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DISCONTINUITIES: WHAT IS THE VALUE OF HAVING THE LOWEST PRICE OR HIGHEST CONSUMER RATING ON A PRICE COMPARISON WEBSITE?

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Discontinuities:

What is the value of having the lowest price or highest consumer rating on a price comparison website?

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Abstract: This paper examines price elasticities on a price comparison website and if there is a discontinuity in demand for retailers having the lowest price, or products having the highest consumer rating. Previous research is extended upon, with a larger, more recent, and more varied dataset, with retailers and products followed over a longer period. It is found that there is a statistically significant positive discontinuity in demand for retailers offering the lowest price. However, the results also show that the magnitude of the effect can vary substantially between product categories. The increase in demand ranges from 58% to 154%, with an average effect of 92%. The results pertaining to consumer ratings are found to be inconclusive. The importance for retailers of maintaining the lowest price therefore remains strong, while consumer ratings seem to have less of an impact on consumer demand.

Keywords: Online retailing, e-commerce, price comparison websites, product ratings, lowest price

JEL classifications: D22, D83, L11, L86

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1. Introduction

With the rise of e-commerce, markets have developed, where the ability to compare prices and products with high levels of ease and convenience online has been made available to the broad masses. One of these marketplaces is that of price comparison websites, where empirical research has shown three main stylized facts regarding posted prices: homogeneous products exhibit remaining price dispersion, despite low search costs (Baye, Morgan, and Scholten 2004b; Brynjolfsson and Smith 2001; Baylis and Jeffery 2002; Brown and Goolsbee 2002; Tang, Smith, and Montgomery 2010; Lindsey-Mullikin and Grewal 2006); the number of firms advertising prices for a given product changes with high frequency (Baye, Morgan, and Scholten 2004a; Baye et al. 2007); and firms offering the lowest price also change frequently (Baye, Morgan, and Scholten 2004a). The observation that price dispersion remains, coupled with the fact that firms are reported to change their price frequently, begs the question, just how important is lowest price as a determinant of consumer demand in these markets? If there is a discontinuity in demand at the lowest price, retailers who do not take this into account will systematically misestimate the impact of their price changes on demand, i.e., they will systematically set their prices incorrectly.

If a discontinuity in demand at the lowest price exists and distorts price elasticity estimates, this will also likely affect policy regarding e-commerce. Einav et al. (2014) report an intense US debate regarding the possibility to tax online sales, and they also report a wide range of online sales tax rates among US states, with some states experiencing no sales tax whatsoever and others with tax rates as high as 7%. When estimating the loss of consumer welfare due to these sales taxes, having a correct measure of price elasticity of demand is crucial, and using models that do not account for discontinuities, when such exist, will misguide policy makers in considering the use and size of internet sales taxes (Baye and Morgan 2009).

A price comparison website gives consumers the ability to find the lowest price directly and without discernible effort, and while the importance of being the firm with the lowest price has been analyzed in the theoretical literature regarding search costs and pricing (Baye and

Morgan 2002; Dana Jr 1994; Narasimhan 1988; Salop and Stiglitz 1977; Varian 1980), it has been subject to less scrutiny empirically. The first empirical study to investigate the possibility of a discontinuity in demand due to being the lowest-priced firm on a price comparison website was by Baye et al. (2009), who analyzed a dataset of 18 personal digital assistants (PDAs), sold by 19 firms over 5 months, in 2003 and early 2004, on the price comparison website Kelkoo.com. It was found that a firm enjoys a 60% increase in click-throughs when it offers the lowest price in this category.

It is reasonable to assume that consumers, in addition to price, also consider product quality information before making a purchase. For example, Mizuno and Watanabe (2013) studied a Japanese price comparison website and found that 20% of retailers in their sample quote prices more than 50% higher than the lowest price, and subsequently hypothesize that retailer attributes other than price are also important in consumption choices. However, the cost of obtaining product quality information is higher than that of obtaining price information (Nelson 1970), especially on a price comparison website, where search costs for price are essentially zero. To obtain quality information for a product, the consumer could either inspect a set of characteristics related to the product in advance of a purchase, while for other products (or services), the consumer can discover their quality only by directly experiencing them. Products associated with the former are called search goods, and those associated with the latter are called experience goods, where it has been shown that there generally should be more monopoly power, and hence lower price elasticities, for experience goods, as opposed to search goods (Nelson 1970). This study, in particular, is interested in studying product quality by using consumer ratings, which are considered to increase demand by virtue of awareness (Anderson and Salisbury 2003; Bowman and Narayandas 2001; Chen, Wu, and Yoon 2004; Godes and Mayzlin 2004; Liu 2006; Van Der Eijk 2001), perceived credibility of the ratings (M. J. Salganik, Dodds, and Watts 2006; M. Salganik and Watts 2008) and perception of quality (Duan, Gu, and Whinston 2008). Zhu and Zhang (2006) find that for a type of experience goods, video games, there is, on average, a 4% increase in sales due to a one-point increase in consumer ratings on a 10-point scale, negative ratings have larger influence than positive consumer ratings, and consumer ratings are more influential for less popular products. Duan et al. (2008) study movies from 2003 – 2004 and find that ratings have no significant impact on movies' box office revenues.

The purpose of this paper is to investigate the value in terms of increased consumer demand, measured as click-through from the price comparison website to the retailer's websites, of having the lowest price or the highest consumer rating on the Swedish price comparison website *PriceSpy*.[1] The analysis and conclusions of Baye et al. (2009) are revisited using a larger, more recent, and more varied dataset. Furthermore, an extension of Baye et al. (2009) is made where the lowest price discontinuity is supplemented by an additional discontinuity, in that the highest consumer ratings are also considered to have an impact on demand. This study covers both search and experience goods categories, whereas Baye et al. (2009) investigated a single search goods category. Finally, compared to Mizuno and Watanabe (2013), this study has a longer time period for analysis.

The results from this study show that the discontinuity in demand for firms holding the lowest price is statistically significant for all categories under study, and a retailer has an increase in demand of at least 58%, on average 92%, and as high as 154% in the categories considered when offering the lowest price. The results also show that the own price elasticity of demand will be distorted if not accounting specifically for the discontinuity related to the lowest price. The results pertaining to ratings are found to be largely inconclusive. The importance of maintaining the lowest price therefore remains strong, and elasticity parameter distortions exist when not specifically accounting for the lowest price discontinuity in the estimations. These distortions are also found to be positively correlated with the size of the estimated own price elasticities and number of firms for the categories. Although the main conclusion regarding the existence of a statistically significant discontinuity in lowest price remains the same as in Baye et al. (2009), this paper can also report that these results are heterogeneous between product categories, as well as between search and experience goods

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[1] As shown by Baye et al. (2009), if conversion rate is independent of the prices listed, then the click-through elasticity of a firm may be interpreted as the firm own price elasticity of demand. As such, click-through will be used as a measure of consumer demand in this paper.

categories.

The paper is outlined as follows. Section 2 describes the theoretical background underlying discontinuities in both the lowest price and ratings on a price comparison website. Section 3 describes the empirical analysis, including descriptive statistics, model selection and the empirical specification used on our data, as well as the results. Section 4 discusses the conclusions of the study and some suggestions for further research.

2. Theoretical background

The aim of this paper is to measure how demand for retailers marketing their products on a price comparison website depends on a set of variables over a range of search and experience goods, with a special focus on prices and consumer ratings. The analysis closely follows Baye et al. (2009) by comparing continuous and discontinuous models to assess whether there is a discontinuity in demand for the lowest price or highest consumer rating at a price comparison website, and how estimates of the elasticity of demand with regard to prices or consumer ratings are affected by such a discontinuity. A site defined as a price comparison website clearly implies that price comparisons are the most important service, giving the consumer a list of prices for each product to choose from. But besides the price, there are a variety of different factors determining the behavior of the consumers on a price comparison website. This study, therefore, as an extension to the study of Baye et al. (2009) also investigates if there are discontinuities for the highest consumer rating on the price comparison website *PriceSpy*.

This article contributes to the empirical literature on clearinghouse models[2], where retailers must simultaneously appeal to two types of consumers: shoppers who search using the price comparison website and who use the available price list to always buy from the retailer offering the lowest price, and non-shoppers who search for alternatives via the price comparison website, but who choose retailer, based on non-price attributes of the retailer offerings as well. For each category there are n_{jt} retailers numbered $i = 1, 2, \ldots, n_{jt}$, posting prices and other attributes

[2] Amongst others, see Baye and Morgan (2001) and Baye et al. (2004). For a more recent empirical use of clearinghouse models, see Lindgren et al. (2020).

for product j, at time t. Following Baye et al. (2009) and the literature of clearinghouse models, for each category of products let Q_{ijt}^{S} be the number of click-throughs from shoppers to the retailers' own websites, and Q_{ijt}^{NS} be the number of click-throughs from non-shoppers to the retailer's website. All shoppers buy from the lowest priced retailer, while non-shoppers choose a retailer also based on preferences for non-price attributes (consumer ratings, delivery times, payment methods, etc.), and the characteristics of these attributes are assumed to be divided among retailers so that each of them will get an equal share of demand from non-shoppers. Let $\mathbb{I}Price_{ijt}$ represent an indicator equal to one for retailer i, marketing product j, at time t, if retailer i has the lowest price on the price comparison website, and zero otherwise. Demand for retailer i can then be written

$$Q_{ijt} = \frac{1}{n_{jt}} Q_{ijt}^{NS} + Q_{ijt}^{S} \quad if\ \mathbb{I}Price_{\mathrm{ijt}} = 1 \tag{1}$$

while other retailers r, who are not offering the lowest price, each face demand given by

$$Q_{rjt} = \frac{1}{n_{jt}} Q_{rjt}^{NS} \quad if\ \mathbb{I}Price_{\mathrm{ijt}} = 0 \tag{2}$$

As such, the lowest priced retailer on the *PriceSpy* website will receive a share of click-throughs from non-shoppers, but in addition, the lowest priced retailer will also get all click-throughs from shoppers, creating a clear positive discontinuity in the number of click-throughs for the retailer offering the lowest price.

In addition to price, the consumer can also study product ratings made by other consumers, and therefore use these to gauge product quality. In this paper, it is also assumed that there are some consumers on the *PriceSpy* website who can be viewed as quality shoppers, and who instead of focusing on the lowest price when choosing product, instead focus on consumer ratings. This would then result in the same type of discontinuity for consumer ratings as described above for price, but regarding product, rather than retailer choice, since ratings are only reported on the product level. Let $\mathbb{I}Rating_{jt}$ represent an indicator equal to one for product j, at time t, if product j has the highest rating on the price comparison website, and zero otherwise. Demand for product j can then be written

$$Q_{jt} = \frac{1}{k_t} Q_{jt}^{NR} + Q_{jt}^{R} \quad if\ \mathbb{I}Rating_{\mathrm{jt}} = 1 \tag{3}$$

where k_t is the number of products available, and Q_{jt}^{NR} stands for quantity demanded by non-ratings interested shoppers, and Q_{jt}^{R} stands for ratings-interested shoppers, analogous to the shopper and non-shopper dichotomy presented above. Other products z, which do not have the highest rating, each face demand given by

$$Q_{jt} = \frac{1}{k_t} Q_{zt}^{NR} \quad if\ \mathbb{I}Rating_{\mathrm{jt}} = 0 \tag{4}$$

In addition to a theoretical reasoning showing how having the lowest price or highest consumer ratings affects demand, the theoretical basis of the demand equation itself also needs to be discussed. The theoretical motivation for the demand equation can be found in most microeconomic textbooks, where demand is, in most cases, modelled as a function of the price of the product, the price of substitutes, and a vector of other factors, including income, consumer ratings, the number of retailers marketing the product, etc. Demand can thus be written:

$$E[Q_{it} \mid p_{it}, p_{st}, X_{it}] \quad = f[p_{it}, p_{st}, X_{it}]. \tag{5}$$

where p_{it} is the price of retailer i, at time t, p_{st} is the price of substitute offers from retailers s, other than i, at time t, and where X_{it} is a vector of all other factors affecting demand. In the empirical section, the measurement of all these variables, including the discontinuity at the lowest price and highest rating, will be presented in detail.

3. Empirical analysis

3.1 Data source and descriptive statistics

As in Baye et al. (2009) with their use of price comparison website Kelkoo.com as the data source, this study also uses data from a price comparison website, namely *PriceSpy*, which is one of the largest price comparison websites in Sweden. The consumer can search for products on the site or browse available products which are ordered, within each product category, according to popularity by click-through.

Retailers marketing a specific product through *PriceSpy* are always presented in descending order of lowest to highest price[3], whereas Baye et al. (2009) report that Kelkoo.com uses a proprietary algorithm to choose which order firms appear in, e.g., not necessarily by order of lowest to highest price. As opposed to the situation at Kelkoo.com, studied in Baye et al. (2009), referral fees are optional for retailers on *PriceSpy*, and participation in the basic *PriceSpy* market is therefore practically costless. On the other hand, retailers who volunteer to participate in the referral system and pay a fee will be presented to consumers with a more profiled approach with prominent logos and text describing the benefits of shopping from the said retailer.

14 categories of goods are included in this study and followed over a time period, ranging from 25 October 2013, to 25 February 2017, where the categories are divided into 7 experience goods categories comprising fully video games[4], with the remaining 7 categories comprising search goods categories, as defined in Section 1, according to the classification made by Nelson (1970). Baye et al. (2009) studied a sample of 18 products in the single category of Portable Digital Assistants (PDA), while the *PriceSpy* data contain a larger sample of products and product categories, which is important since the impact of the price- or ratings discontinuity

[3] When there is a tie in pricing between two retailers, the following breaks the tie, in order: price excluding shipping; price including shipping; stock; retailer rating; volume of retailer ratings; and volume of products, in which the retailer holds the lowest price. Profiled retailers are not given preference.
[4]This study is consistent with Zhu and Zhang (2006, 2010) who study video games in particular, and define these set of product categories as experience goods, according to the definition of Nelson (1970). The archetypal experience good is a service.

could differ among product categories. This article uses all products available in the categories during the time period in the main analysis, while results for a sample of the top 20 products in each of the 14 categories according to click-through are included in Appendix A, thus giving a comparable sample size to that of Baye et al. (2009) in terms of number of products.

Click-through data is available on the retailer-product level, enabling identification of consumers' choice of product at specific retailers. These click-through data do not provide information in the form of cookies, which means that it is not possible to track individual consumers. This is of less concern since the product categories under study are not considered to be subject to repeated purchases, at least not in the short run. Furthermore, even though Baye et al. (2009) had cookie data, they did not utilize this for their study, instead using the click-through of the consumer, as is done in this study.

In addition, this paper will incorporate consumer ratings into the analysis, e.g., product ratings by individual consumers on a numerical scale. It is expected that higher demand will result from higher consumer ratings (Floyd et al. 2014). The ratings are measured on the product level and on a scale from 1 to 10, and *PriceSpy* also presents a numerical summary of the ratings for the consumers. To deal with the issue of potential bias when the volume of ratings is low, *PriceSpy* attempts to balance the proportion of positive ratings with the uncertainty of a small number of observations using their own adjusted *PriceSpy* Rating (PSR), in this case, the straightforward use of the equation

$$PSR_t = \frac{5 + \overline{x}_{ratings_t} n_{ratings_t}}{n_{ratings_t} + 1} \tag{6}$$

is employed, where $\overline{x}_{ratings_t}$ equals the mean of the ratings, and $n_{ratings_t}$ is the total number of consumers having rated the product at time t. For example, if only one single consumer has given the maximum score of 10, then PSR_t will equal to 7.5 and is presented both in searches and in the initial product presentation summary. This adjustment may, however, lead the ill-informed consumer to believe that the product has a lower score than what might be the case if more consumers would contribute with ratings, but accounts for uncertainty due to low amount of consumer ratings. The actual score, however large or small, that the individual consumer sharing ratings have given to a product is still visible upon opening the product specific ratings panel, but the prospective consumer would then have to actively choose to inspect this by means of browsing to this panel.

Descriptive statistics for click-through, price, ratings and number of retailers are presented in Table 1. The mean click-through is much higher than the reported median values, all found to be approximately zero, suggesting a highly positively skewed distribution of click-through. Prices are presented in SEK including VAT, and after CPI adjustment, using 1980 as base-year. Prices are significantly higher in the search goods categories than the experience goods categories. The exception being the search goods category of headphones having a similar lower price point in the mean and median, as found in the experience goods categories. The ratings are given according to the adjustment in Equation (6), which is why the ratings tend to be around 7, the typical case being a single consumer giving a rating of 10, which then is translated to 7.5 with this formula. According to the standard deviation, the distribution of ratings is more compact for consoles and the Nintendo game categories as opposed to the other categories. Number of retailers are more numerous when it comes to the search goods categories compared to the experience goods categories, except in the search goods category of TV. Table A1 of the Appendix replicates Table 1, but instead for the sample of top 20 products by click-through. Mean click-throughs are higher in Table A1, as one would expect, while there is also evidence of more competition with more retailers posting prices for the top 20 products, as compared to products in general.

This study does not have any close substitutes to that of Baye et al. (2009). This is the case, since the PDAs sold between 2002 and 2003 are not really comparable to any of the products in this study, due to the substantial technological advancements over the years. With respect to the descriptive statistics, the closest substitutes in terms of price would be the consoles category. In terms of numbers of retailers, any given video game or the consoles category would be comparable categories. Finally, PDAs may reasonably be classified as search goods.

Table 1. Descriptive statistics for search and experience goods categories.

Category	n	Click-through			Price			Ratings			Sellers		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Search Goods													
Cellphones	781013	1.80	0.00	13.45	4282	3445	3038	7.01	7.33	1.33	15	10	15
Consoles	80492	5.91	0.00	41.43	3384	3390	1675	7.96	8.29	1.04	8	5	8
Headphones	11953605	0.16	0.00	2.33	1144	629	1707	6.53	6.85	1.42	11	8	10
Laptops	1755501	0.25	0.00	2.61	15662	14495	8963	6.80	7.00	1.31	10	9	6
Mobile Speakers	2111929	0.21	0.00	2.66	1989	995	2979	7.13	7.38	1.23	9	7	8
Tablets	901256	0.46	0.00	4.25	8704	6433	7435	6.89	7.00	1.36	12	10	10
TV	837359	1.00	0.00	10.55	14009	7990	31076	6.83	7.00	1.37	9	6	9
Total	18421155	0.32	0.00	5.14	3722	1060	9047	6.68	7.00	1.41	11	8	10
Experience Goods													
Nintendo 3DS	607312	0.16	0.00	1.46	387	398	155	7.29	7.50	1.09	4	4	4
Nintendo Wii U	304920	0.32	0.00	1.67	487	479	230	7.40	7.50	1.05	6	4	4
PC	4390739	0.10	0.00	2.54	270	185	1434	6.57	7.00	1.41	3	3	3
PlayStation 3	1559406	0.09	0.00	2.05	359	289	307	6.65	7.00	1.48	3	2	3
PlayStation 4	1070994	0.63	0.00	6.25	485	499	211	6.79	7.00	1.41	7	6	5
Xbox 360	1540499	0.07	0.00	1.24	365	280	374	6.66	7.00	1.41	3	2	3
Xbox One	990122	0.25	0.00	2.25	486	495	226	6.32	6.50	1.43	8	7	5
Total	10463992	0.17	0.00	2.87	353	289	958	6.68	7.00	1.42	4	3	4

3.2 Model specification

Following Baye et al. (2009), this study will treat click-throughs as count data in the empirical modelling. While a specific distributional assumption of the stochastic process, for example, Poisson or Negative binomial, with maximum likelihood (ML) estimation of the underlying parameters could be suitable, this relies on the assumption that the true stochastic process does not differ from the one used for obtaining the ML estimates (Gourieroux, Monfort, and Trognon 1984b; 1984a; Cameron and Trivedi 1986). Gourieroux et al. (1984b) showed, roughly, for the pseudo-maximum likelihood approach that as long as the mean specification is correct, any estimator for the underlying parameters obtained by maximizing the likelihood function, based on the linear exponential class, will be consistent for these parameters, even if the underlying distribution is misspecified. For this reason, this study will align with Baye et al. (2009) in using the Poisson pseudo-maximum likelihood (PPML) estimator as the preferred estimation method since it is of the linear exponential class, unlike, for instance, negative binomial and other common specifications for count data. It has also been established, after the publication of Baye et al. (2009), that the PPML estimator used in their article behaves well when the proportion of zeros in the sample is very large (Silva and Tenreyro 2011). This is often the case for click-through data and is certainly the case for the full sample used in this article, as evident by the median values reported in Table 1.

Assuming that the underlying stochastic process has finite mean, the following model is specified and estimated for each of the product categories under study

$$E\left[Q_{ijt} \mid p_{ijt}, p_{sjt}, X_{jt}\right] \quad = \exp\left[\beta_1 \ln p_{ijt-1} + \beta_2 \ln p_{sjt-1} + \gamma X_{jt}\right]. \qquad (7)$$

As such, the model is specified for retailer i, marketing product j, at time t, in the product category under study, where time is measured in daily frequency. $\ln p_{ijt-1}$ is the CPI adjusted price measured in SEK and expressed in logarithms, $\ln p_{sjt-1}$ is the CPI adjusted price of substitute offers from other retailers measured in logarithms, both lagged one period to alleviate a potential endogeneity problem. Following Daunfeldt and Rudholm (2014), the price of substitute offers is measured as the average price of the retailers not having the lowest price. The vector X_{jt} of controls includes

$$X_{jt} = [\ln PSR_{jt-1}, \ln Volume_{jt-1}, \ln CoV_{jt-1}, Weekend_t, Month_t] \tag{8}$$

where PSR_{jt-1} is the *PriceSpy* specific measure of ratings described in Section 3.1, $Volume_{jt-1}$ is the volume of ratings in terms of count, $\ln CoV_{t-1}$ is the coefficient of variation for the ratings, and n_{jt-1} is the number of retailers marketing the product at the *PriceSpy* website, all of which are measured at time $t-1$ to alleviate possible endogeneity, and, finally, the model includes weekend and month indicator variables. The ratings-related variables follow from previous research on consumer ratings (Chevalier and Mayzlin 2006; Zhang and Dellarocas 2006; Zhu and Zhang 2010), with the exception being that the PSR_{jt-1} measure acts as an substitute for the mean of ratings, owing to how this is presented on the *PriceSpy* price comparison website, as described in Section 3.1. The mean of ratings, and by extension PSR_{jt-1}, reflect the consumer satisfaction, which is expected to increase demand. $\ln CoV_{t-1}$ captures the degree of consumer disagreement, the latter variable having both negative and positive impact on demand in previous studies (Martin, Barron, and Norton 2008; Sun 2012). Finally, the volume of ratings may carry information about exposure and hence signal the popularity of a product.

A variable for the dependency of the elasticity on the number of firms is included, as in Baye et al. (2009), in the form of

$$\left(\beta_0 + \left(n_{jt-1} - 1\right)\beta_1\right) \ln p_{ijt-1} + \beta_2 \ln p_{sjt-1} + \beta_3 n_{jt-1} \tag{9}$$

and incorporating this into Equation (7) gives:

$$E\left[Q_{ijt} \mid p_{ijt}, p_{sjt}, X_{jt}\right] = \exp\begin{bmatrix} \left(\beta_0 + \left(n_{jt-1} - 1\right)\beta_1\right) \ln p_{ijt-1} \\ + \beta_2 \ln p_{sjt-1} + \beta_3 n_{jt-1} + \gamma X_{jt} \end{bmatrix} \tag{10}$$

where X_{jt} contains the same controls as above. The derivative of Equation (10) with respect to $\ln p_{ijt}$

$$\frac{\partial \ln E[Q_{ijt} | p_{ijt}, p_{sjt}, X_{jt}]}{\partial \ln p_{ijt}} = \beta_0 + (n_{jt-1} - 1)\beta_1 \tag{11}$$

can therefore be interpreted as a discrete continuum measure of market power: monopoly $(n_{jt-1} = 1)$, duopoly $(n_{jt-1} = 2)$ and oligopoly and further competition $(n_{jt-1} > 2)$.

The possibility of discontinuities at the lowest price or highest consumer rating is modelled by indicator variables, $\mathbb{I}Price_{ijt}$ and $\mathbb{I}Rating_{jt}$. Let $\mathbb{I}Price_{ijt}$ be an indicator equal to one for retailer i, marketing product j, at time t, if retailer i has the lowest price on the price comparison website, and zero otherwise, while $\mathbb{I}Rating_{jt}$ represents an indicator equal to one for product j, at time t, if product j has the highest rating on the price comparison website, and zero otherwise. Including the indicator $\mathbb{I}Price_{ijt}$ gives the mean specification from Baye et al. (2009) that allows for a discontinuous jump in click-through at the lowest price, and with the addition of $\mathbb{I}Rating_{jt}$ Equation (10) can now be written

$$E[Q_{ijt} \mid p_{ijt}, p_{sjt}, X_{jt}] = \exp\begin{bmatrix} \lambda\mathbb{I}Price_{ijt} + \delta\mathbb{I}Rating_{jt} + \\ (\beta_0 + (n_{jt-1} - 1)\beta_1)\ln p_{ijt-1} + \\ + \beta_2 \ln p_{sjt-1} + \beta_3 n_{jt-1} + \gamma X_{jt} \end{bmatrix} \tag{12}$$

where $\mathbb{I}Price_{ijt}$ is the indicator variable equal to one, when retailer i has the lowest price for product j, on day t, and $\mathbb{I}Rating_{jt}$ is the indicator variable equal to one, when product j has the highest rating on day t. With regards to $\mathbb{I}Price_{ijt}$, this will then be a nested version of the previous model as they will be the same, if $\mathbb{I}Price_{ijt}$ was equal to zero for all t, and one can therefore compare the parameter estimates for the market's own price elasticity of click-through. Finally, the dummy $\mathbb{I}Price_{ijt}$ is also replaced, as in Baye et al. (2009), with demand discontinuities represented in Table 4 by $\mathbb{I}FourPrice_{ijt}$ to account for the possibility that the discontinuity reaches beyond the lowest price, which are four dummy variables equal to one for the lowest price, and zero otherwise, equal to one for the second lowest price, and zero otherwise, etc.. As such, the results are compared to the average for the fifth to the highest price.

Baye et al. (2009) also give an estimate of how many shoppers, i.e., consumers focusing on the lowest price, who act on the price comparison website. This estimate is given by

$$ShareShopper = \frac{S}{S + NS} = \frac{\lambda}{\bar{n} + \lambda} \tag{13}$$

with the theoretical basis of this measure presented in Baye et al. (2009, p. 960). In Equation (13), S is the number of shoppers, and NS is the number of non-shoppers, effectively providing a fraction of consumers being shoppers within the category considered, while $\bar{n}$ is the mean number of retailers. This is admittedly a crude measure, some of the crudeness of the estimate stems from the assumption of symmetry between retailers, but it does, nonetheless, provide a figure to compare the share of shoppers in different categories, as well as to that calculated by Baye et al. (2009) and it is therefore included.

Provided that price elasticity estimates have been retrieved from Equation (12) with and without the variable $\mathbb{I}Price_{ijt}$ included, it is possible to also interpret the results from a policy makers perspective regarding a potential tax on online transactions. Using the formula for the excess burden of a tax

$$EBT = \frac{1}{2}\theta\tau^2 p_k q_k$$

where k is the consumer paying the tax for q_k units at initial price p_k, and where θ is the price elasticity of demand (Stiglitz 2000, 518–41), one can use the ratio of EBT between the models' specifications price elasticity to assess how excluding the price discontinuity affects the excess burden of the tax[5].

3.3 Estimation results

Table 2 reports the PPML regression estimates, with the dependent variable being count data on click-through for the search and experience goods, respectively, without inclusion of the $\mathbb{I}Price_{ijt}$ dummy variable given in Equation (10). Throughout this paper, unobserved

[5] The excess burden of taxation is the efficiency cost, or deadweight loss, associated with taxation.

retailer-product heterogeneity is controlled for by including product-retailer fixed effects in the estimations of Equations (10) and (12). The reported elasticity estimates related to the lagged log price variable, according to Equation (11) of Section 3.2, may be interpreted as the elasticity of demand for the monopoly retailer, while the marginal effect of the said variable, which is evaluated at the mean of the other regressors, is also reported and represents the observed market situation in a specific product category in the mean (Baye et al. 2009). From this point forward, mentioned price elasticities always refer to the marginal effects, e.g., the observed market situation for the specific product category.

Table 2 reports the results of estimating Equation (10) for the search and experience goods categories, respectively. The main feature of these PPML regression models is the exclusion of the $\mathbb{I}Price_{ijt}$ dummy variable, thereby not including the discontinuity in demand. The results in Table 2 show that the search goods categories have higher price elasticities than experience goods categories, the elasticities for search goods range between -4.552 and -15.564, while for experience goods they range between -1.866 and -4.917[6]. The elasticity estimates for PDAs, given in Baye et al. (2009), are -4.370, which roughly equals the upper bound for the experience goods categories and the lower bound of the search goods categories studied in this paper.[7] Higher elasticities for search goods are found, as predicted by (Nelson 1970), with the mean elasticity being almost twice as high for search goods categories than experience goods.

[6] The results for the category of PlayStation 3 games have non-significant parameter estimates.

[7] This value is retrieved by calculating the marginal effect of Model 1 from Table V in Baye et al. (2009) evaluated at the mean number of sellers, 4.05, given in the descriptive statistics.

Table 2. PPML regression results, no lowest price dummy variables included.

	Search Goods Categories							Experience Goods Categories						
	Headph.	Cellph.	M.Speak.	Tablets	TV	Laptops	Consoles	3DS	Wii U	PS3	PS4	PC	Xb. One	Xb. 360
$\ln p_{ijt-1}$	-4.556***	-5.682***	-4.330***	-8.218***	-5.822***	-13.631***	-6.622***	-3.776***	-3.456***	1.498	-2.427***	-1.493***	-1.114**	-0.371
	(0.170)	(0.790)	(0.375)	(0.327)	(0.596)	(1.726)	(1.781)	(0.560)	(1.002)	(1.853)	(0.290)	(0.398)	(0.437)	(0.972)
$\ln p_{ijt-1} \times$	0.000	-0.012	-0.016**	-0.011	-0.158***	-0.124***	-0.246***	-0.068	-0.186**	-0.708**	-0.129***	-0.135***	-0.087***	-0.452**
$(n_{jt-1} - 1)$	(0.002)	(0.007)	(0.008)	(0.007)	(0.032)	(0.042)	(0.068)	(0.063)	(0.076)	(0.341)	(0.025)	(0.030)	(0.022)	(0.207)
$\mathbb{I}Ratings_{jt}$	0.083	-0.188	0.300*	-0.188	0.250*	-0.129	-	-0.383	0.007	-1.420***	-0.435**	1.097***	-0.174	-0.214
	(0.151)	(0.166)	(0.177)	(0.215)	(0.143)	(0.144)	-	(0.246)	(0.189)	(0.212)	(0.170)	(0.123)	(0.207)	(0.247)
$\ln p_{sjt-1}$	0.000	0.000	0.000***	0.000***	-0.000	-0.001***	0.002***	0.005***	0.003	0.004***	0.007***	0.007***	0.000	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$\ln PSR_{jt-1}$	0.648***	0.247	0.065	0.312	-1.249*	2.469	1.060	-13.824**	4.822***	0.699	0.263	-0.527	-1.274	1.270
	(0.226)	(0.341)	(0.573)	(0.981)	(0.675)	(3.609)	(0.830)	(6.362)	(1.393)	(0.906)	(0.384)	(0.450)	(1.239)	(7.956)
$\ln Volume_{jt-1}$	-0.039*	0.083**	0.033	-0.144*	-0.135	-0.137	-0.052	1.087**	0.058	-0.257***	-0.071	-0.070	0.347*	-0.982**
	(0.020)	(0.036)	(0.043)	(0.084)	(0.142)	(0.213)	(0.077)	(0.438)	(0.187)	(0.083)	(0.063)	(0.080)	(0.188)	(0.396)
$\ln CoV_{jt-1}$	-0.056	-0.045	-0.149	-0.043	0.134	0.010	0.047	2.224	0.411	0.236	-0.162	0.076	0.068	-0.647
	(0.040)	(0.060)	(0.093)	(0.146)	(0.165)	(0.335)	(0.191)	(1.488)	(0.285)	(0.846)	(0.108)	(0.195)	(0.165)	(1.567)
n_{jt-1}	-0.022*	0.049	0.124**	0.035	1.462***	1.183***	1.839***	0.315	0.921**	3.369*	0.600***	0.590***	0.433***	2.138**
	(0.013)	(0.065)	(0.052)	(0.057)	(0.305)	(0.402)	(0.531)	(0.335)	(0.442)	(1.737)	(0.140)	(0.160)	(0.128)	(1.010)
$Weekend_t$	-0.112***	-0.043*	0.019	-0.020	0.020	-0.036	0.029	0.040	0.120***	0.096***	0.057***	0.154***	0.081***	-0.009
	(0.009)	(0.024)	(0.017)	(0.031)	(0.035)	(0.037)	(0.062)	(0.035)	(0.026)	(0.027)	(0.020)	(0.023)	(0.022)	(0.084)
$\frac{\partial \ln E[Q_{ijt}]}{\partial \ln p_{ijt-1}}$	-4.552***	-5.929***	-4.557***	-8.403***	-7.254***	-15.564***	-9.728***	-4.200***	-4.917***	-0.776	-3.416***	-2.206***	-1.866***	-1.969***
	(0.162)	(0.788)	(0.320)	(0.306)	(0.637)	(1.376)	(1.412)	(0.424)	(0.833)	(0.914)	(0.207)	(0.361)	(0.319)	(0.415)
Observations	1671349	258644	260813	94245	38401	20996	21024	28999	54845	140763	178657	223166	96474	92694

Notes: Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The marginal effects are evaluated at the mean.

Tables 3 and 4 extend upon Table 2 to include additional variables. The dummy variable $\mathbb{I}Price_{ijt}$, e.g., the discontinuity in demand, is included in contrast to Table 2. The $ShareShopper_j$ and $EBT\ Ratio$ measures are presented in Table 3, while individual indicator variables for the four lowest priced products, $\mathbb{I}FourPrice_{ijt}$, are presented in Table 4.

The results in Table 3 reaffirm the results found in Baye et al. (2009) in that there is a discontinuity in the lowest price, as given by the statistically significant parameter estimate for the variable $\mathbb{I}Price_{ijt}$ for all product categories. The increase in demand from holding the lowest price ranges from 58% to 154%, with an average increase of 92%, which can be compared to Baye et al. (2009), who found a corresponding 60% increase in the PDA category considered in their study.

A direct comparison of the price elasticities given by the partial derivatives in Tables 2 and 3 for all product categories, along with the corresponding estimate given in Baye et al. (2009), is given a visual representation in Fig. 1. The left panel presents the results provided by Baye et al. (2009), while the middle and right panels present the results from this study for experience and search goods, respectively. The dark grey circles represent the elasticity estimates without $\mathbb{I}Price_{ijt}$ included, e.g., the partial derivatives in Table 2, while the light gray circles represent the elasticity estimates when including the discontinuity dummy in the estimations, e.g., the partial derivatives in Table 3, in both cases measured at the mean number of retailers. The size of the circles in the graph represents the mean number of retailers marketing the product, and a higher vertical position in the graph represents a higher elasticity estimate. The mean number of retailers in Baye et al. (2009) is most similar to those found in the experience goods categories. The results highlight that in all cases the elasticity is overstated when not accounting for the lowest price. It appears that there is no particular relationship between the mean number of sellers and the size of the demand discontinuity, as evident from Fig. 1, while the demand discontinuity appears to be rising with more elastic product categories, which can be seen particularly in the case of the laptop category.

Table 3. PPML regression results, lowest price dummy variables included.

	Search Goods Categories							Experience Goods Categories						
	Headph.	Cellph.	M.Speak.	Tablets	TV	Laptops	Consoles	3DS	Wii U	PS3	PS4	PC	Xb. One	Xb. 360
$\ln p_{ijt-1}$	-4.009***	-4.028***	-3.690***	-6.723***	-4.660***	-9.084***	-5.271***	-3.324***	-2.263**	2.029	-1.464***	-0.473	-0.613*	-0.045
	(0.175)	(0.344)	(0.404)	(0.394)	(0.694)	(1.976)	(1.492)	(0.575)	(0.964)	(1.876)	(0.258)	(0.393)	(0.338)	(1.017)
$\ln p_{ijt-1} \times$	0.002	-0.016**	-0.010	-0.017**	-0.139***	-0.137***	-0.201***	-0.030	-0.174**	-0.699**	-0.102***	-0.111***	-0.059***	-0.396**
$(n_{jt-1} - 1)$	(0.002)	(0.007)	(0.008)	(0.008)	(0.033)	(0.038)	(0.062)	(0.062)	(0.077)	(0.318)	(0.024)	(0.022)	(0.018)	(0.197)
$\mathbb{I}Price_{ijt}$	0.626***	1.051***	0.652***	0.747***	0.679***	0.736***	1.070***	0.545***	0.586***	0.990***	1.293***	1.538***	1.501***	0.889***
	(0.038)	(0.086)	(0.110)	(0.081)	(0.090)	(0.194)	(0.131)	(0.107)	(0.130)	(0.250)	(0.093)	(0.162)	(0.121)	(0.210)
$\mathbb{I}Ratings_{jt}$	0.122	-0.210	0.410**	-0.211	0.107	-0.085	-	-0.513**	0.178	-1.592***	-0.465**	1.040***	-0.338**	-0.212
	(0.153)	(0.139)	(0.181)	(0.200)	(0.094)	(0.117)	-	(0.229)	(0.188)	(0.200)	(0.181)	(0.104)	(0.151)	(0.212)
$\ln p_{sjt-1}$	-0.000	0.000***	0.000**	0.000	-0.000***	-0.001***	0.002***	0.003**	0.000	0.003**	0.004***	0.004*	-0.000	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
$\ln PSR_{jt-1}$	0.687***	0.068	0.455	-0.093	-1.479**	1.078	0.033	-11.990**	3.941**	0.773	0.458	-0.602	-0.833	1.054
	(0.239)	(0.322)	(0.523)	(0.882)	(0.704)	(3.513)	(0.802)	(5.568)	(1.555)	(0.891)	(0.303)	(0.394)	(1.080)	(7.252)
$\ln Volume_{jt-1}$	-0.056***	0.074**	-0.011	-0.123	-0.097	-0.053	0.007	1.038***	0.096	-0.244***	-0.049	-0.064	0.380**	-0.937***
	(0.021)	(0.035)	(0.043)	(0.081)	(0.133)	(0.189)	(0.074)	(0.363)	(0.199)	(0.082)	(0.064)	(0.069)	(0.168)	(0.363)
$\ln CoV_{jt-1}$	-0.079**	-0.013	-0.201**	0.048	0.193	0.059	0.363**	1.950	0.376	0.167	-0.238**	0.140	0.063	-0.650
	(0.039)	(0.063)	(0.089)	(0.132)	(0.176)	(0.366)	(0.174)	(1.379)	(0.280)	(0.794)	(0.100)	(0.170)	(0.139)	(1.390)
n_{jt-1}	-0.022*	0.107*	0.094*	0.096	1.282***	1.318***	1.499***	0.121	0.881**	3.372**	0.466***	0.507***	0.308***	1.893**
	(0.013)	(0.061)	(0.053)	(0.060)	(0.311)	(0.356)	(0.490)	(0.330)	(0.443)	(1.625)	(0.133)	(0.126)	(0.106)	(0.963)
$Weekend_t$	-0.112***	-0.065***	0.016	-0.018	0.022	-0.005	0.023	0.044	0.121***	0.096***	0.048***	0.140***	0.087***	-0.010
	(0.010)	(0.020)	(0.018)	(0.032)	(0.031)	(0.039)	(0.059)	(0.034)	(0.025)	(0.027)	(0.019)	(0.023)	(0.023)	(0.085)
$\frac{\partial \ln E[Q_{ijt}]}{\partial \ln p_{ijt-1}}$	-3.986***	-4.378***	-3.834***	-6.999***	-5.916***	-11.218***	-7.808***	-3.509***	-3.628***	-0.216	-2.246***	-1.062***	-1.120***	-1.446***
	(0.167)	(0.335)	(0.359)	(0.350)	(0.794)	(1.738)	(1.209)	(0.561)	(0.810)	(0.989)	(0.228)	(0.371)	(0.242)	(0.511)
$ShareShopper$	4%	12%	6%	7%	7%	6%	11%	12%	9%	25%	30%	18%	33%	10%
$EBT\ Ratio$	14%	35%	19%	20%	23%	39%	25%	20%	36%	-	52%	107%	67%	36%
Observations	1671349	258644	260813	94245	38401	20996	21024	28999	54845	140763	178657	223166	96474	92694

Notes: Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The marginal effects are evaluated at the mean.

Table 4. PPML regression results, four lowest price dummy variables included.

	Search Goods Categories							Experience Goods Categories						
	Headph.	Cellph.	M.Speak.	Tablets	TV	Laptops	Consoles	3DS	Wii U	PS3	PS4	PC	Xb. One	Xb. 360
$\ln p_{ijt-1}$	-3.811***	-3.382***	-3.580***	-6.402***	-4.689***	-8.060***	-4.626***	-3.314***	-1.934**	2.012	-1.456***	-0.405	-0.669**	-0.033
	(0.180)	(0.269)	(0.421)	(0.448)	(0.701)	(2.068)	(1.338)	(0.578)	(0.944)	(1.851)	(0.261)	(0.410)	(0.328)	(1.013)
$\ln p_{ijt-1} \times$	0.002	-0.008	-0.009	-0.017**	-0.138***	-0.136***	-0.195***	-0.016	-0.139*	-0.715**	-0.066**	-0.090***	-0.020	-0.416**
$(n_{jt-1} - 1)$	(0.003)	(0.007)	(0.008)	(0.008)	(0.033)	(0.037)	(0.058)	(0.060)	(0.081)	(0.324)	(0.026)	(0.022)	(0.019)	(0.212)
$\mathbb{I}FourPrice_{ijt}$	1.180***	1.878***	1.159***	1.466***	0.540***	1.189***	1.414***	0.962***	1.247***	-0.099	2.357***	2.712***	2.821***	0.228
$(= 1)$	(0.073)	(0.096)	(0.147)	(0.132)	(0.152)	(0.249)	(0.155)	(0.303)	(0.249)	(0.566)	(0.204)	(0.281)	(0.155)	(0.581)
$\mathbb{I}FourPrice_{ijt}$	0.679***	1.154***	0.608***	0.846***	-0.135	0.530***	0.653***	0.535***	0.709***	-1.105*	1.377***	1.551***	1.839***	-0.688
$(= 2)$	(0.061)	(0.072)	(0.104)	(0.117)	(0.130)	(0.119)	(0.191)	(0.241)	(0.201)	(0.671)	(0.185)	(0.237)	(0.153)	(0.594)
$\mathbb{I}FourPrice_{ijt}$	0.385***	0.767***	0.415***	0.660***	-0.243*	0.158*	-0.019	0.146	0.379**	-1.043*	0.783***	0.910***	0.932***	-0.557
$(= 3)$	(0.059)	(0.060)	(0.102)	(0.119)	(0.138)	(0.092)	(0.281)	(0.199)	(0.163)	(0.572)	(0.165)	(0.174)	(0.191)	(0.508)
$\mathbb{I}FourPrice_{ijt}$	0.247***	0.424***	0.323***	0.445***	0.108	-0.076	-0.449	0.181	0.127	-0.743***	0.416***	0.447***	0.401**	-0.610**
$(= 4)$	(0.052)	(0.051)	(0.108)	(0.118)	(0.292)	(0.139)	(0.295)	(0.198)	(0.148)	(0.261)	(0.142)	(0.110)	(0.161)	(0.298)
$\mathbb{I}Ratings_{jt}$	0.091	-0.160	0.431**	-0.202	0.139	-0.107	-	-0.618***	0.309	-1.597***	-0.485***	1.028***	-0.328**	-0.214
	(0.135)	(0.139)	(0.175)	(0.205)	(0.103)	(0.109)	-	(0.226)	(0.206)	(0.200)	(0.180)	(0.106)	(0.142)	(0.214)
$\ln p_{sjt-1}$	-0.000	0.000***	0.000**	-0.000	-0.000***	-0.001***	0.002***	0.003*	-0.001	0.003**	0.003***	0.003	-0.000	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
$\ln PSR_{jt-1}$	0.651***	-0.128	0.463	-0.245	-1.507**	1.048	0.520	-11.412**	3.997**	0.781	0.791**	-0.676*	-0.334	0.942
	(0.238)	(0.302)	(0.517)	(0.949)	(0.704)	(3.453)	(0.755)	(5.541)	(1.588)	(0.904)	(0.318)	(0.381)	(1.053)	(7.242)
$\ln Volume_{jt-1}$	-0.060***	0.114***	-0.015	-0.111	-0.098	-0.041	-0.014	1.110***	0.047	-0.242***	-0.072	-0.044	0.363**	-0.929**
	(0.021)	(0.034)	(0.042)	(0.088)	(0.133)	(0.185)	(0.071)	(0.323)	(0.207)	(0.084)	(0.063)	(0.072)	(0.152)	(0.364)
$\ln CoV_{jt-1}$	-0.069*	0.061	-0.190**	0.096	0.193	0.041	0.334**	1.762	0.305	0.163	-0.301***	0.144	0.012	-0.616
	(0.040)	(0.059)	(0.089)	(0.132)	(0.177)	(0.354)	(0.163)	(1.362)	(0.287)	(0.796)	(0.099)	(0.171)	(0.143)	(1.389)
n_{jt-1}	-0.017	0.053	0.087	0.103	1.275***	1.307***	1.463***	0.057	0.708	3.447**	0.271*	0.399***	0.100	1.989*
	(0.016)	(0.064)	(0.054)	(0.063)	(0.318)	(0.347)	(0.456)	(0.310)	(0.468)	(1.648)	(0.142)	(0.126)	(0.116)	(1.027)
$Weekend_t$	-0.110***	-0.070***	0.016	-0.017	0.022	-0.004	0.018	0.045	0.120***	0.095***	0.048***	0.135***	0.084***	-0.010
	(0.010)	(0.020)	(0.018)	(0.032)	(0.031)	(0.039)	(0.058)	(0.034)	(0.025)	(0.027)	(0.018)	(0.024)	(0.024)	(0.086)
$\frac{\partial \ln E[Q_{ijt}]}{\partial \ln p_{ijt-1}}$	-3.788***	-3.557***	-3.706***	-6.676***	-5.939***	-10.172***	-7.084***	-3.412***	-3.026***	-0.286	-1.967***	-0.883**	-0.837***	-1.507***
	(0.173)	(0.242)	(0.381)	(0.384)	(0.802)	(1.968)	(1.131)	(0.596)	(0.817)	(0.965)	(0.243)	(0.390)	(0.235)	(0.492)
Observations	1671349	258644	260813	94245	38401	20996	21024	28999	54845	140763	178657	223166	96474	92694

Notes: Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The marginal effects are evaluated at the mean.

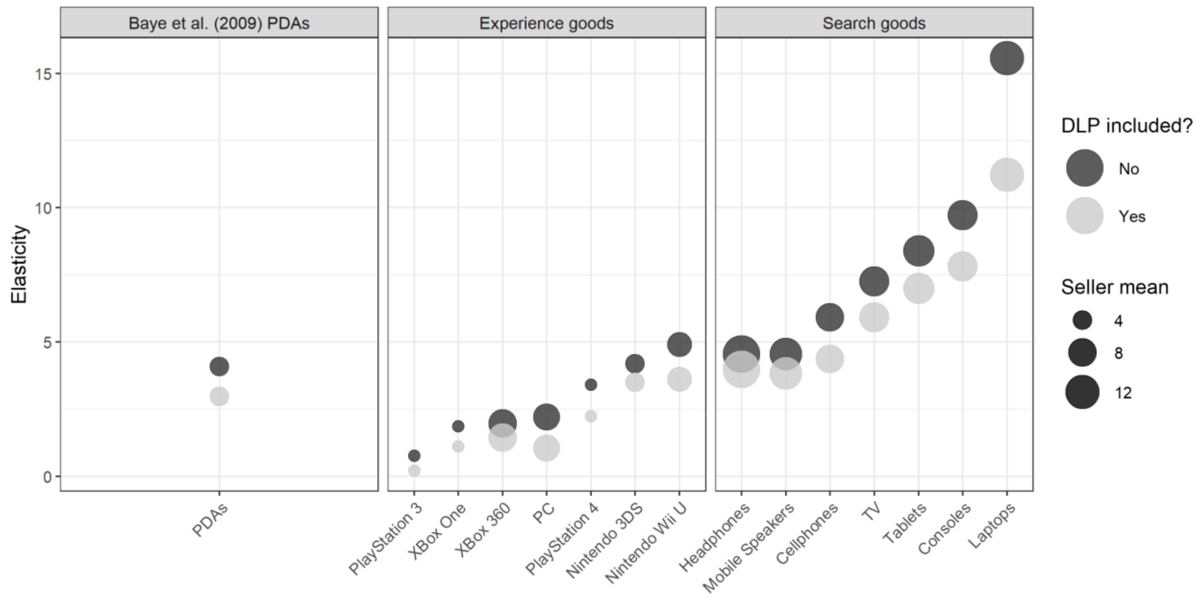

Fig. 1. Elasticity estimates for experience and search goods compared to Baye et al. (2009), elasticities given in absolute values.

With regards to the ratings, inspecting the results for $\ln PSR_{jt-1}$ in Tables 2 through 4 shows that the parameter estimates are largely non-significant, the notable exceptions being the 3DS and Nintendo Wii U games categories. These estimates are also somewhat perplexing, since, for instance, the 3DS result shows that higher ratings reduce demand, while the results for Nintendo Wii U show the opposite effect.[8]

Baye et al. (2009) report that 13% of consumers at the price comparison website Kelkoo.com were shoppers for the category of PDAs. In this study, the share of shoppers ranges between 4% and 12% in the search goods categories, and between 9% and 33% in the experience goods categories. The lowest share of shoppers is found for headphones, while the highest share is found for Xbox One. The result from Baye et al. (2009) is most similar to the cellphones and consoles categories regarding search goods, and the Nintendo 3DS and Xbox 360 categories regarding the experience goods categories. Coincidentally, as mentioned in Section 3.1, the closest substitute to the PDA category investigated in Baye et al. (2009) was the consoles category in terms of price and number of retailers in the search goods categories.

[8] Table A2 in the Appendix gives similar results, even when focusing on the top 20 most popular products.

By and large, the experience goods category has a greater number of shoppers than the search goods categories. This, of course, stems from how Equation (14) in Section 3.2 is constructed, in that, for a given parameter estimate λ, fewer retailers favor an estimate of a larger fraction of shoppers. This effect is, however, to some extent counteracted by the result that elasticities are much lower in the experience goods categories.

As shown by Baye et al. (2009), the $EBT\ Ratio$ measure of Table 3 reduces to the ratio of price elasticities of demand given in Fig. 1, here given in percentage terms. For example, the Laptop category has a ratio of excess burden of 1.39, and the PlayStation 4 category has a ratio of excess burden of 1.52, which translates into the values 39% and 52%, respectively, given in Table 3. The $EBT\ Ratio$ measure for PlayStation 3 is omitted, since this category did not have significant results for the price elasticity, neither in Table 2, nor Table 3. A higher excess burden is expected for models excluding the discontinuity, since models including it always produce estimates that are less elastic, but it is again important to highlight that the excess burden of taxation will differ depending on category. Baye et al. (2009) provided an $EBT\ Ratio$ measure of 54% for PDAs, which is higher than the majority of the corresponding estimates in this paper.

Analyzing the estimates related to the four lowest prices in Table 4, it can be seen that there is some nuance in how important the price ranks are. For example, the TV category depicts a competitive environment where there is an emphasis on being the retailer with the lowest price, which could be due to the high price of these products. Meanwhile, the categories PlayStation 4 and Xbox One, while still showing that is important to hold the position of lowest price, also support statistically significant discontinuities in demand for the second, third and fourth lowest price, as compared to the fifth and higher prices.

4. Summary and discussion

The purpose of this paper is to study whether there is a discontinuity in demand for retailers having the lowest price on a price comparison website. The main research question to be answered is: What is the value of having the lowest price or highest consumer rating in terms of consumer demand on a price comparison website?

Clearinghouse models (Rosenthal 1980; Varian 1980) are the most commonly used models to analyze firm behavior on price comparison websites (Baye and Morgan 2001; Baye, Morgan, and Scholten 2004b), and state that retailers must simultaneously appeal to two types of consumers: shoppers and non-shoppers Shoppers are well-informed, know the price of all retailers marketing a product and choose the retailer with the lowest price. Non-shoppers buy from the first retailer they encounter who markets the product at a price lower than the consumers reservation price, and they know only the price of that specific retailer. In such an environment, the lowest priced retailer will capture the demand of all shoppers and an equal share of the demand from non-shoppers, resulting in a clear discontinuity in demand for the lowest priced retailer. As such, this work can be seen as an informal test of the predictions from the clearinghouse models since it is expected that a discontinuity exists only for the lowest priced retailer. The results of this paper clearly show that discontinuities in demand exist for the lowest price in all categories under consideration. However, the results in this paper also show that discontinuities exist for the second, third and fourth lowest price, which clearly contradicts predictions from clearinghouse models.

The main finding in this paper is that there is strong support for the discontinuity in demand for the retailer holding the lowest price, and that one needs to account for this discontinuity in estimations of price elasticities. Failure to account for the discontinuity appears to have the greatest consequences in the search goods categories, where larger estimates of price elasticities are found, although the effect is found to be statistically significant across all categories under study. This can, in turn, have wider economic consequences if decision-making is based on the biased estimates, examples being retailers setting prices, or policymakers contemplating setting taxes for online transactions. Since including the discontinuity reduces the price elasticity estimates, this suggests that the lowest price retailers could actually have increased their prices somewhat more than what would follow from using the incorrect estimates excluding the discontinuity, provided they can also maintain their position as the lowest priced retailer.

As for policymakers deciding if, and by how much, online sales should be taxed, the excess burden estimates provided in this paper show that policymakers who do not account for these estimates will, in most categories, overstate the severity of taxation in e-commerce markets. This may, in turn, lead to rejection of taxation policies, despite a valid assertion that such taxes should be introduced. However, the results regarding the excess burden of taxation in this paper also show that the welfare losses generated vary greatly between different product categories, making it difficult for policymakers to set a correct overall tax level. As the findings of this paper show many similarities to those of the UK setting, studied in Baye et al. (2009), an interesting avenue for future research would be to compare the results from European markets to those in a US setting, especially considering the ongoing US debate, regarding taxation of e-commerce as pointed out by Einav et al. (2014).

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Appendix A

Table A1. Descriptive statistics for search and experience goods categories, top 20 products in terms of click-through.

		Click-through			**Price**			**Ratings**			**Sellers**		
Category	**n**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
Search Goods													
Cellphones	143709	6.43	0.00	29.00	6199	6199	2446	7.58	7.69	0.89	34	32	15
Consoles	47287	9.76	0.00	53.69	3625	3490	1344	7.99	8.11	0.90	12	10	9
Headphones	284219	2.06	0.00	13.08	1059	799	969	7.43	7.66	1.03	26	21	19
Laptops	58129	2.90	0.00	12.01	16069	14841	5247	7.15	7.00	1.53	21	22	9
Mobile Speakers	192888	1.28	0.00	7.67	2370	2490	1090	7.89	8.25	1.08	20	19	10
Tablets	135040	2.07	0.00	10.40	7185	6695	4751	7.39	7.50	0.98	22	22	12
TV	43662	9.17	1.00	41.14	21616	17690	15212	7.54	7.78	1.21	9	9	5
All	904934	3.39	0.00	21.55	5159	2890	6816	7.57	7.69	1.07	24	21	16
Experience Goods													
Nintendo 3DS	106490	0.64	0.00	3.31	417	428	91	7.76	7.67	0.78	7	6	4
Nintendo Wii U	105690	0.58	0.00	2.50	480	495	121	7.72	7.67	1.02	7	7	5
PC	128005	2.19	0.00	13.97	390	399	152	7.06	7.33	1.25	9	8	5
PlayStation 3	98628	0.68	0.00	7.94	333	259	186	7.52	7.50	0.93	6	5	4
PlayStation 4	107313	2.74	0.00	17.92	562	599	124	7.13	7.50	1.67	11	10	6
Xbox 360	101697	0.57	0.00	4.58	332	259	195	6.63	6.67	1.74	6	5	4
Xbox One	121932	0.99	0.00	5.62	578	599	259	6.26	6.50	1.78	12	12	6
All	769755	1.23	0.00	9.80	445	449	195	7.14	7.50	1.47	9	7	6

Table A2. PPML regression results top 20 products by click-through, no lowest price dummy variables included.

	Search Goods Categories							Experience Goods Categories						
	Headph.	Cellph.	M.Speak.	Tablets	TV	Laptops	Consoles	3DS	Wii U	PS3	PS4	PC	Xb. One	Xb. 360
$\ln p_{ijt-1}$	-5.444***	-10.934***	-4.505***	-8.257***	-5.302***	-16.002***	-6.723***	-3.554***	-3.268***	2.243	-2.923***	-2.206***	-0.187	0.439
	(0.278)	(0.741)	(0.438)	(0.342)	(0.677)	(2.150)	(1.816)	(0.575)	(1.064)	(2.065)	(0.507)	(0.546)	(0.732)	(1.212)
$\ln p_{ijt-1} \times$	0.005*	-0.023***	-0.019**	-0.009	-0.224***	-0.012	-0.247***	-0.074	-0.211**	-0.988***	-0.116***	-0.142***	-0.138***	-0.601***
$(n_{jt-1} - 1)$	(0.002)	(0.007)	(0.008)	(0.008)	(0.047)	(0.042)	(0.066)	(0.067)	(0.083)	(0.352)	(0.032)	(0.033)	(0.036)	(0.197)
$\mathbb{I}Ratings_{jt}$	0.040	0.066	-0.191**	-0.276*	0.377**	0.715**	0.287***	-0.380	-0.106	1.236*	-0.468**	0.561***	-0.287	0.104
	(0.070)	(0.088)	(0.088)	(0.159)	(0.160)	(0.294)	(0.090)	(0.241)	(0.203)	(0.640)	(0.186)	(0.202)	(0.194)	(0.581)
$\ln p_{sjt-1}$	0.001***	0.001**	0.001***	0.000***	-0.000	-0.001	0.003***	0.005**	0.003	0.004***	0.010***	0.013***	0.000	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$\ln PSR_{jt-1}$	0.346	0.776**	0.085	-0.135	-1.020	2.745	1.659*	-12.942**	4.540***	0.493	0.347	-0.208	-1.492	-1.946
	(0.516)	(0.377)	(0.593)	(0.992)	(0.709)	(5.257)	(0.920)	(6.505)	(1.481)	(0.582)	(0.467)	(0.522)	(1.463)	(6.014)
$\ln Volume_{jt-1}$	-0.045	0.045	0.047	-0.115	-0.155	-0.456	-0.078	1.061***	0.153	-0.305***	-0.113	-0.131*	0.377**	-0.840***
	(0.032)	(0.040)	(0.042)	(0.087)	(0.151)	(0.331)	(0.082)	(0.409)	(0.202)	(0.097)	(0.085)	(0.068)	(0.191)	(0.325)
$\ln CoV_{jt-1}$	0.006	-0.065	-0.259**	0.047	0.088	1.036*	-0.149	2.246	0.529*	0.156	-0.096	0.069	0.134	0.110
	(0.076)	(0.075)	(0.101)	(0.146)	(0.191)	(0.554)	(0.228)	(1.436)	(0.282)	(0.813)	(0.198)	(0.295)	(0.168)	(1.160)
n_{jt-1}	-0.051***	0.200***	0.139***	0.016	2.108***	0.091	1.842***	0.354	1.067**	4.959***	0.543***	0.662***	0.759***	2.913***
	(0.014)	(0.067)	(0.054)	(0.060)	(0.445)	(0.409)	(0.522)	(0.359)	(0.480)	(1.842)	(0.192)	(0.189)	(0.220)	(0.993)
$Weekend_t$	-0.135***	-0.045	0.016	-0.027	0.013	0.016	0.036	0.048	0.112***	0.113***	0.053	0.157***	0.085***	-0.032
	(0.019)	(0.033)	(0.021)	(0.035)	(0.040)	(0.057)	(0.063)	(0.037)	(0.028)	(0.042)	(0.033)	(0.027)	(0.027)	(0.101)
$\frac{\partial \ln E[Q_{ijt}]}{\partial \ln p_{ijt-1}}$	-5.328***	-11.747***	-4.856***	-8.453***	-7.441***	-16.287***	-10.012***	-4.028***	-4.952***	-1.536	-4.325***	-3.373***	-1.927***	-2.525***
	(0.263)	(0.731)	(0.368)	(0.318)	(0.675)	(1.391)	(1.441)	(0.466)	(0.889)	(1.441)	(0.352)	(0.428)	(0.376)	(0.483)
Observations	209548	88540	140089	51926	21732	8216	19702	21860	42076	26620	49490	67105	41576	29072

Notes: Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The marginal effects are evaluated at the mean.

Table A3. PPML regression results top 20 products by click-through, lowest price dummy variables included.

	Search Goods Categories							Experience Goods Categories						
	Headph.	Cellph.	M.Speak.	Tablets	TV	Laptops	Consoles	3DS	Wii U	PS3	PS4	PC	Xb. One	Xb. 360
$\ln p_{ijt-1}$	-4.829***	-7.510***	-3.892***	-6.650***	-4.056***	-11.657***	-5.329***	-3.004***	-1.972*	2.876	-1.785***	-1.119***	0.298	0.824
	(0.297)	(0.765)	(0.481)	(0.425)	(0.780)	(2.701)	(1.502)	(0.577)	(1.047)	(2.038)	(0.506)	(0.362)	(0.566)	(1.227)
$\ln p_{ijt-1} \times$	0.005**	-0.027***	-0.013*	-0.014*	-0.210***	-0.054	-0.203***	-0.033	-0.206**	-0.900***	-0.087***	-0.118***	-0.102***	-0.529***
$(n_{jt-1} - 1)$	(0.002)	(0.007)	(0.008)	(0.008)	(0.052)	(0.050)	(0.061)	(0.069)	(0.085)	(0.321)	(0.034)	(0.024)	(0.029)	(0.190)
$\mathbb{I}Price_{ijt}$	0.612***	0.862***	0.602***	0.793***	0.676***	0.604***	1.068***	0.579***	0.605***	1.231***	1.428***	1.469***	1.613***	1.042***
	(0.069)	(0.080)	(0.121)	(0.089)	(0.100)	(0.166)	(0.133)	(0.115)	(0.149)	(0.339)	(0.137)	(0.163)	(0.138)	(0.284)
$\mathbb{I}Ratings_{jt}$	0.067	0.162**	-0.201**	-0.355**	0.265*	0.737***	0.332***	-0.516**	0.042	1.167*	-0.410**	0.612***	-0.376***	0.087
	(0.069)	(0.070)	(0.098)	(0.143)	(0.156)	(0.264)	(0.074)	(0.220)	(0.210)	(0.610)	(0.184)	(0.190)	(0.140)	(0.577)
$\ln p_{sjt-1}$	0.000	0.000	0.001*	-0.000	-0.000***	-0.001**	0.002***	0.003	0.000	0.003	0.005***	0.008***	-0.000	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
$\ln PSR_{jt-1}$	0.626	0.225	0.474	-0.637	-1.330*	1.478	0.730	-10.572*	3.614**	0.686	0.502	-0.523	-1.059	-1.949
	(0.542)	(0.332)	(0.563)	(0.865)	(0.755)	(5.846)	(0.845)	(5.565)	(1.700)	(0.635)	(0.411)	(0.428)	(1.259)	(5.479)
$\ln Volume_{jt-1}$	-0.070**	0.040	0.018	-0.085	-0.109	-0.381	-0.022	0.979***	0.214	-0.295***	-0.107	-0.104	0.383**	-0.786**
	(0.032)	(0.039)	(0.045)	(0.084)	(0.141)	(0.319)	(0.073)	(0.323)	(0.217)	(0.097)	(0.081)	(0.064)	(0.170)	(0.308)
$\ln CoV_{jt-1}$	-0.068	-0.061	-0.289***	0.156	0.145	1.241**	0.134	1.940	0.505*	0.063	-0.258	0.232	0.109	0.056
	(0.079)	(0.072)	(0.101)	(0.130)	(0.202)	(0.603)	(0.196)	(1.327)	(0.281)	(0.742)	(0.185)	(0.236)	(0.143)	(1.023)
n_{jt-1}	-0.048***	0.238***	0.106**	0.074	1.965***	0.512	1.512***	0.152	1.073**	4.552***rrrr	0.397**	0.556***	0.583***	2.579***
	(0.013)	(0.063)	(0.053)	(0.065)	(0.490)	(0.481)	(0.480)	(0.366)	(0.489)	(1.680)	(0.198)	(0.144)	(0.175)	(0.956)
$Weekend_t$	-0.112***	-0.065***	0.016	-0.018	0.022	-0.005	0.023	0.051	0.113***	0.112**	0.040	0.141***	0.095***	-0.035
	(0.010)	(0.020)	(0.018)	(0.032)	(0.031)	(0.039)	(0.059)	(0.036)	(0.027)	(0.044)	(0.031)	(0.027)	(0.028)	(0.102)
$\frac{\partial \ln E[Q_{ijt}]}{\partial \ln p_{ijt-1}}$	-4.692***	-8.468***	-4.127***	-6.957***	-6.054***	-12.983***	-8.035***	-3.218***	-3.623***	-0.567	-2.839***	-2.086***	-0.989***	-1.787***
	(0.286)	(0.742)	(0.426)	(0.361)	(0.864)	(1.766)	(1.226)	(0.653)	(0.877)	(1.411)	(0.401)	(0.276)	(0.273)	(0.614)
$ShareShopper$	2%	7%	2%	4%	3%	3%	11%	8%	8%	12%	19%	12%	21%	8%
$EBT\ Ratio$	14%	39%	18%	22%	23%	26%	25%	25%	37%	-	52%	62%	95%	41%
Observations	209548	88540	140089	51926	21732	8216	19702	21860	42076	26620	49490	67105	41576	29072

Notes: Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The marginal effects are evaluated at the mean.

Table A4. PPML regression results top 20 products by click-through, four lowest price dummy variables included.

	Search Goods Categories							Experience Goods Categories						
	Headph.	Cellph.	M.Speak.	Tablets	TV	Laptops	Consoles	3DS	Wii U	PS3	PS4	PC	Xb. One	Xb. 360
$\ln p_{ijt-1}$	-4.624***	-5.404***	-3.788***	-6.304***	-4.093***	-10.618***	-4.742***	-2.984***	-1.664	2.852	-1.769***	-1.026***	0.314	0.842
	(0.304)	(0.801)	(0.504)	(0.499)	(0.785)	(2.953)	(1.351)	(0.587)	(1.029)	(2.016)	(0.518)	(0.379)	(0.555)	(1.215)
$\ln p_{ijt-1} \times$	0.005*	-0.020***	-0.011	-0.013	-0.211***	-0.055	-0.196***	-0.021	-0.170*	-0.947***	-0.052	-0.097***	-0.066**	-0.557***
$(n_{jt-1} - 1)$	(0.003)	(0.007)	(0.008)	(0.008)	(0.052)	(0.047)	(0.057)	(0.067)	(0.088)	(0.325)	(0.035)	(0.023)	(0.028)	(0.202)
$\mathbb{I}FourPrice_{ijt}$	1.121***	1.748***	1.039***	1.551***	0.400**	1.255***	1.402***	0.893***	1.253***	-0.641	2.440***	2.588***	3.004***	0.258
$(= 1)$	(0.123)	(0.088)	(0.175)	(0.136)	(0.157)	(0.314)	(0.153)	(0.329)	(0.270)	(0.811)	(0.251)	(0.279)	(0.148)	(0.595)
$\mathbb{I}FourPrice_{ijt}$	0.649***	1.144***	0.522***	0.900***	-0.284**	0.663***	0.644***	0.437*	0.714***	-1.912**	1.406***	1.502***	1.978***	-0.829
$(= 2)$	(0.097)	(0.086)	(0.111)	(0.119)	(0.131)	(0.209)	(0.190)	(0.259)	(0.214)	(0.830)	(0.230)	(0.246)	(0.155)	(0.521)
$\mathbb{I}FourPrice_{ijt}$	0.306***	0.753***	0.362***	0.699***	-0.362***	0.403**	-0.030	0.050	0.289	-1.472*	0.807***	0.852***	1.058***	-0.561
$(= 3)$	(0.100)	(0.067)	(0.116)	(0.118)	(0.136)	(0.163)	(0.281)	(0.212)	(0.176)	(0.825)	(0.200)	(0.179)	(0.191)	(0.470)
$\mathbb{I}FourPrice_{ijt}$	0.216**	0.385***	0.290**	0.472***	0.008	0.166	-0.446	0.081	0.121	-1.201**	0.437***	0.446***	0.492***	-0.743***
$(= 4)$	(0.093)	(0.064)	(0.125)	(0.121)	(0.298)	(0.151)	(0.297)	(0.199)	(0.162)	(0.531)	(0.168)	(0.112)	(0.165)	(0.270)
$\mathbb{I}Ratings_{jt}$	0.034	0.168**	-0.191*	-0.394***	0.307*	0.719***	0.268***	-0.621***	0.169	1.165*	-0.379**	0.588***	-0.361***	0.089
	(0.069)	(0.071)	(0.098)	(0.132)	(0.162)	(0.260)	(0.070)	(0.221)	(0.237)	(0.609)	(0.184)	(0.198)	(0.135)	(0.570)
$\ln p_{sjt-1}$	0.000	-0.000	0.001	-0.000	-0.000***	-0.001***	0.002***	0.002	-0.001	0.003	0.004**	0.007***	-0.000	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
$\ln PSR_{jt-1}$	0.551	-0.113	0.504	-0.885	-1.363*	2.495	1.088	-9.893*	3.720**	0.665	0.768*	-0.609	-0.424	-2.052
	(0.541)	(0.264)	(0.563)	(0.938)	(0.757)	(5.204)	(0.798)	(5.569)	(1.729)	(0.635)	(0.415)	(0.411)	(1.214)	(5.461)
$\ln Volume_{jt-1}$	-0.072**	0.100***	0.013	-0.065	-0.110	-0.420	-0.039	1.042***	0.159	-0.290***	-0.138*	-0.083	0.358**	-0.779**
	(0.033)	(0.036)	(0.044)	(0.091)	(0.140)	(0.297)	(0.071)	(0.290)	(0.231)	(0.099)	(0.075)	(0.066)	(0.149)	(0.308)
$\ln CoV_{jt-1}$	-0.056	0.078	-0.274***	0.222*	0.141	1.220**	0.150	1.759	0.431	0.065	-0.353*	0.235	0.031	0.087
	(0.083)	(0.068)	(0.102)	(0.133)	(0.203)	(0.577)	(0.185)	(1.327)	(0.291)	(0.739)	(0.183)	(0.231)	(0.148)	(1.010)
n_{jt-1}	-0.039**	0.193***	0.100*	0.078	1.976***	0.527	1.471***	0.097	0.893*	4.786***	0.195	0.447***	0.395**	2.710***
	(0.016)	(0.062)	(0.054)	(0.068)	(0.493)	(0.450)	(0.446)	(0.348)	(0.509)	(1.703)	(0.203)	(0.139)	(0.178)	(1.013)
$Weekend_t$	-0.135***	-0.073***	0.012	-0.022	0.017	0.045	0.024	0.053	0.113***	0.111**	0.039	0.137***	0.093***	-0.036
	(0.021)	(0.027)	(0.022)	(0.037)	(0.036)	(0.059)	(0.059)	(0.036)	(0.027)	(0.044)	(0.030)	(0.028)	(0.028)	(0.103)
$\frac{\partial \ln E[Q_{ijt}]}{\partial \ln p_{ijt-1}}$	-4.508***	-6.108***	-4.002***	-6.598***	-6.104***	-11.973***	-7.356***	-3.121***	-3.026***	-0.771	-2.396***	-1.823***	-0.517**	-1.907***
	(0.296)	(0.828)	(0.453)	(0.404)	(0.871)	(2.197)	(1.148)	(0.705)	(0.888)	(1.414)	(0.427)	(0.290)	(0.262)	(0.588)
Observations	209548	88540	140089	51926	21732	8216	19702	21860	42076	26620	49490	67105	41576	29072

Notes: Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The marginal effects are evaluated at the mean.

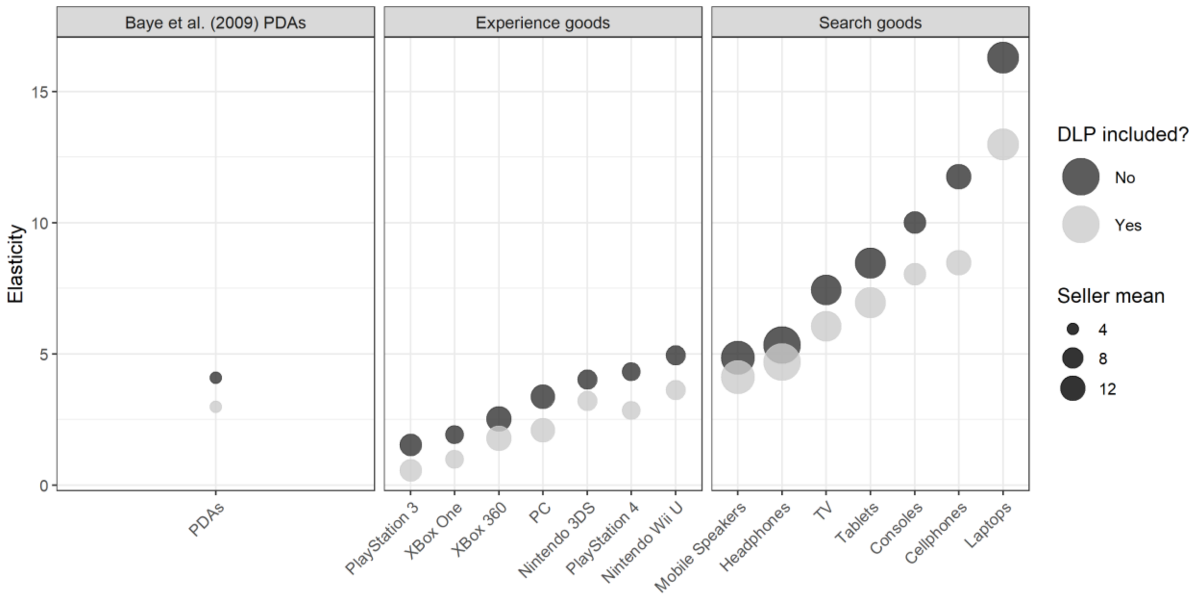

Fig. A1. Elasticity estimates for experience and search goods compared to Baye et al. (2009), top 20 products by click-through with elasticities given in absolute values.