percentage	0.534	**0.561**	0.532	*0.522*
O Coef. of Variation of rel. Price	0.057	0.062	**0.066**	*0.048*
O Var. Coef. of rel. Rank	0.285	0.326	**0.356**	*0.224*
Observations	149,862	33,479	43,414	72,969
in percent	100.00%	22.34%	28.97%	48.69%

Note: Values in the table represent means of the respective variables. The observational unit is the firm-product-level. Highest values are marked bold (italics).

Table 14: Descriptives (Means) for the Different Firm Types

	ALL	F1: In-Stock-Firms	F2: Specialized-Suppliers	F3: Long-Shot-Firms	F4: Power-Sellers-	F5: Short-Term-Suppliers	F6: Large-Department-Stores	F7: Mixed-Strategy-Type
Clustering Variables								
C Availability Percentage	38.0	88.1	4.2	3.0	50.4	49.6	7.0	4.11
C End of Offer	317.3	304.0	124.6	413.6	179.6	379.4	277.7	221.9
C Listing Percentage	31.0	29.3	67.5	13.5	58.2	21.4	43.6	43.8
C Beginning of Offer	358.1	395.4	175.7	476.5	198.1	380.1	210.1	304.4
C Daily Price Changes	0.066	0.058	0.018	0.093	0.022	0.082	0.065	0.030
C Planned Price Rank	8.252	7.405	6.698	9.409	7.238	8.088	9.193	6.484
C Coef. of Variation of Price	0.056	0.051	0.068	0.055	0.053	0.036	0.076	0.060
C Absolut Shipping Costs	7.333	6.086	6.894	8.071	7.076	8.239	8.187	5.482
Success Variables								
S Click Share (in %)	5.548	6.552	15.020	1.829	10.540	2.795	5.843	6.558
S Number of Clicks	27.000	36.590	37.510	11.320	56.180	18.480	24.890	28.430
S Number of LCT	1.908	2.522	2.383	0.878	3.803	1.427	1.843	2.062
S Revenue	12,522	12,487	40,977	4,297	30,882	7,431	10,339	8,265
S Still Alive in 2012 (in %)	68.6	71.3	86.8	50.9	91.5	59.8	82.1	90.0
Firm Characteristics								
F Pick-Up Possibility	0.562	0.543	0.623	0.451	0.712	0.540	0.735	0.400
F Product Mix (HHI)	1806	2374	3158	1597	1493	1344	980	1677
F Firm Rating	1.502	1.444	1.393	1.579	1.427	1.553	1.549	1.345
F Total Clicks on Firm	87638	146132	44688	17533	86742	61864	151278	25178
F No. of Products Offered	7748	5057	5469	7011	3303	5211	20116	1034
F No. Of Firms on market	14.270	14.690	11.070	13.750	14.980	16.260	14.240	11.870
F Average Relative Price	0.991	0.962	1.008	1.011	0.978	0.978	1.020	0.966
Product Characteristics								
P Median Absolute Price	366.8	281.9	512.2	344.1	488.4	365.9	449.8	381.3
P PLC Duration	1016	1037	1009	1052	1002	994	939	985
P No. of Offering Firms	14.270	14.690	11.070	13.750	14.980	16.260	14.240	11.870
P Price Density	11.920	10.260	16.620	10.500	17.410	11.440	13.510	9.945
P Total Clicks on Product	1423	1696	741.300	1210	2039	1582	1187	1236
Observations	780	230	53	224	59	87	117	10
in percent	100.00	29.49	6.79	28.72	7.56	11.15	15.00	1.28

Note: The observational unit for all variables is the firm-level. There is no multiple counting of firms. Highest values are marked bold! A firm has been assigned to a certain firm pool if the number of offers for the respective combination of e-commerce strategies exceeds the classification limit of 70% of all offers.

(Web-)Appendix:

A Managerial perspective of e-commerce strategies and e-tailer types

This section discusses our three e-commerce strategies at the product level and the seven different firm types. The relations of our findings to other variables at the firm-, product-, or offer-level, which have not been used in our clustering procedure, stress the importance of our results and bring a more detailed managerial perspective of the e-commerce business. For our analysis we refer to further descriptives in Table 13 and Table 14 which we use in addition to the variables listed in Table 2. In Table B.10 additional firm and product characteristics of e-commerce strategies can be found.

A.1 Characterization of e-commerce strategies at the product level

As far as listing and availability decisions are concerned Figure 3 summarizes our average results proportionally to the complete product life cycle. Note, that although there is not so much variation in the length of the products' life cycle we observe clear differences in the strategies regarding the price, listing, and availability decisions. The respective figures for the *No. of Availability Changes* and *No. of Listing Changes* in Figure 3 are shown true to scale.

In-Stock-Offers ask for low and relative stable prices for immediately available products. Compared to Permanent-Offers, In-Stock-Offers are listed later and for a shorter time period. The availability percentage is, however, extremely high. Offers in the C1-cluster are listed on average for 297 days (out of an average product life cycle of 898 days) from which they are available on 258 days. Offers in the C1-cluster are immediately available from the beginning of their listing (see *Availability at First Offering Day*). In-Stock-Offers are most common among the top-listed products (see *Top-10 Percentage*) as they ask for low relative prices (see *Planned Price Rank*). As expected the *Average Relativ Price*, the *Relative Price at First Day*, the *Relative Price at Last Day*, as well as the *Average Relative Price Rank* show the expected pattern - they are mostly favorable for consumers in the In-Stock-Cluster. This strategy could be profitable as consumers are interested in cheap and available products. Cheap prices are possible as retailers order in larger amounts from wholesalers. Obviously there is the problem of storage cost and the risk that the stocked products cannot be sold.

Permanent-Offers are more or less listed from the beginning till the end of the product life cycle although they are hardly immediately available. Based on an average product life cycle of 878 days these offers are listed in total for 574 days from which they are instantaneously available only for 26 days. According to the price and rank variables these offers occupy the midfield. Permanent-Offers show a high number of effective price changes (e.g. *No. of Price changes*). At the first glance, only *Losses Until Reaction* might show a contradiction with other price-related variables. Obviously retailers of Permanent-Offers do only lose 2.473 ranks until they respond with adequate price reactions. The finding, that these offers show faster price reactions than other clusters, might contradict with other clustering vars (especially *Daily Price Changes* which indicate the most active price setters for the Long-Shot-cluster). Note, however, that Long-Shot-Offers are located in the higher price ranks and show relatively small and therefore ineffective price changes. In contrast to this timid price reactions in the Long-Shot-Cluster, the Permanent-Cluster indicate higher and therefore more effective prices changes (e.g. *Coefficient of Variation of Absolute Price*). Moreover, Permanent-Offers show the lowest *Rank at First Offering*

Day - a fact which results from the early time of entry during the product life cycle at which only a smaller number of retailers can be observed.

Long-Shot-Offers appear seldomly among the *Top-10 percentages* as they show relatively high prices. As expected the *Average Relativ Price*, the *Relative Price at First Day*, the *Relative Price at Last Day*, as well as the *Average Relative Price Rank* show the expected pattern - they are the highest in the Long-Shot-Cluster and not favorable for consumers. Price changes are frequent *No. of price changes* but ineffective (e.g. *Coef. of Variation of rel. Price*). Offers in this cluster are listed only for a very short period (129 days out of the product life cycle of 896 days) and on most of the days these offers are not immediately available (in total on average only for 2.7 days). Overall, the descriptives give the impression that e-commerce traders want to make windfall profits with these offers: they try to make high profits with a small financial commitment (e.g. Long-Shot-Traders do not have the products immediately available but order products at the wholesaler only after incoming orders by the customer) and a low probability that consumers will actually buy. If they buy, however, the high prices allow a high profit per sold product.

To sum up, all of our observables at the offer level show a pattern which is perfectly compatible with our clustering variables indicating that our selection process of clustering variables was not an arbitrary process. On the contrary we argue, that our clustering variables cover the essentials of the universe of e-commerce strategies.

A.2 Characterization of e-tailer types

"F1: In-Stock-Firms" – with a total of 230 assigned retailers the largest pool observed in our dataset. The percentage of immediately available offers is extremely high (*C Availability Percentage*). Obvious, such firms put most of their products in stock. The offered price and therefore the price rank is very low (*F Average Relative Price*). This may stem from the fact that F1 retailers buy large quantities from wholesalers and realize quantity discounts. In addition, we observe low shipping costs. So we can consider offers by F1 retailers as quite competitive. F1 retailers are highly frequented by customers resulting in many clicks per retailer (*F Total Clicks on Firm*) even though the number of products offered is significantly below the average of all retailers (*F No. of Products Offered by Firm*). F1 retailers are more specialized on few product categories than the average firm (*F Product Mix (HHI)*). F1 retailers offer products with a low absolute price (*P Median Absolute Price*) which are able to create rather high consumer demand (*P Total Clicks on Product*). Those products are long-living goods (*P PLC Duration*) offered on markets of average size (*P No of Offering Firms*) with low price dispersion (*P Price Density*). The number of the price changes and also the variation of prices are nearby the average (*C Daily Price Changes*, *C Coef. of Variation of Price*). That applies to the time offered (*C Listing Percentage*), the pick-up possibility (*F Pick-Up Possibility*) and the firm rating (*F Firm Rating*), too.

"F3: Long-Shot-Firms" – we assign 224 retailers to this pool. All of them apply mainly "Long-Shot-Offers". Products offered are not in stock and have to be ordered from wholesalers after the customer has placed a purchase order (*C Availability Percentage*). Offers are only listed for a very short time of the product life-cycle (*C Listing Percentage*). But during this time prices are changed quite often (*C Daily Price Changes*) even if those adjustments do not lead to a good price ranking on the price comparison site (*C Planned Price Rank*). The relative price level is high (*F Average Relative Price*). In addition, the observed shipping costs (*C Absolute Shipping Costs*) are also far beyond the average. According to the pick-up possibility (*F Pick-Up Possibility*) we speak about firms which operate their business only in the virtual world without stock and without brick and mortar facilities. Further retailer characteristics show that the average assortment of a F3 retailer is distributed over many product categories (*F Product Mix (HHI)*). Such retailers are offering many products (*F No. of Products Offered by Firm*) but can only generate few referral clicks (*F Total clicks on Firm*) which may be the result from the rather bad retailer rating (*F Firm Rating*). The average product offered by F3 retailers has a long lasting product life-cycle (*P PLC Duration*) and an average price level (*P Median Absolute Price*). Price dispersion (*P Price Density*) and induced demand based on referral clicks (*P Total Clicks on Product*) is both low for their products. Looking at those facts one might have the presumption, that these retailers try to skim off rents from uninformed customers.

"F6: Large-Department-Stores" – This pool is the third largest retailer strategy pool (117 retailers). It is interesting to notice that Permanent-Offers are the dominant e-commerce strategy for these Large-Department-Stores. Moreover, the number of offers from F6 retailers is the highest among all firm pools: out of 149,862 offers in our sample 58,649 offers are listed by F6 retailers (about 40 percent). Hence, on average F6 retailers are by far the biggest firms among all other firm types offering a lot of products (*F No. of Product Offered by Firm*) and also generate a lot of clicks on geizhals.at (*F Total Clicks on Firm*). Retailers have a wide product portfolio (*F Product Mix (HHI)*, lowest number among all firm types) combined with brick and mortar facilities (*F Pick-Up Possibility*, highest number among all firm types). Compared to other firm pools the relative average price (*F Average Relative Price*) and also the shipping costs (*C Absolut Shipping Costs*) are high. Subsequently, such retailers do not aim at best-price rankings on geizhals.at (*C Planned Price Rank*). It seems that such retailers try to keep storage costs low by ordering most of their products from wholesalers after the customer order (*C Availability Percentage*). Products are listed almost half of the product life-cycle (*C Listing Percentage*) and the number of price changes is at an average level (*C Daily Price Changes*). However, if prices are changed, the variation is quite high (*C Coef. of Variation of Price*). Products offered by F6 retailers are more expensive (*P Median Absolute Price*) than the average product and do have a shorter product life-cycle than the average (*P PLC Duration*). So, F6 retailers offer a wide product portfolio and usually they do have a brick and mortar store. Obviously their customer accept higher prices for these services.

"F5: Short-Term-Suppliers" – This pool of 87 retailers is characterized by offering products only for a short time of the product life-cycle (21.4% of the product life-cycle, see *C Listing Percentage*). But during this time the availability of the products is high (*C Availability Percentage*). Such retailers do a lot of price changing (*C Daily Price Changes*), but the variation of price is low (*C Coef. of variation of Prices*). While the shipping costs of F5 retailers are very high (*C Absolut Shipping Costs*), the relative offered price (*F Average Relative Price*) and also the planned price rank (*C Planned Price Rank*) is below the average of all firm types. Note, however, that the low relative price does not result in a very low planned price rank, because markets served by F5 retailers consist of many sellers (see variables *C Planned Price Rank* and *F Average Market Size*). The firms have a wide product portfolio (*F Product Mix (HHI)*) at low relative prices (*F Average Relative Price*). The firms are rather badly rated by customers (*F Firm Rating*) and sell products with a short product life-cycle (*P PLC Duration*) and a high demand in terms of clicks (*P Total Clicks on Product*).

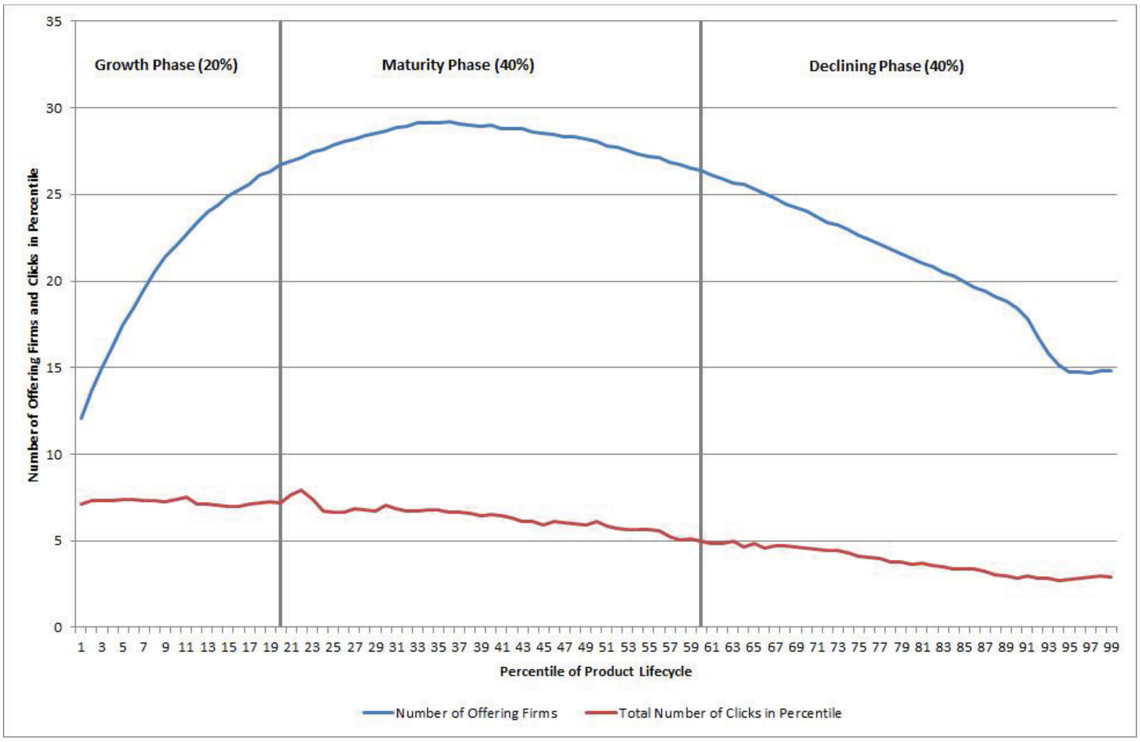
"F4: Power-Sellers" – Power sellers are only a small pool of retailers in our sample (59 out of 780 retailers). Analyzing the offered products, we see that F4 retailers really cherry-pick the goods they are listing in their assortment: Products have a high price level (*P Median Absolut Price*) and the products sold by power sellers induce high customer demand (*P Total Clicks on Product*). In case a product is listed then it is offered for more than half of the product life-cycle (*C Listing Percentage*). The availability of products is relatively high (*C Availability Percentage*). So, it seems that Power-Sellers select very carefully, which products they put into storage. Power sellers only make few price changes. These retailers use robust prices and do not react nervously on competitors' price changes (see *C Daily Price Changes*). F4 retailers only offer a small number of attractive products (*F No. of Products Offered by Firm*) but the assortment is not concentrated on certain product categories (*F Product Mix (HHI)*). The relative offered price (*F Average Relative Price*) and also shipping costs (*C Absolut Shipping costs*) are low which may also influence the good retailer rating (*F Firm Rating*). Furthermore, a majority of firms in the F4 pool operate brick and mortar facilities (*F Pick-Up Possibility*). Obviously, this strategy pool consists of high performance e-commerce retailers with high managerial skills. There are some similarities with "F1: In-Stock-Firms" but the power sellers are obviously really good in composing their assortment. So one could say that these firms are the better F1 retailers!

"F2: Specialized Suppliers" – This e-commerce firm strategy pool consists of 53 retailers which accounts for only 6.79% of all retailers in the sample. Apparently, these retailers are very specialized firms offering products only in a few product categories (*F Product Mix (HHI)*). The dominant e-commerce strategy are Permanent-Offers. They are offering their products over a long period of the product life-cycle (*C Listing Percentage*), but they do not put many of the offered products into storage (*C Availability Percentage*). Only few price changes are made by F2 retailers (*C Daily Price Changes*), but if they adjust prices the magnitude of the change is quite high (*C Coef. of Variation of Price*). Products offered by F2 retailers are only offered by a few other retailers (*P No. of Offering Firms*). Further, the absolute product price level is the highest (*P Median Absolute Price*) and the demand based on clicks is the lowest (*P Total Clicks on Product*) among all firm pools. This is a clear signal for the specialization of these retailers. Although, the relative price is above the average (*F Average Relative Price*) the firm rating for F2 retailers is very good in comparison to the other firm types (*F Firm Rating*). In summary, F2 firms are niche suppliers with a narrow product portfolio for very specialized products operating on markets with low demand but also low competitive pressure.

"F7: Mixed-Strategy-Type" – For retailers who cannot be assigned to one of the six strategies above we observe low shipping costs (*C Absolute Shipping Costs*), very good firm ratings (*F Firm Rating*) and low pick-up possibilities. F7 retailers are small firms, offering only few products (*F No. of Products Offered by Firm*) on markets with few competitors (*P No. of Offering Firms*) for a relatively low price (*F Average Relative Price*). In total, there are only 10 F7 retailers accounting for 0.14% of all offers in the dataset. Given the relative importance of this group we will not present further details for this firm type.

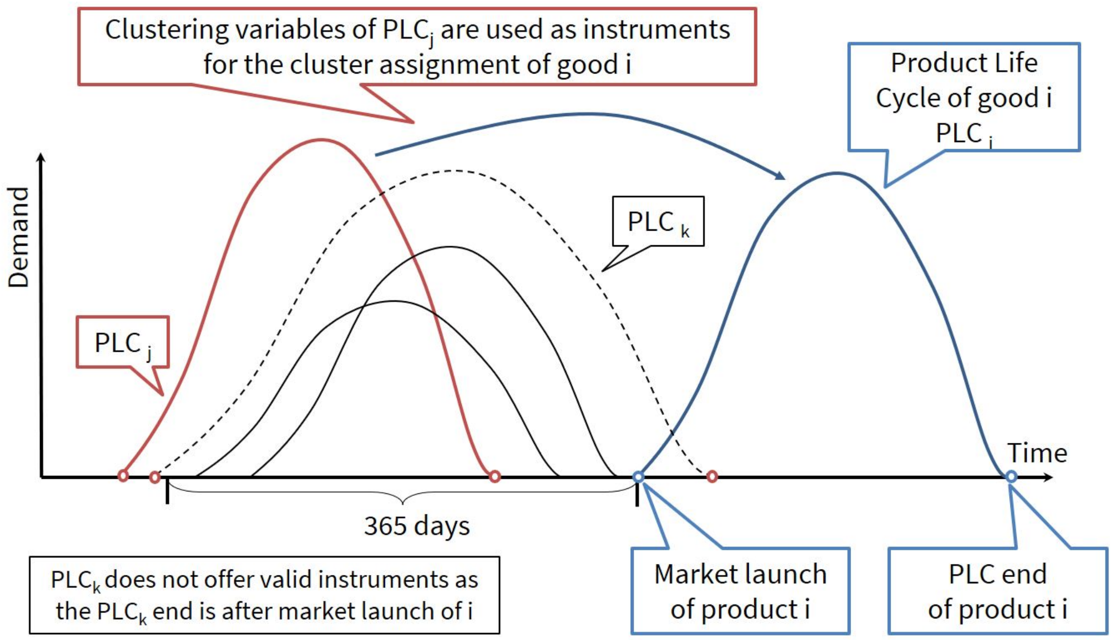
B Additional Tables and Figures

Figure B.1: Product Life Cycle



Note: The graphs show the average number of clicks by consumers for the product and the average number of Online-shops offering the product for each percentile of the life cycle for those products included in our dataset.

Figure B.2: Instrumentation Strategy



Note: We use clustering variables from a predecessor good which has been listed by the same firm and has finished its PLC before the market launch of the products in our inflow data set.

Table B.1: First Stage for Instrumented Clusters at the Offer Level from Table 6

	(1)	(2)
Instrumented Variable: Permanent-Offers		
Instr. Daily Price Changes	0.0481***	0.0234
	(0.0144)	(0.0160)
Instr. Listing Percentage	0.299***	0.0906***
	(0.00909)	(0.00979)
Instr. Availability Percentage	-0.325***	-0.0349***
	(0.00986)	(0.0126)
Instr. Absolute Shipping Costs	0.00395***	-0.000510
	(0.000432)	(0.000654)
Constant	0.325***	0.428***
	(0.00707)	(0.00795)
R-squared	0.065	0.488
Instrumented Variable: Long-Shot-Offers		
Instr. Daily Price Changes	0.0338**	-0.0412**
	(0.0142)	(0.0160)
Instr. Listing Percentage	-0.243***	-0.0974***
	(0.00901)	(0.00981)
Instr. Availability Percentage	-0.214***	-0.0441***
	(0.00977)	(0.0126)
Instr. Absolute Shipping Costs	-0.000375	-4.66e-05
	(0.000428)	(0.000656)
Constant	0.518***	0.443***
	(0.00701)	(0.00797)
Observations	34,357	34,357
R-squared	0.034	0.459
F-Stat (Cragg-Donald)	240.498	22.349
Product Fixed-Effects		X
Etailer Fixed-Effects		X
Observations	34,357	34,357

Note: Coefficients show the first stage results for the IV regressions in Table 6. Instruments are the firm's chosen strategy variables for predecessor goods with the following requirements: The product life cycle started at least 365 days and ended at least one day before the 'birth date' of the products in our dataset. In all regressions In-Stock-Offers represent the base scenario. Columns (1) and (4) should facilitate the comparison and can also be found in columns (1) and (3) of Table 3. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.2: Classification of Firm Pools Using Different Classification Limits

	60% Limit			70% Limit			80% Limit		
	No. of Firms	Avg. Offers	% of Offers	No. of Firms	Avg. Offers	% of Offers	No. of Firms	Avg. Offers	% of Offers
F1: In-Stock-Firms									
In-Stock-Offers	279	88.5	81.71%	230	92.9	85.20%	188	76.61	89.06%
Permanent-Offers	279	5.674	5.24%	230	5.174	4.75%	188	1.713	1.99%
Long-Shot-Offers	279	14.14	13.05%	230	10.96	10.05%	188	7.702	8.95%
F2: Specialized-Suppliers									
In-Stock-Offers	82	2.78	0.97%	53	2.151	1.76%	30	0.5	1.36%
Permanent-Offers	82	195	67.96%	53	90.17	73.93%	30	30.2	81.92%
Long-Shot-Offers	82	89.15	31.07%	53	29.64	24.30%	30	6.167	16.73%
F3: Rent-Skimming-Firms									
In-Stock-Offers	255	5.933	3.03%	224	3.83	2.00%	188	1.043	0.72%
Permanent-Offers	255	25.73	13.14%	224	21.28	11.09%	188	8.106	5.59%
Long-Shot-Offers	255	164.1	83.83%	224	166.7	86.91%	188	135.9	93.69%
F4: Power-Sellers									
In-Stock-Offers	41	31.59	36.30%	59	35.25	43.19%	65	82.28	67.09%
Permanent-Offers	41	37.93	43.58%	59	32.02	39.24%	65	29.54	24.08%
Long-Shot-Offers	41	17.51	20.12%	59	14.34	17.57%	65	10.83	8.83%
F5: Short-Term-Suppliers									
In-Stock-Offers	43	67.81	45.46%	87	67.34	50.12%	119	72.07	54.32%
Permanent-Offers	43	13.23	8.87%	87	8.471	6.30%	119	4.395	3.31%
Long-Shot-Offers	43	68.14	45.68%	87	58.55	43.58%	119	56.21	42.37%
F6: Large-Department-Stores									
In-Stock-Offers	73	38.01	7.70%	117	26.62	5.31%	148	14.35	2.95%
Permanent-Offers	73	234.3	47.44%	117	256.3	51.13%	148	232.3	47.68%
Long-Shot-Offers	73	221.6	44.87%	117	218.4	43.56%	148	240.6	49.38%
F7: Mixed-Strategy-Type									
In-Stock-Offers	7	8.714	36.75%	10	8.7	41.23%	42	67.07	29.85%
Permanent-Offers	7	8.286	34.94%	10	6.9	32.70%	42	91.55	40.75%
Long-Shot-Offers	7	6.714	28.31%	10	5.5	26.07%	42	66.07	29.40%

Note: The table shows the varying assignment of firms to different firm pools. To be assigned to firm pool F1 a firm has to offer more than 60, 70, or 80% of all offers in the cluster "In-Stock-Offers". To be assigned to firm pool F4 a firm has to offer more than 60, 70, or 80% of all offers as "In-Stock-" or "Permanent-Offer" and has not been already assigned to the F1 or F2 pool. In this sense the following assignment rules are to understand: F1 predominately "In-Stock-Offers", F2 predominately "Permanent-Offers", F3 . . . "Long-Shot-Offers", F4 . . . "In-Stock-Offers" or "Permanent-Offers", F5 . . . "In-Stock-Offers" or "Permanent-Offers", F6 . . . "Permanent-Offers" or "Long-Shot-Offers", F7 the remaining firms. Note that columns 'No. of Firms' of the 70% limit corresponds with the number of observations in Table B.4 in the paper.

Table B.3: Success of Firm Types Using 60% and 80% Classification Limit

	S Still Alive in 2012			
	60% Classification Limit		80% Classification Limit	
	(1)	(2)	(3)	(4)
F2: Specialized-Suppliers	0.175***	0.182***	0.226***	0.265***
	(0.0424)	(0.0432)	(0.0566)	(0.0570)
F3: Long-Shot-Firms	-0.206***	-0.191***	-0.202***	-0.186***
	(0.0413)	(0.0421)	(0.0495)	(0.0504)
F4: Power-Sellers	0.150***	0.165***	0.169***	0.150***
	(0.0579)	(0.0612)	(0.0528)	(0.0560)
F5: Short-Term-Suppliers	-0.123	-0.126*	-0.111**	-0.123**
	(0.0795)	(0.0766)	(0.0561)	(0.0556)
F6: Large-Department-Stores	0.0532	0.0508	0.0493	0.0256
	(0.0555)	(0.0551)	(0.0486)	(0.0510)
F7: Mixed-Strategy-Type	0.130	0.101	0.221***	0.204***
	(0.136)	(0.152)	(0.0520)	(0.0533)
F Pick-Up Possibility		-0.104***		-0.103***
		(0.0328)		(0.0327)
F Product Mix (HHI)		6.38e-06		7.81e-06
		(7.86e-06)		(7.92e-06)
F Firm Rating		-0.0527**		-0.0438*
		(0.0267)		(0.0260)
F Imputed Firm Rating		-0.183***		-0.175***
		(0.0411)		(0.0419)
F Total Clicks on Firm		9.66e-09		-7.14e-09
		(2.17e-08)		(2.11e-08)
F No. of Products Offered by Firm		1.20e-06		1.61e-06**
		(7.54e-07)		(7.80e-07)
Constant	0.728***	0.885***	0.707***	0.853***
	(0.0268)	(0.0550)	(0.0333)	(0.0588)
Observations	780	774	780	774
R^2	0.083	0.131	0.087	0.131

Note: This table replicates Columns (3) and (4) from Table 5 of the paper for the 60% and 80% classification limit. Estimation method: OLS-regressions. Firm type 'F1: In-Stock-Firms' represents the base group. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.4: Firm Types (70% level) and Assigned Offers

Etailer Type(Using 70% Classification Limit)	**Offer Type (Result of k-means Clustering)**										
	In-Stock-Offers			Permanent-Offers			Long-Shot-Offers				
	Abs.	Hor.Share	Ver.Share	Abs.	Hor.Share	Ver.Share	Abs.	Hor.Share	Ver.Share	Hor.Sum	
F1: In-Stock-Firms (230 retailers)	21,366	85%	64%	1,190	5%	3%	2,521	10%	3%	25,077	100%
F2: Specialized-Suppliers (53 retailers)	114	2%	0%	4,779	74%	11%	1,571	24%	2%	6,464	100%
F3: Long-Shot-Firms (224 retailers)	858	2%	3%	4,767	11%	11%	37,331	87%	51%	42,956	100%
F4: Power-Sellers (59 retailers)	2,080	43%	6%	1,889	39%	4%	846	18%	1%	4,815	100%
F5: Short-Term-Suppliers (87 retailers)	5,859	50%	18%	737	6%	2%	5,094	44%	7%	11,690	100%
F6: Large-Department-Stores (117 retailers)	3,115	5%	9%	29,983	51%	69%	25,551	44%	35%	58,649	100%
F7: Mixed-Strategy-Type (10 retailers)	87	41%	0%	69	33%	0%	55	26%	0%	2,11	100%
Vertical Sum	33,479		100%	43414		100%	72,969		100%		

Note: The table indicates how the offers from the original clusters can be assigned to different firmpools. Whereas the percentage values in columns indicated with a superscript ^{a} sum up horizontally to 100%, the percentage values in columns indicated with a superscript ^{b} sum up vertically to 100%. Note that 64% of "In-Stock-Offers" can be found in the firm type "F1: In-Stock-Firms". 69% of "Permanent-Offers" are to be found in the firm type "F6: Large-Department-Stores", and 51% of the "Long-Shot-Offers" can be attributed to "F3: Rent-Skimming-Firms".

Table B.5: Success of Different Firm Types

	S Number of Clicks		S Revenue		S Click Share (in Percent)		S Number of LCT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F2: Specialized-Suppliers	0.924	-0.186	28.491***	26.776***	8.473***	8.069***	-0.139	-0.323
	(8.224)	(7.871)	(7.212)	(7.191)	(1.490)	(1.445)	(0.723)	(0.700)
F3: Long-Shot-Firms	-25.27***	-14.22***	-8.190*	-3.033	-4.723***	-3.241***	-1.643***	-0.776*
	(5.067)	(4.978)	(4.443)	(4.548)	(0.918)	(0.914)	(0.445)	(0.443)
F4: Power-Sellers	19.59**	20.64***	18.395***	20.197***	3.988***	4.854***	1.281*	1.415**
	(7.877)	(7.573)	(6.908)	(6.919)	(1.427)	(1.390)	(0.692)	(0.674)
F5: Short-Term-Suppliers	-18.11***	-12.32*	-5.056	-1.313	-3.756***	-2.450**	-1.095*	-0.579
	(6.794)	(6.562)	(5.958)	(5.995)	(1.231)	(1.205)	(0.597)	(0.584)
F6: Large-Depart-ment-Stores	-11.70*	-1.756	-2.148	3.844	-0.709	1.598	-0.679	0.105
	(6.129)	(6.175)	(5.375)	(5.642)	(1.110)	(1.134)	(0.539)	(0.550)
F7: Mixed-Strategy-Type	-8.158	-6.858	-4.222	-2.719	0.00641	0.587	-0.460	-0.235
	(17.44)	(16.62)	(15.290)	(15.183)	(3.158)	(3.051)	(1.533)	(1.479)
F Pick-Up Possibility		5.311		1.774		-0.296		0.641*
		(3.866)		(3.532)		(0.710)		(0.344)
F Product Mix (HHI)		0.00551***		3.585***		0.00105***		0.000492***
		(0.000904)		(0.826)		(0.000166)		(8.04e-05)
F Firm Rating		-3.704		-1.460		-0.436		-0.177
		(2.989)		(2.731)		(0.549)		(0.266)
F Imputed Firm Rating		-21.51***		-7.477*		-1.035		-1.462***
		(4.483)		(4.096)		(0.823)		(0.399)
F Total Clicks on Firm		1.95e-05***		0.00652**		3.12e-06***		1.37e-06***
		(3.47e-06)		(0.00317)		(6.37e-07)		(3.09e-07)
F No. of Products Offered by Firm		-0.000396***		-0.150		-6.13e-05***		-2.71e-05**
		(0.000120)		(0.109)		(2.20e-05)		(1.07e-05)
Constant	36.59***	31.09***	12.487***	7.010	6.552***	5.016***	2.522***	1.598***
	(3.559)	(6.598)	(3.121)	(6.028)	(0.645)	(1.211)	(0.313)	(0.587)
Observations	780	774	780	774	780	774	780	774
R^2	0.058	0.161	0.045	0.078	0.122	0.197	0.032	0.117

Note: Estimation method: OLS-regressions. Firm type ‘F1: In-Stock-Firms’ represents the base group. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.6: Success of Different Clusters across Product Groups - Coefficients

	All	Hardware	Software	Games	TV	Phone	Audio	Movies	Household	Sport	Drugstore
					Number of Clicks						
Permanent-Dummy	-13.35	-14.81	-16.09	-50.72	-14.66	21.63	-15.58	-24.38	-8.215	-15.22	5.587
	(1.018)	(0.918)	(2.697)	(14.83)	(3.051)	(9.766)	(4.622)	(10.01)	(2.899)	(12.06)	(9.178)
Long-Shot Dummy	-23.35	-19.69	-16.79	-50.38	-24.47	-10.13	-19.97	-24.53	-31.04	-31.61	-10.36
	(0.943)	(0.848)	(2.515)	(13.16)	(2.893)	(8.930)	(4.412)	(9.806)	(2.714)	(11.42)	(8.446)
Constant	102.0	73.52	32.87	238.1	94.09	358.0	89.13	113.8	92.30	47.07	179.9
	(4.755)	(6.284)	(4.889)	(63.08)	(10.15)	(51.36)	(15.43)	(30.33)	(8.818)	(93.11)	(17.82)
Observations	149,862	94,414	4,575	4,054	22,869	7,251	9,786	1,969	12,371	1,217	2,044
R-squared	0.234	0.243	0.269	0.317	0.279	0.227	0.246	0.367	0.304	0.533	0.381
					Number of Last-Click-Throughs						
Permanent-Dummy	-0.787	-0.886	-1.378	-2.856	-1.201	2.417	-0.774	-1.990	-0.378	-0.587	-0.0779
	(0.0818)	(0.0731)	(0.203)	(0.831)	(0.264)	(0.949)	(0.341)	(1.014)	(0.180)	(0.586)	(0.501)
Long-Shot Dummy	-1.511	-1.294	-1.326	-3.153	-1.871	-0.480	-0.966	-1.524	-1.409	-1.403	-0.686
	(0.0758)	(0.0675)	(0.189)	(0.737)	(0.250)	(0.868)	(0.325)	(0.993)	(0.168)	(0.555)	(0.461)
Constant	8.924	7.083	3.564	20.30	9.484	42.70	7.232	11.20	5.462	-0.494	8.556
	(0.382)	(0.500)	(0.368)	(3.534)	(0.877)	(4.991)	(1.137)	(3.072)	(0.547)	(4.522)	(0.974)
Observations	149,862	94,414	4,575	4,054	22,869	7,251	9,786	1,969	12,371	1,217	2,044
R-squared	0.208	0.219	0.268	0.299	0.265	0.200	0.231	0.340	0.259	0.623	0.371
					Revenues by Clicks						
Permanent-Dummy	362.9	310.3	7,573	-12,523	1,161	7,563	-2,828	-3,424	746.4	-6,730	-136.8
	(428.1)	(355.4)	(1,558)	(3,769)	(1,902)	(2,464)	(1,331)	(3,893)	(1,201)	(5,306)	(1,444)
Long-Shot Dummy	-4,756	-2,821	3,330	-11,401	-6,858	401.8	-4,764	-2,761	-10,619	-16,978	-1,367
	(396.8)	(328.1)	(1,453)	(3,344)	(1,804)	(2,253)	(1,270)	(3,814)	(1,124)	(5,024)	(1,329)
Constant	31,221	32,365	-2,349	61,384	37,946	98,663	17,928	33,828	23,244	26,997	16,588
	(2,000)	(2,432)	(2,824)	(16,032)	(6,330)	(12,958)	(4,440)	(11,797)	(3,653)	(40,968)	(2,803)
Observations	149,862	94,414	4,575	4,054	22,869	7,251	9,786	1,969	12,371	1,217	2,044
R-squared	0.260	0.255	0.134	0.299	0.265	0.187	0.285	0.352	0.318	0.806	0.325
					Revenues by Last-Click-Throughs						
Permanent-Dummy	-6.995	-1.947	57.21	-672.3	-149.7	670.3	-42.09	-201.3	45.12	137.4	-44.29
	(37.99)	(33.75)	(68.03)	(213.5)	(174.3)	(226.6)	(107.8)	(425.6)	(77.58)	(292.6)	(92.79)
Long-Shot Dummy	-385.5	-278.2	-21.45	-668.0	-688.7	40.99	-136.4	4.013	-503.9	-738.8	-94.88
	(35.21)	(31.16)	(63.44)	(189.4)	(165.2)	(207.2)	(102.9)	(417.0)	(72.64)	(277.1)	(85.39)
Constant	3,300	3,901	499.8	5,336	4,124	12,691	1,601	3,740	1,410	1,328	835.4
	(177.5)	(230.9)	(123.3)	(908.1)	(579.9)	(1,192)	(359.8)	(1,290)	(236.0)	(2,259)	(180.1)
Observations	149,862	94,414	4,575	4,054	22,869	7,251	9,786	1,969	12,371	1,217	2,044
R-squared	0.240	0.229	0.141	0.278	0.264	0.188	0.254	0.305	0.261	0.866	0.329

Note: In all regressions In-Stock-Offers represent the base scenario. Standard errors in parentheses.

Table B.7: Descriptives (Means) for the Clustering with Competition Influenced Variables

	ALL	In-Stock-Offers	Permanent-Offers	Long-Shot-Offers
Clustering Variables				
Availabilty Percentage	21.8	**86.8**	4.5	*2.1*
End of Offer	324.0	315.9	*114.2*	**453.6**
Listing Percentage	33.3	33.2	**65.2**	*14.3*
Beginning of Offer	222.0	244.9	*80.1*	**296.5**
Daily Price Changes	0.153	*0.139*	*0.139*	**0.168**
Planned Price Rank	11.810	*11.010*	11.530	**12.340**
Coef. of Variation of abs. Price	0.085	0.081	**0.121**	*0.065*
Absolut Shipping Costs	7.745	*7.495*	7.766	**7.847**
Clustering Competition Influenced				
Bestprice Percentage	0.082	**0.132**	0.071	*0.066*
Loses Until Reaction	3.565	3.446	*2.415*	**4.310**
Var. Coef. of rel. Rank	0.285	0.328	**0.360**	*0.221*
Success Variables				
Click Share (in Percent)	3.180	**7.168**	4.047	*0.820*
Number of Clicks	17.240	**45.870**	18.630	*3.198*
Number of LCT	1.247	**3.170**	1.432	*0.248*
Revenue	6060	**12919**	8263	*1571*
Observations	149,862	33,573	43,588	72,701
in percent	100.00%	22.40%	29.09%	48.51%

Note: The observational unit is the firm-product-level. Highest (lowest) values are marked bold (italics)!

Table B.8: Success of different Clusters using Competition Influenced Variables

	(1)	(2)	(3)
	S Number of Clicks		
Permanent-Offers	-27.24***	-14.96***	-22.82***
	(0.715)	(1.007)	(0.720)
Long-Shot-Offers	-42.67***	-25.09***	-39.97***
	(0.649)	(0.938)	(0.650)
Constant	45.87***	33.77***	43.27***
	(0.537)	(0.747)	(0.532)
R^2	0.028	0.144	0.129
	S Revenue		
Permanent-Offers	-4,652***	1,437***	-4,385***
	(308.3)	(440.2)	(296.5)
Long-Shot-Offers	-11,346***	-3,421***	-11,209***
	(280.2)	(409.9)	(267.8)
Constant	12,917***	7,302***	12,773***
	(231.8)	(326.4)	(219.1)
R-squared	0.012	0.108	0.193
	S Click Share (%)		
Permanent-Offers	-3.120***	-1.166***	-2.642***
	(0.0660)	(0.0725)	(0.0620)
Long-Shot-Offers	-6.348***	-3.075***	-6.480***
	(0.0600)	(0.0675)	(0.0560)
Constant	7.168***	5.011***	7.093***
	(0.0496)	(0.0537)	(0.0458)
R-squared	0.073	0.505	0.277
	S Number of LCT		
Permanent-Offers	-1.738***	-0.807***	-1.505***
	(0.0566)	(0.0809)	(0.0571)
Long-Shot-Offers	-2.922***	-1.632***	-2.722***
	(0.0515)	(0.0753)	(0.0516)
Constant	3.170***	2.273***	3.005***
	(0.0426)	(0.0600)	(0.0422)
R-squared	0.021	0.117	0.122
Observations	149,862	149,862	149,862
Etailer Fixed-Effects		X	
Number of Retailers		780	
Product Fixed-Effects			X
Number of Products			4,888

Note: This table replicates Table 3 of the paper for a clustering procedure which uses additionally competition influenced variables. In all regressions "In-Stock-Offers" represents the base scenario. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.9: Descriptives (Means) of Clustering Variables for all Phases of the PLC-Clustering

		In-Stock-Offers	Permanent-Offers	Long-Shot-Offers
Clustering Variables - Growth Phase				
P1 Availabilty Percentage	0.195	**0.872**	0.0291	*0.0165*
P1 Listing Percentage	0.580	0.581	**0.841**	*0.244*
P1 Daily Price Changes	0.189	*0.143*	0.165	**0.246**
P1 Planned Price Rank	11.43	11.61	*10.91*	**11.99**
P1 Coef. of Variation of abs. Price	0.0438	0.0450	**0.0536**	*0.0305*
P1 Absolut Shipping Costs	7.431	*7.256*	**7.506**	7.437
Clustering Variables - Maturity Phase				
P2 Availabilty Percentage	0.213	**0.894**	0.0322	*0.0168*
P2 Listing Percentage	0.533	0.549	**0.847**	*0.231*
P2 Daily Price Changes	0.152	*0.136*	0.139	**0.171**
P2 Planned Price Rank	12.79	*11.29*	12.87	**13.52**
P2 Coef. of Variation of abs. Price	0.0635	0.0646	**0.0753**	*0.0520*
P2 Absolut Shipping Costs	7.597	*7.234*	**7.766**	7.634
Clustering Variables - Decline Phase				
P3 Availabilty Percentage	0.231	**0.903**	0.0282	*0.0129*
P3 Listing Percentage	0.463	0.503	**0.800**	*0.204*
P3 Daily Price Changes	0.152	0.145	*0.117*	**0.180**
P3 Planned Price Rank	10.40	*8.689*	10.70	**11.11**
P3 Coef. of Variation of abs. Price	0.0732	0.0637	**0.113**	*0.0503*
P3 Absolut Shipping Costs	7.402	*6.873*	**7.628**	7.527

Note: The observational unit of is the firm-product-level. Highest (lowest) values are marked bold (italics)!

Table B.10: Descriptives (Means) for the Cluster

	ALL	C1: In-Stock-Offers	C2: Permanent-Offers	C3: Long-Shot-Offers
Clustering Variables				
C Availability Percentage	21.8	**86.9**	4.6	*2.1*
C End of Offer (in days till end of PLC)	324.0	316.6	*113.0*	**453.0**
C Listing Percentage	33.3	33.1	**65.3**	*14.4*
C Beginning of Offer (in days from start of PLC)	222.0	245.2	*80.2*	**295.8**
C Daily Price Changes	0.153	0.139	*0.138*	**0.168**
C Planned Price Rank	11.810	*11.070*	11.600	**12.270**
C Coef. of Variation of abs. Price	0.085	0.080	**0.121**	*0.066*
C Absolute Shipping Costs	7.745	*7.496*	7.768	**7.845**
Success Variables				
S Click Share (in %)	3.180	**7.056**	4.097	*0.857*
S Number of Clicks	17.240	**45.530**	18.660	*3.423*
S Number of LCT	1.247	**3.153**	1.429	*0.264*
S Revenue	6,060	**12,781**	8,269	*1,662*
Firm Characteristics				
F Pick-Up Possibility	0.562	0.609	**0.650**	*0.569*
F Product Mix (HHI)	1806	**1668**	*1389*	1409
F Dummy for Imputed Rating	0.264	0.178	*0.140*	**0.243**
F Firm Rating	1.544	*1.493*	1.512	**1.552**
F Total Clicks on Firm	87,638	123,576	**153,060**	*108,511*
F No. of Products Offered by Firm	7,748	*8,941*	**12,062**	9,681
Product Characteristics				
P No. of Offering Firms	10.60	11.09	**11.54**	*10.98*
P Price Density	11.59	10.89	**12.06**	*11.58*
P Median Absolute Price	377.7	*342.6*	**393.2**	372.9
P Total Clicks on Product	541.7	566.3	**579.8**	*557.3*
P Product-Life-Cycle Duration	890.9	**897.5**	*877.5*	895.4
Observations	149,862	33,479	43,414	72,969
in percent	100.0	22.3	**29.0**	48.7

Note: The observational unit of C and S variables is the firm-product-level. For F and P variables the observational unit is either the firm- or the product-level, respectively. There is no multiple counting of firms or products for F and P variables. Highest(Lowest) values are marked bold (italics)!