We investigate the welfare of intermediaries in oligopolistic markets where intermediaries offer additional services. We exploit the unique circumstance that in the empirical setting studied, outdoor advertising, consumers can purchase from manufacturers or intermediaries. Intermediaries provide additional services to the consumers and charge a margin for them. Intermediaries provide the following additional services: search services (information about products), purchase-aggregation services (access to quantity discounts), and consulting services. We specify an equilibrium

model and structurally estimate it using market-level data. The demand includes consumers with costly search and channel-specific preferences. The supply includes two distribution channels. One features bargaining about wholesale prices between manufacturers and intermediaries, and downstream price competition. The other is vertically integrated. We show how Google-search data can be used to identify the search-cost parameters. We use the estimated model to simulate counterfactual scenarios where intermediaries do not offer additional services. We find that the three services considered provide value to consumers, with search playing a prominent role. Our analysis helps explain why intermediaries are ubiquitous in modern economies despite the double marginalization.

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5 August 2021

Measuring the Welfare of Intermediaries*

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August 5, 2021.

Abstract

We investigate the welfare of intermediaries in oligopolistic markets where intermediaries offer additional services. We exploit the unique circumstance that in the empirical setting studied, outdoor advertising, consumers can purchase from manufacturers or intermediaries. Intermediaries provide additional services to the consumers and charge a margin for them. Intermediaries provide the following additional services: search services (information about products), purchase-aggregation services (access to quantity discounts), and consulting services. We specify an equilibrium model and structurally estimate it using market-level data. The demand includes consumers with costly search and channel-specific preferences. The supply includes two distribution channels. One features bargaining about wholesale prices between manufacturers and intermediaries, and downstream price competition. The other is vertically integrated. We show how Google-search data can be used to identify the search-cost parameters. We use the estimated model to simulate counterfactual scenarios where intermediaries do not offer additional services. We find that the three services considered provide value to consumers, with search playing a prominent role. Our analysis helps explain why intermediaries are ubiquitous in modern economies despite the double marginalization.

JEL Codes: D83; L42; L51; L81; M37.

Keywords: Intermediaries, vertical integration, double marginalization, search frictions, bargaining, advertising.

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1 Introduction

Intermediaries play an important role in contemporary economies. In the U.S. they represent over a third of the value added to the economy.[1] They provide a wide variety of services to consumers. Intermediaries often add value by transforming products (adding transportation, packaging, or assembling services) or by providing information and consulting services about the characteristics of the products sold by the manufacturers (Spulber 1996). Intermediaries improve welfare to consumers by reducing search frictions, thus improving the coordination of the actions of consumers and manufacturers (Rubinstein and Wolinsky 1987). When negotiating with a manufacturer, intermediaries centralize transactions of multiple consumers, thus supplanting consumers' decentralized bargaining with the manufacturer. The resulting increase in intermediaries' bargaining power translates into lower marginal costs for the intermediaries, which results in lower prices for the consumers. In the absence of market power, intermediaries improve consumers' welfare when they provide these additional services (see Spulber 1999). However, as noted by Salinger (1988), when market power is present intermediaries may also lead to *double marginalization*, whereby the product is marked up above the marginal cost of production twice, once by the manufacturer and once again by the intermediary.[2] In such cases, intermediaries may reduce welfare. A natural question arises: What are the welfare implications of intermediaries in oligopolistic markets where intermediaries offer additional services to differentiate their products from the ones of the manufacturers?

There is a vast literature studying the role of intermediaries in different markets. Two major explanations why intermediaries arise are to facilitate the matching of buyers and sellers and to guarantee quality. There is also a large empirical literature studying specific roles of intermediaries in many markets, such as online markets, two-sided platforms, financial markets, banking, asset pricing, labor markets, and facilitating trade. However, there has been little empirical work to address the central question of what are the overall welfare implications of intermediaries in the industry when intermediaries offer additional services to differentiate their products from the ones of the manufacturers. Yet ignoring these additional services has significant consequences on the theoretical and empirical predictions for the determination of prices and consumer choices in these markets.

We provide empirical estimates of the welfare of intermediation in vertical markets when intermediaries simultaneously provide consulting, search, and purchase-aggregation services. There are two major challenges to identifying the value of intermediaries in such cases. The first challenge

[1] U.S. Bureau of Economic Analysis (2017). The estimate corresponds to the year 2016 using the definition by Spulber (1996) in Table 1, whereby intermediation includes retail trade (5.9 percent of GDP for the year 2016), wholesale trade (5.9 percent), finance and insurance (7.3 percent), business services (12.4 percent), and other services (2.3 percent). This estimate assumes that intermediation activities in all other sectors are zero. It is a conservative estimate.

[2] This is the well-known result when there are successive monopolies at two layers of production and goes back to Lerner (1934) (for further references see, *e.g.*, Spengler 1950 and Tirole 1988, pp. 174-6). When the manufacturer and intermediary layers are both oligopolistic and vertically integrated and unintegrated manufacturers coexist the presence of intermediaries may increase or decrease the price of the final good (see Salinger 1988). With consumer search, the double marginalization problem is worsened, resulting in higher wholesale and retail prices due to manufacturer's demand being more inelastic (Janssen and Shelegia 2015).

arises due to the non-existence of a counterfactual scenario without intermediaries in industries where intermediaries are present.[3] It precludes evaluating the performance of the market without intermediaries. The second challenge arises due to the difficulty of observing all the transactions between manufacturers, intermediaries, and consumers in the industry. It may introduce a selection problem when evaluating the behavior of the unobserved participants. Recovering consumer demand preferences in both cases requires strong assumptions about market participants.

To address these issues we collected a novel dataset with all meaningful transactions among manufacturers and intermediaries in the Portuguese outdoor advertising industry for the year 2013. These data allow us to exploit two unique features of the industry to quantify the welfare effects of intermediaries. First, there are two distribution channels in the outdoor advertising industry. Consumers may purchase the product directly from manufacturers or through intermediaries. This feature helps us overcome the first challenge by comparing instances where the same combination of display format—the physical products in the industry studied— and manufacturer is sold in both distribution channels. We then use a model of conduct to compute the counterfactual value that the consumer would have obtained had the purchase been made in a distribution channel different from the one observed. Second, we collected market-level data directly from all the meaningful manufactures and intermediaries in the industry. The data encompass more than 95 percent of the volume of transactions in the industry. This feature helps us overcome the second challenge.

To quantify the value of intermediation we develop an econometric model of the industry. The model features two distribution channels where consumers may buy advertising: the direct sales channel (DSC), where consumers purchase directly from the manufacturers, and the vertical sales channel (VSC), where consumers purchase using the intermediaries. On the demand side, consumers have preferences that are specific to each distribution channel and engage in costly search. We use a random-coefficient nested-logit model with costly search. Crucially, our model allows for consumers to endogenously choose which channel they prefer to use, based on their idiosyncratic characteristics, such as price sensitivity and unobserved channel-specific shocks. The latter is introduced via within-channel correlation of the different product-level utility shocks. It captures, for example, that some customers may have larger in-house marketing departments and therefore obtain less value from the services provided by intermediaries to design the advertising campaign. On the supply side, the industry consists of two vertical layers modeled using a two-stage game. In the top layer, manufacturers produce display formats for the display of outdoor advertising (*manufacturer* products) that they sell to the intermediaries at wholesale prices. Manufacturers and intermediaries bargain over wholesale prices through Nash bargaining. We call the top layer the manufacturer game. In the second layer, manufacturers and intermediaries sell the display formats (*final* products) to the consumers, competing on prices. We call the bottom layer the retail game. The distribution channels are represented by two types of retailers: DSC and VSC retailers. The DSC retailers are the manufacturers who sell final products to the consumers charging DSC prices. The VSC retailers

[3] Alternatively, the counterfactual scenario with intermediaries is unobserved in industries where intermediaries are not present.

are the intermediaries who charge VSC prices to the consumers.[4]

We estimate the model in two steps. First, we estimate the parameters that characterize demand without using the supply-side model. To identify the price coefficient and the heterogeneity parameters we rely on instruments with exclusion restrictions. To identify the search-cost parameters, we construct additional micro moments using Google-search data. We then estimate the parameters that characterize supply conditional on the demand estimates from the first step. To identify the supply-side parameters we use the equilibrium conditions from the model and additional restrictions using the vertical structure in our empirical setting. We use the first-order conditions from the manufacturer and retail games and assume that the manufacturer marginal costs are the same for display formats sold to VSC retailers and consumers.

Our strategy to estimate the welfare implications of intermediaries consists of comparing circumstances where the same combination of display format and manufacturer is sold by DSC and VSC retailers, and using the model to estimate the value to consumers of each of the additional services provided by the VSC retailers. The VSC retailers provide three additional services to consumers. They charge a margin for them. The first additional services are *search services*, whereby VSC retailers provide information to consumers about display formats from multiple manufacturers, thus decreasing consumers' search costs. The second are *purchase-aggregation services*, whereby consumers benefit from quantity discounts that VSC retailers obtain because they aggregate purchases from multiple consumers. The third are *consulting services*, defined as the residual gross utility of buying from VSC retailers relative to a DSC retailer. The market structures in the vertical layers determine the prices and margins charged by the manufacturers and retailers.

We use the estimated equilibrium model to simulate four counterfactual scenarios to quantify the value of intermediaries. First, we simulate the equilibrium of an industry where retailers do not offer consulting services. Second, we simulate the equilibrium of an industry where retailers do not offer search services. Third, we simulate the equilibrium of an industry where retailers do not offer purchase-aggregation services. Finally, we remove simultaneously the three types of services to evaluate the total impact on welfare due to the intermediaries.

We report the following findings: (1) removing consulting services reduces consumer surplus by one Euro per square meter; (2) removing search services increases the overall cost of the search by 35 percent, which translates into a reduction of consumer surplus of 12 Euros per square meter; (3) removing purchase-aggregation services increases retail prices, which translates into a reduction of consumer surplus of two Euros per square meter; (4) removing simultaneously the three services provided by intermediaries increases consumer surplus by 14 Euros per square meter. Overall, we find that the presence of intermediaries increases welfare because the value of their services outweighs the additional margin charged.

In summary, we make three main contributions. First, we combine a novel data set with a new econometric equilibrium model to estimate consumer demand preferences and marginal costs in the presence of intermediation, consumers' costly search, and bargaining between manufacturers

[4]We use the terms intermediaries, retailers, and VSC retailers interchangeably.

and intermediaries. The model includes consumers who have preferences that are specific to each distribution channel and engage in costly search on the demand side, and two layers of activity with two distribution channels on the supply side. Second, we quantify the value of intermediaries in oligopolistic markets where intermediaries offer these additional services to differentiate their products from the ones of the manufacturers. Finally, from a normative perspective, our estimates show that the presence of intermediaries in the outdoor advertising industry is welfare improving because the benefits to consumers from the additional services provided by the intermediaries outweigh the additional margin charged by the intermediaries.

Related Literature

We contribute to the literature that studies intermediaries. Spulber (1999) presents a comprehensive study of intermediation, including how intermediaries alleviate problems associated with search costs and a detailed discussion of additional services provided by intermediaries. The role of firms as intermediaries has been studied extensively. Articles include, *e.g.*, Yanelle (1989), Gehrig (1993), Rust and Hall (2003), Hagiu and Jullien (2011), Wright and Wong (2014), and Edelman and Wright (2015). Some explanations why intermediaries arise are to facilitate the matching of buyers and sellers as in Rubinstein and Wolinsky (1987), to guarantee quality as in Biglaiser (1993) and Spulber (1996), and, recently, as rent extraction (Farboodi, Jarosch, and Menzio 2017). Our case is closest to that in Rubinstein and Wolinsky (1987) and Spulber (1995, 1999) in that intermediaries create value by reducing search costs and by providing additional services to the consumers.

The role of intermediaries has been studied a many markets. There is a large literature studying the role of intermediaries in online markets (*e.g.*, Brynjolfsson and Smith 2000; Morton, Zettelmeyer, and Silva-Risso 2001; Brown and Goolsbee 2002; Brynjolfsson, Hu, and Smith 2003; Baye, Morgan, and Scholten 2003; Ellison and Ellison 2009; Quan and Williams 2016),[5] and in financial markets, banking, and asset pricing (*e.g.*, James 1987, Diamond 1984, He and Krishnamurthy 2013; Brunnermeier and Sannikov 2014; Gavazza 2016).[6] Intermediation also plays an important role in labor markets (*e.g.*, Stanton and Thomas 2016), agrifood chains (*e.g.*, Lee, Gereffi, and Beauvais 2012), facilitating trade (*e.g.*, Ahn, Khandelwal, and Wei 2011), and certifying information in markets with adverse selection (*e.g.*, Biglaiser 1993; Lizzeri 1999; Biglaiser, Li, Murry, and Zhou 2017). Relative to these papers, our contribution is to estimate the welfare implications due to the presence of intermediaries in the industry, accounting for the change in the market structure created by the presence of the intermediaries and the additional services that intermediaries offer to consumers which differentiates their products from the ones of the manufacturers. The literature studying outdoor advertising is non-existent. The only article that we are aware is Pereira and Ribeiro (2018); they study capacity divestitures in this industry, not intermediation.

Our demand model is related to the literature that uses models of discrete-choice between

[5] Some references in the growing literature on two-sided platforms as intermediaries include, *e.g.*, Bernard and Jullien (2003), Evans (2003), Rochet and Tirole (2003), Armstrong (2006), Galeotti and Moraga-González (2009), Boik (2016).

[6] See O'Hara (1995), Freixas and Rochet (2008), and Frankel, Galli, and Giovannini (2009) for surveys.

differentiated products with costly search.[7] Our demand model is closest to De los Santos, Hortaçsu, and Wildenbeest (2012), Honka (2014), and Moraga-González, Sándor, and Wildenbeest (2015). They develop discrete-choice models of demand in which consumers engage in costly search with fixed-sample size.[8,9] None of these papers consider preferences specific to the distribution channel, which is the main focus of this paper.[10] We incorporate these preferences using the distribution assumptions of the nested logit, that we embed into a random-coefficient discrete-choice demand model with costly search.[11] For the estimation of the demand, we use an adapted version of the procedure proposed by Moraga-González, Sándor, and Wildenbeest (2015). This procedure adapts the nested fixed-point algorithm from Berry (1994) and Berry, Levinsohn, and Pakes (1995) to account for the additional term in the choice probability introduced by the distribution-channel preferences. It modifies the computation of the market share function in the estimation algorithm.

On the supply side, our model is related to the literature about vertical relations between manufacturers and intermediaries/retailers. Our model features two layers of activity (manufacturers and VSC retailers) and two distribution channels where consumers can purchase (VSC and DSC retailers). The two layers of activity are related vertically as in, *e.g.*, Brenkers and Verboven (2006), Mortimer (2008), Bonnet and Dubois (2010), Villas-Boas (2007), and Dubois and Sæthre (2016). The main difference between these papers and ours is that in our model manufacturers and VSC retailers bargain over wholesale prices through Nash bargaining.[12] Our bargaining model is similar to, *e.g.*, Crawford and Yurukoglu (2012), Draganska, Klapper, and Villas-Boas (2010), Grennan (2013), Crawford, Lee, Whinston, and Yurukoglu (2018), Noton and Elberg (2018). The main difference between the bargaining models in these papers and ours is that in our model the retailers

[7] For studies of the formation of consideration sets with fixed-sample search see, *e.g.*, Roberts and Lattin (1991) and Mehta, Rajiv, and Srinivasan (2003) in the marketing literature.

[8] We refer to the 2015 Working Paper by Moraga-González, Sándor, and Wildenbeest which uses a non-sequential search model. The 2018 (and subsequent) version(s) of their paper with the same title uses a different—a sequential search—model to the one in this paper.

[9] See also Goeree (2008), Ershov (2018), and Murry and Zhou (2020).

[10] The information structure is also different in our model relative to these papers. In our model, consumers face uncertainty over both the price and the realization of the random shock of each product (similar to Pires 2016), while in De los Santos, Hortaçsu, and Wildenbeest (2012) consumers only face uncertainty about the price of the product (not about the realization of the random shock) and in Moraga-González, Sándor, and Wildenbeest (2015) consumers only face uncertainty about the realization of the random shock (not about the price of the product).

[11] For other recent applications of the random-coefficient nested-logit model see, *e.g.*, Grennan (2013), Ciliberto and Williams (2014), and Miller and Weinberg (2017). None of these papers incorporate costly search.

[12] Nash bargaining is a way to generate quantity discounts or non-linear pricing schemes. In a Nash bargaining model, the larger the value of the bargaining parameter and the larger the value of the outside option, the better the terms a party can negotiate. In our setting, when negotiating with a VSC retailer, the outside option of a manufacturer is the profit if its products are not sold by the VSC retailer. For a given manufacturer, the *larger* is the VSC retailer that is negotiating with, the smaller is the value of its outside option and the smaller is the wholesale price it is willing to charge the VSC retailer. There there are no volumes/quantities explicitly involved in our bargaining game. However, the volumes/quantities define how *large* is the VSC retailer and, thus, determine its outside option in the Nash bargaining game. The bargaining model does not generate quantity discounts *per se*. It rather rationalizes the observed quantity discounts in the setting through larger estimated outside options for larger VSC retailers. The quantity discounts between manufacturers and VSC retailers are then partially transferred to the consumers by the VSC retailers. There is a large literature studying quantity discounts and nonlinear pricing (see, *e.g.*, Miravete 2002; Busse and Rysman 2005; McManus 2007; Cohen 2008; Chu, Leslie, and Sorensen 2011; Miravete and Röller 2004a; Miravete and Röller 2004b; Nevo, Turner, and Williams 2016; Donna and Pires 2016).

in both distribution channels can sell their products to the consumers. Such sales occur in our model after the bargaining process, where prices are set to consumers through standard Bertrand competition. Thus, the instruments and identifying assumptions to recover equilibrium margins as a function of the demand primitives, and bargaining power of VSC retailers and manufacturers are different. Similar to Grennan (2013), we do not estimate all bargaining and cost parameters because we do not have enough information. Similar to our paper, the model in Donna, Pereira, Trindade, and Yoshida (2021, DPTY) features both direct-to-consumer sales by manufacturers, and bargaining between manufacturers and retailers. The main focus of DPTY, however, is the supply side. The central feature in the model of DPTY is that a direct-to-consumer channel enhances the manufacturer's bargaining power, which can harm retail consumers. In contrast, our main focus here is the demand side to estimate the value of intermediaries to consumers.

The rest of the article is organized as follows. Section 2 describes the industry, the data, and presents stylized facts about the industry. Section 3 presents the model. Sections 4 and 5 discuss identification and estimation of the demand and supply, respectively. Section 6 presents the estimation results. The welfare analysis is performed in Section 7. Section 8 presents the concluding remarks. Appendix A extends the search model to allow for unobserved search-cost heterogeneity. Robustness analysis, extensions, and details about the data and the model are in the Online Appendix.

2 Portuguese Outdoor Advertising Industry

2.1 Industry Overview

Agents. There are three main economic agents in the Portuguese outdoor advertising industry: manufacturers, retailers, and consumers. A *manufacturer*, also called media owner, is a firm that installs and commercially exploits equipment for the display of outdoor advertising. Examples include J.C. Decaux Group, Cemusa, and Mop. A *retailer*, also called media group, is an intermediary that buys advertising from the manufacturer on behalf of the consumer. Examples include Omnicom Media Group, WPP Plc., and Power Media Group Inc. Retailers offer consumers additional services such as consulting services, advertising planning campaigns, and information about the display formats of several manufacturers.[13] All manufacturers and retailers operate in the same geographic market. This feature follows from Portugal being a small country, where the population is concentrated along the coast.[14] A *consumer*, also called advertiser, is a firm that demands advertising to promote its products. Consumers in this industry are firms that buy exposure in the manufacturer's advertisement network.[15] For example, consumers buy 200 panels of 2 m^2 panels (called faces) distributed in the national network of J.C. Decaux Group. They cannot choose, how-

[13] A retailer is a set of media agencies and a central purchasing agency with a common owner. Media agencies plan and buy advertising campaigns. The central purchasing agency aggregates purchases of media agencies and places orders to the manufacturers. A retailer might own several media agencies either because they specialize in different industries or to avoid confidentiality issues with advertisers.

[14] In 2014, in a merger review case on the outdoor advertising industry—case Ccent. 15/2014 JCDecaux/Cemusa—the Portuguese Competition Authority considered that the geographic market for this industry is Portugal. We follow that same approach in this paper.

[15] The advertisement network refers to the location of the display formats of the manufacturers.

ever, specific 2 m^2 panels located at a particular place. Most of the purchases are in the national network, which is the focus of this paper. The exposition is similar across manufacturers.

Vertical Relations. Consumers make 85 percent of their purchases from the retailers and the remaining 15 percent directly from the manufacturers (Table 1). There are two active distribution channels. In the *Vertical Sales Channel* (VSC), consumers purchase manufacturers' display formats through the intermediation of retailers. In the *Direct Sales Channel* (DSC), consumers purchase manufacturers' display formats directly from the manufacturers. We refer the manufacturers that sell directly to consumers in the DSC as *DSC retailers* and to the retailers in the VSC as *VSC retailers*. We refer to the price charged to the consumers by the DSC retailers (VSC retailers) as *DSC price* (*VSC price* or retail price). Figure 1 displays the vertical relations in the industry. Advertisers' choice of the distribution channel is determined by their advertising needs, which may or may not be related to the size of their firm. The two channels offer different services. The direct channel offers a basic service. The intermediated channel offers the basic service plus additional services, such as consulting. Firms that advertise only occasionally or that make simple campaigns typically use the direct channel. Advertisers that advertise frequently or make elaborate campaigns, that require complex planning, typically use the intermediated channel.

Retailers' Services. Retailers provide three main services to the consumers in this industry. First, they provide consulting services. Retailers assist consumers with their advertisement campaigns by helping them to make decisions such as the type and number of display formats to buy (*i.e.*, type and the total number of panels) and the duration of the advertising campaign. Second, retailers provide purchase-aggregation services to the consumers. Retailers negotiate rebate scales with manufacturers. Retailers aggregate the purchases from multiple consumers when buying from the manufacturers. These discounts are partially transferred to the consumers (Subsection 2.3). Retailers aggregate the purchases of many advertisers. It gives retailers larger bargaining power to negotiate with the manufacturers, enabling them to obtain lower prices per unit relative to the consumers (*i.e.*, *quantity discounts* as defined in Subsection 2.3). A retailer attains a larger volume of purchases, and thereby of rebate levels, than individual advertisers. Buying through a retailer therefore gives consumers access to larger rebate opportunities than they could obtain by themselves. Finally, retailers provide search services to consumers. Retailers provide information about the prices available for the display formats of multiple manufacturers in the industry. Retailers collect this information once per period (*e.g.*, month) and use it for the orders of multiple consumers. Retailers benefit from economies of scale relative to the consumers (we document this in Subsection 2.3). Retailers have more experience than consumers collecting this information. It allows them to do it more efficiently (*i.e.*, lower search costs due to better search technology).

Display Formats. There are three main display formats: 2 m^2 panels (mupis), seniores, and (iii) others. Panels of 2 m^2 include city information panels, bus shelters, kiosks, *etc.* A *senior* is an advertising panel with an area between 8 and 24 m^2. The last category, *others*, encompasses transports and special formats. A *transport* includes panels on moving vehicles (*e.g.*, buses, trains, taxis) or transport hubs (*e.g.*, airports, railway's stations, subways' stations). Finally, a *special format* is large panel typically made by special request to be displayed, *e.g.*, on buildings' gables. We define a product as a combination of display format, manufacturer, and retailer. Examples of products are: J.C. Decaux Group's 2 m^2 panels sold by Havas Media Group, Cemusa's seniors sold by WPP Plc., and J.C. Decaux Group's 2 m^2 panels sold directly by J.C. Decaux Group.

See Online Appendix B.1 for a discussion about product differentiation, payment schedules, productive capacity, and market concentration.

2.2 Data

The Data Set. The data were obtained from various sources. We obtained administrative data from all the meaningful manufactures and retailers in the industry for the year 2013 aggregated at the monthly market level. By *meaningful* we mean that our data encompass more than 95 percent of the volume of transactions in the industry. We consider three display formats: 2 m^2 panel, senior, and an additional category aggregating the remaining formats that have negligible weight individually. We consider four manufacturers: the three main manufacturers in the industry (J.C. Decaux Group, Cemusa, and Mop) and an additional manufacturer that aggregates the smaller manufacturers. We consider nine retailers: the five main VSC retailers in the industry (Omnicom Media Group, WPP Plc., Power Media Group Inc., Havas Media Group, and Interpublic Group of Companies), one additional VSC retailer that aggregates the smaller VSC retailers, and three DSC retailers representing the direct sales of each of the three larger manufacturers (J.C. Decaux Group, Cemusa, and Mop). There are no direct sales from the other manufacturers. Henceforth, for confidentiality reasons, we refer to the three main manufacturers as m_1, m_2, and m_3, not necessarily in the order above, to the additional manufacturer as m_4, to the retailers in the DSC as r_1^d, r_2^d, r_3^d, by the same order as the three main manufacturers, to the five main VSC retailers as $r_4^v, \ldots, r_8^v$, not necessarily in the order above, and to the additional VSC retailer as r_9^v. Figure 1 summarizes this information. See Online Appendix B.2.1 for details about the procedures to clean the data.

Characteristics of the manufacturers and retailers were collected by inspecting their websites. Google-search data—used to construct micro moment conditions to identify the search-cost parameters on the demand side—were obtained from Google Trends Portugal. See Online Appendix B.2.2 for details.

In each month and for each triplet of display format, manufacturer, and retailer we observe: the total sales, measured in Euros; the total quantity of advertising sold, measured in advertising faces and square meters; the wholesale prices charged from the manufacturers to the retailers, measured in Euros; the commissions, fees, and quantity discounts paid to the manufacturers, measured in Euros; and the installed capacity, measured in advertising faces. We also observe characteristics for each manufacturer and retailer, such as the number of offices.

Products. We define a product as a combination of display format, manufacturer, and retailer (including DSC and VSC retailers). Panel A in Table 1 shows the percentage of sales to consumers by each combination of manufacturer-retailer in the sample. Panel B in Table 1 shows the percentage of sales of each of the 57 inside products in the sample. The total number of inside products in the sample is 57. This number is lower than the total possible products in the market, 81.[16] This feature is because some VSC retailers only sell a subset of display formats from certain manufacturers (the subset with which they contracted; *e.g.*, Panel B in Table 1 shows that retailer r_8^v does not sell 2 m^2 panels manufactured by m_3) and some DSC retailers do not sell certain display formats directly to consumers (*e.g.*, Panel B in Table 1 shows that retailer r_1^d, which corresponds to manufacturer m_1 selling directly to consumers, does not sell seniors in the DSC). All VSC retailers contract with all of the three largest manufacturers. This feature rules out the possibility that some retailers do not negotiate with some of the manufacturers due to selection based on unobservables.

Wholesale and Retail Prices in the VSC. Table 2 reports summary statistics on wholesale and VSC prices for each display format. VSC prices, *i.e.*, retail prices, are higher than wholesale prices. Panel B shows large differences in prices across both manufacturers and retailers holding constant the display format. These price differences and the differences in the observed market shares suggest that differentiation is important. Table A1 in the Online Appendix compares wholesale and retail prices in the VSC by manufacturer and by retailer for the display format 2 m^2 panel. There are substantial differences in VSC and wholesale prices across VSC retailers holding constant the display format and the manufacturer. For example, retailer r_9^v is the most expensive retailer, including DSC retailers, for 2 m^2 panels manufactured by m_2, but the cheapest retailer for seniors manufactured by m_2. Tables 2 and A1 show that differences in wholesale and VSC prices are small. They suggest that most of the differences in VSC prices are explained by differences in wholesale prices. The profit margins of VSC retailers are small.

Sales to Consumers in the VSC and DSC. Panel A in Table 1 shows that 85.2 percent of the sales to consumers are made through VSC retailers The remaining 14.8 percent of the sales are made through DSC retailers. There is substantial variation across months in the market shares of VSC and DSC sales (see Figure 2 and Online Appendix B.3.2). Monthly sales in the DSC range between 13.9 and 42.6 percent (Figure 2). DSC prices are higher than wholesale prices holding constant the manufacturer and the display format. It is the result of manufacturers offering quantity discounts to retailers. It suggests that manufacturers use direct sales as a price discrimination mechanism in the DSC.

Table 3 shows that the median price paid by consumers is higher in the DSC than in the VSC. Occasionally, prices in the DSC are lower than in the VSC (*e.g.*, senior manufactured by m_1 in Panel B in Table 3). There are two effects at play. On the one hand, VSC retailers aggregate the purchases of several consumers. It allows them to obtain lower prices per unit (due to quantity discounts) when negotiating with the manufacturers (see Subsection 2.3). This effect lowers VSC prices and increases VSC price dispersion relative to the DSC prices.[17] On the other hand, VSC retailers offer

[16]From Table 1, the total possible number of products to the consumers in the market is:

$$\underbrace{\text{(3 Display Formats)} \times \text{(4 Manufacturers)} \times \text{(6 VSC Retailers)}}_{\text{VSC}} + \underbrace{\text{(3 Display Formats)} \times \text{(3 DSC Retailers)}}_{\text{DSC}} = 81.$$

[17]Conditional on quantity discounts, however, the distribution of prices in the VSC is less disperse than in the DSC, as discussed on page 10.

additional services to the consumers that are not offered by DSC retailers. VSC retailers charge a price for the additional services. This effect increases VSC relative to DSC prices.

Market Shares. We use the described data to build a data set of products sold in the DSC and VSC for each month of the year 2013 and their characteristics. Market shares are defined by dividing volume sales by the total potential sales in a given month. These potential sales (or market size) were assumed to be twenty percent greater than the maximum observed total monthly sales of the year 2013. The market share of the outside good was defined as the difference between one and the sum of the market shares of the inside goods in each month. The outside good can be conceptualized as including goods outside the sample (*e.g.*, special request panels), outdoor advertising sold by other manufacturers and retailers (*e.g.*, small manufacturers and retailers that operate locally), and not buying outdoor advertising. An observation in this data set represents a market share of a product as defined above in a given month. We define a market as a month. We consider 12 markets, one for each month of the year.

2.3 Three Stylized Facts

The Portuguese outdoor advertising industry is characterized by quantity discounts in the VSC, seasonal effects and large variation in the market shares, and substantial price dispersion conditional on quantity discounts and seasonal effects.

Quantity Discounts in the VSC. Consumers' purchases exhibit quantity discounts in the VSC but not in the DSC. By *quantity discounts* we mean that the price paid per square meter decreases with the volume purchased. Table 4 presents evidence about quantity discounts. It displays OLS regressions of the price paid by consumers per square meter of advertising on the total volume of advertising in a logarithmic scale, denoted by "Log(m^2)." Column 1 shows that the price paid by consumers per square meter of advertising decreases nonlinearly with the volume purchased of advertising. In column 2 we include an interaction between "Log(m^2)" and "VSC." The variable "VSC" is a dummy variable that equals 1 if the consumer performed the purchase through a VSC retailer and 0 if the consumer performed the purchase through a DSC retailer. The interaction term is negative and statistically different from zero while the coefficient on "Log(m^2)" is no longer statistically different from zero. The purchases made by consumers in the VSC exhibit quantity discounts while the ones made in the DSC do not. Columns 3 and 4 show similar results when we include fixed effects for manufacturers, retailers, display formats, and months. Columns 2 and 4 show that the effect of quantity discounts is only present in the VSC.[18]

Seasonalities and Monthly Variation. Seasonal variations are substantial. The total volume purchased increases during the summer. See Online Appendix B.3.2 for details. For the estimation, we use monthly indicator variables to account for these seasonal effects.

Price Dispersion and Returns to Consumer Search. There is substantial price dispersion: (i) across retailers holding constant the display format (product heterogeneity), the month of the year

[18] We obtain similar results by regressing the price paid by consumers per square meter using a polynomial function of square meters of advertising purchased.

(seasonal effects), and the volume percentile (quantity discounts); and (ii) across months holding constant the display format, the manufacturer, the retailer, and the volume percentile. This feature indicates that the returns to consumers' search (for product's prices) are high in this market.

Figure 3 shows that price dispersion is lower in the VSC than in the DSC conditional on quantity discounts. The top panel displays the distribution of the coefficient of variation of prices (CV) holding constant the display format, the month, and the volume percentile. That is, each CV is computed within the unit of analysis in the tuple (Display Format, Month, Volume Percentile).[19] The mean CV is 45 percent (pooling together sales in the VSC and DSC). The mean CV for sales made in the VSC is 43 percent and for sales made in the DSC is 54 percent. This result indicates that returns to consumers' search for product's prices vary substantially by distribution channel.[20]

The bottom panel in Figure 3 shows that the empirical CDF for sales made in the DSC first-order stochastically dominates the one for sales made in the VSC. It indicates that consumers who buy in the VSC face lower price dispersion consistently. Buying in the VSC can provide substantial returns to consumers with large search costs in this market. Figure 3 is consistent with VSC retailers providing search services to the consumers. The covariates included in the model explain over 90 percent of the price variation in the data (adjusted $R^2 = 0.927$ of regressing prices on covariates). We interpret this fact as products being relatively homogeneous after accounting for these covariates and in favor of using a random-coefficient demand model with costly search to account for the remaining unobserved product heterogeneity.

3 Model

3.1 Consumers

We use a random-coefficient nested-logit model with costly search. Consumers know the products available in each market but do not know the price nor the realization of the random shock associated with each product. To learn this information consumers engage in costly search for retailers.

Consumer's choice is a two-step process. In the first step, the consumer chooses the subset of retailers to search. After searching for a retailer, the consumer learns the information of the products sold by that retailer, prices and realizations of the random shocks. This step determines the *consideration set* of each consumer type. The consideration set is given by the subset of products sold by all the retailers searched and the outside product. In the second step, after observing the prices and random shocks of the products sold by the retailers searched, the consumer chooses the product to purchase; that is, the consumer chooses among the subset of products from the retailers searched.

[19] We obtain similar results using other measures of price dispersion such as percentile differences (*e.g.*, the difference between the 95th and the 5th price percentiles, the difference between the 90th and the 10th price percentiles, *etc.*), range, and price gap. Substantial price variation is explained by quantity discounts. Ignoring quantity discounts one would incorrectly conclude that the price distribution is more disperse for sales made in the VSC than for sales made in the DSC (bottom panel in Figure 2).

[20] VSC retailers offer additional services to consumers (*e.g.*, consulting services, advertising planning campaigns, information about the products of all manufacturers, *etc.*) that are not offered by DSC retailers. Figure A1 in the Online Appendix shows similar patterns to the ones in Figure 3 when we measure price dispersion across months holding constant the display format, the manufacturer, the retailer, and the volume percentile (*i.e.*, identical products sold by the same seller holding constant the volume percentile). The additional services provided by VSC retailers shift the distribution of prices charged by each VSC retailer but do not affect price dispersion in the market.

This step is a standard discrete-choice problem similar to, *e.g.*, Berry, Levinsohn, and Pakes (1995) and Nevo (2001). The difference is that the choice set for each consumer is endogenously determined in the first step. We refer to the first step as the *search step* and the second step as the *purchase step*.

We assume that there are $t = 1, \ldots, T$ markets, each with a continuum of rational, utility-maximizing consumers. Consumers have different preferences for different products. A market is defined as a month. In each market t, there are J_t horizontally differentiated and mutually exclusive inside products, indexed by $j = 1, \ldots, J_t$. We index with $j = 0$ the outside product. It allows consumers not to purchase any of the inside products. In each market, each consumer purchases one inside product or the outside product.

Step 2: Purchase step. Consider consumer i who searched R_i retailers in the search step in market t.[21] The indirect utility of consumer i for inside product j in market t, denoted by U_{ijt}, is:

$$U_{ijt} = -\alpha_i p_{jt} + x_{jt}\beta + \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D + \xi_{jt} + \hat{\varepsilon}_{ijt}, \tag{1}$$

$$j \in \hat{J}_{tR_i} = \{\hat{j} : \hat{j} \in J_t \text{ is sold by retailer } r \in R_i\} \cup \{0\}, \qquad t = 1, \ldots, T,$$

where R_i denotes the subset of retailers searched by consumer i in market t; $\hat{J}_{tR_i}$ is the consideration set of consumer i, given by the subset of products sold by all the retailers searched and the outside product; p_{jt} is the price of product j in market t; x_{jt} is a S-dimensional row-vector of observable characteristics of product j in market t; τ_d^D, τ_m^D, τ_r^D, and τ_t^D capture the preferences for display format d, manufacturer m, retailer r, and monthly seasonal effects in market t, using fixed dummy variables for display format, manufacturer, retailer, and monthly seasonal effects, respectively; ξ_{jt} is the valuation of unobserved, by the econometrician, characteristics of product j in market t; $\hat{\varepsilon}_{ijt}$ is a stochastic term described below;[22] α_i are individual-specific parameters that capture consumers' preferences for price, described below; and β is a S-dimensional vector of parameters. In each market t, we normalize the characteristics of the outside product, $j = 0$, such that $p_{0t} = x_{0t} = \tau_0^D = \xi_{0t} = 0$ for all t. Denote by $\overline{U}_{i\hat{j}t} \equiv -\alpha_i p_{\hat{j}t} + x_{\hat{j}t}\beta + \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D + \xi_{\hat{j}t}$ the indirect utility of consumer i for product $\hat{j} \in \hat{J}_{tR_i}$ in market t, net of the stochastic term, $\hat{\varepsilon}_{ijt}$. We model the distribution of consumers' preferences for price as $\alpha_i = \alpha + \sigma_\nu \nu_i$ with $\nu_i \sim P_\nu(\nu_i) = \mathcal{N}(0, 1)$, where α and σ_ν are parameters, ν_i captures unobserved, by the econometrician, individual characteristics, and $P_\nu(\cdot)$ is a parametric distribution assumed to be a standardized Normal, $\mathcal{N}(0, 1)$, for the estimation. Denote by $\delta_{\hat{j}t} \equiv -\alpha p_{\hat{j}t} + x_{\hat{j}t}\beta + \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D + \xi_{\hat{j}t}$ the mean utility for product $\hat{j}$ in market t; that is, the portion of the utility that is constant across consumer types. Then $\overline{U}_{i\hat{j}t} = \delta_{\hat{j}t} - \sigma_\nu \nu_i p_{\hat{j}t}$ for all i, $\hat{j}$, and t.

Consumers have preferences that are specific to each distribution channel (or retailer type) and the outside product. We capture it by decomposing the stochastic term, $\hat{\varepsilon}_{ijt}$, using the distributional assumptions of the nested-logit with a factor structure: $\hat{\varepsilon}_{ijt} = \zeta_{igt} + (1 - \lambda)\varepsilon_{ijt}$. The subindex

[21]The set of searched retailers is market specific. To simplify the notation, we omit the market subscript and we refer to the set of searched retailers as R_i instead of R_{it}.

[22]Heterogeneity in the value to consumers within product (for example, due to the specific location of the billboard) is of horizontal nature (for example, some consumers may prefer space near a school while others may prefer it close to a highway). This feature is captured in our model by $\hat{\varepsilon}_{ijt}$.

$g \in \{0,1,2\}$ define three groups (or nests) of nonoverlapping products for the outside product (denoted by $g = 0$, with only one product), the products sold by the DSC retailers (denoted by $g = 1$), and the products sold by the VSC retailers (denoted by $g = 2$). The random variable ζ_{igt} has a unique distribution such that $\hat{\varepsilon}_{ijt}$ is extreme value (Cardell 1997). The parameter λ is a nesting parameter such that $0 \leq \lambda < 1$. A larger value of λ corresponds to a greater correlation in preferences for products in the same distribution channel and the outside product. A larger value of λ is therefore associated with less substitution between products in different distribution channels and the outside product. When $\lambda = 0$ the model in the second step collapses to a standard random-coefficient mixed-logit model (*e.g.*, Berry, Levinsohn, and Pakes 1995; Nevo 2001) with no preference heterogeneity for distribution channels or the outside product but with an endogenous choice set selection from the search step.

For the estimation, it is convenient to write the nested-logit choice probability as the product of two standard logit probabilities. Denote by $\mathbb{P}_{i\hat{j}t|R_i}$ the nested-logit probability that individual i chooses product $\hat{j}$ in period t conditional on the searched retailers, R_i. Then:[23]

$$\mathbb{P}_{i\hat{j}t|R_i} = \mathbb{P}_{i\hat{j}t|\hat{g}R_i} \times \mathbb{P}_{i\hat{g}t|R_i}, \tag{2a}$$

$$= \frac{\exp(I_{i\hat{g}R_i})}{\exp(I_{\hat{g}R_i})} \times \frac{\exp\left(\frac{\overline{U}_{i\hat{j}t}}{1-\lambda}\right)}{\exp\left(\frac{I_{i\hat{g}R_i}}{1-\lambda}\right)}, \tag{2b}$$

$$i = 1,\ldots,I_t, \qquad \hat{j} \in (\hat{g} \cap \hat{J}_{tR_i}), \qquad \hat{g} \in \{0,1,2\}, \qquad t = 1,\ldots,T,$$

where the first equality follows from the law of total probability; $\mathbb{P}_{i\hat{j}t|\hat{g}R_i}$ is the conditional probability of choosing product $\hat{j}$ given that the product is in group $\hat{g}$ and in the consideration set, $\hat{J}_{tR_i}$; $\mathbb{P}_{i\hat{g}t|R_i}$ is the marginal conditional probability of choosing a product in group $\hat{g}$ given that the product is in the consideration set $\hat{J}_{tR_i}$; the last equality follows from the nested-logit structure using the decomposition into two standard logit probabilities; and the terms $I_{i\hat{g}R_i}$ and $I_{\hat{g}R_i}$ are *inclusive values* given in Online Appendix C.2.

Step 1: Search step. Consumers know the products available in each market but do not know the price, p_{jt}, or the realization of the random shocks, $\hat{\varepsilon}_{ijt}$, associated with each inside product. Before searching consumers only know the distributions of the prices, $\tilde{F}_p(p)$, and random shocks, $\hat{\varepsilon}_{ijt}$.[24] Consumers can purchase an inside product only if they collect information about its price and random shock. They can engage in costly search to collect this information. A consumer who does not search can only buy the outside product. Let SC_{R_i} be the cost of consumers of collecting information about prices and random shocks of retailer R_i.[25] We assume that if consumers search a retailer, they collect information about all the products sold by that retailer. Our search costs are therefore the cost of searching for a retailer, not the cost of searching for a product. VSC retailers sell the products from multiple manufacturers. Searching for a VSC retailer allows consumers to collect information about a larger set of products than searching for a DSC retailer. It allows us to

[23] See Online Appendix C.2 for details.
[24] See page 14 and footnote 28 for details.
[25] The search cost includes the time spent to find and collect information about retailers, and processing costs (*e.g.*, investigating in the retailer's webpage). Our definition of search costs encompasses the cost of including a product at the purchase occasion and an evaluation cost (Hauser and Wernerfelt 1990).

rationalize the lower price dispersion observed in the VSC relative to the DSC.

We consider a fixed-sample stochastic search process. First, consumers commit to searching a fixed number of retailers. The number could be zero, in which case the consumer buys the outside product in the purchase step. This commitment is done before beginning the search. The search finishes after consumers searched all the retailers they committed to even if they obtain a favorable search outcome early on.[26] The expected net value for consumer i of searching a subset of retailers R_i in market t, denoted by V_{tR_i}, is the difference between the expected maximum utility of buying the most preferred product in that subset and the cost of searching for these retailers, denoted by SC_{R_i}:[27]

$$V_{tR_i} = \int \max_{j\in \hat{J}_i} U_{ijt} \, \mathrm{d}F_{\hat{\varepsilon}}(\hat{\varepsilon}) \, \mathrm{d}\tilde{F}_{pt}(p) - SC_{R_i} + \tilde{\varepsilon}_{itR_i} = \int \log \left(1 + \sum_{\hat{g}=1}^{2} e^{I_{\hat{g}R_i}}\right) \mathrm{d}\tilde{F}_{pt}(p) + \hat{\gamma} - SC_{R_i} + \tilde{\varepsilon}_{itR_i}, \quad (3)$$

where $\tilde{F}_p(p)$ is the distribution of inside products' prices known by the consumers in market t, described below; SC_{R_i} is the cost of searching the subset of retailers R_i, described below; $\tilde{\varepsilon}_{itR_i}$ is a random shock to the subset of searched retailers, described below; the equality in the second line follows from the expected maximum utility of the nested-logit model conditional on the searched retailers; $\hat{\gamma} = 0.5772$ is the Euler's constant; and the term $I_{\hat{g}R_i}$ is the inclusive value of the set of products from the searched retailers that belong to subset $\hat{g}$ excluding the outside product, given in Online Appendix C.3.

Before searching, consumers only know the distribution of prices of the inside products available in market t, $\tilde{F}_p(p)$. We assume that consumers know the true empirical distribution of prices disaggregated by distribution channel (or type of retailer). This assumption is equivalent to say that consumers know *two* distributions of prices: the distribution of prices for the DSC retailers and the distribution of prices for the VSC retailers. Consumers learn the prices of the set of products sold by each retailer when they search for such retailer.[28] We model the cost of searching a subset R_i of retailers in t, SC_{R_i}, as:

$$SC_{R_i} = \bar{S} \times \{\#m_{r_1}\} + \cdots + \bar{S} \times \{\#m_{r_Q}\}, \quad (4)$$

where $R_i = \{r_1, \ldots, r_Q\}$ is the subset of searched retailers, r_q with $q = 1, \ldots, Q$, each of the searched retailers in t, $\bar{S}$ is a parameter, and $\{\#m_{r_q}\}$ denotes the number of different manufacturer for which r_q has product availability in market t. Conditional on selling products in t, $\{\#m_{r_{qt}}\} = 1$ for DSC retailers, and $\{\#m_{r_{qt}}\} \geq 1$ for VSC retailers. In words, equation (4) says that consumers pay a search cost $\bar{S}$ for each manufacturer sold by the retailer searched.

[26] In our model, consumers are firms demanding advertisement. The decision of how many retailers to contact is typically made *ex ante*. The fixed-sample search assumption in our model is intended to capture such practice.

[27] See Online Appendix C.3 for details.

[28] We have also performed the analysis using the following information structures for $\tilde{F}_p(p)$. (i) Consumers only know the overall distribution of prices. That is, consumers only know *one* distribution with the prices for all the products in the market. (ii) Consumers know the distribution of each product in the market disaggregated by distribution channel and by product. That is, consumers know 57 distribution of prices, where the number 57 corresponds to the number of inside products in the sample (see footnote 16). Under the information structure in (i), consumers have less information than in the benchmark. Under the information structure in (ii), consumers have more information than in the benchmark. We obtained similar results in terms of the welfare analysis under the benchmark, (i), and (ii). Models 2 and 3 in Table A2 in the Online Appendix shows the results under (i) and (ii), respectively. For the estimation and for each information structure in the benchmark, (i), and (ii), we pool the relevant prices across all markets to compute the empirical distribution observed by the consumers before searching, $\tilde{F}_p(p)$.

We model the search problem of the consumer from a stochastic point of view. We add a random shock to the subset of searched retailers, $\tilde{\varepsilon}_{itR_i}$ in equation (3), as in De los Santos, Hortaçsu, and Wildenbeest (2012) and Moraga-González, Sándor, and Wildenbeest (2015). We do this for two reasons. First, the variance of the shock can be interpreted as measuring the degree of heterogeneity in the errors that consumers make when evaluating the net expected gain of a subset of retailers (De los Santos, Hortaçsu, and Wildenbeest 2012). Alternatively, by positing the random shock directly in the search-cost equation, one can interpret it as a shock to the total cost of searching a subset of retailers. Second, solving for a consumer's optimal search strategy is a difficult problem. The consumer must simultaneously choose among a set of ranked stochastic options. Each choice is costly and only the best-realized option is exercised. When there are many alternatives available in the market finding the optimal choice set is extremely complex because there are many choice sets to be evaluated. By approaching this problem from a stochastic perspective, we smooth the choice set probabilities of choosing a given subset of retailers. We therefore do not need to solve the search problem of every consumer. Instead, we compute the probability that a given subset of retailers is searched by a consumer. We assume that the term $\tilde{\varepsilon}_{itR_i}$ is drawn *i.i.d.* (across individuals, markets, and sets of retailers) from a type I extreme value distribution with location parameter $\mu_{\tilde{\varepsilon}} = 0$ and scale parameter $\sigma_{\tilde{\varepsilon}} > 0$.[29] Denote by $\Psi \equiv (\bar{S}, \sigma_{\tilde{\varepsilon}})$ the vector of search-cost parameters.

Consumer i chooses the subset of searched retailers, R_i, that maximizes the expected net benefit of searching, V_{tR_i}. The probability that consumer i finds optimal to sample the subset of retailers R_i in market t, denoted by $\mathbb{P}_{R_i}$, is:

$$\mathbb{P}_{R_i} = \frac{e^{\overline{V}_{tR_i}/\sigma_{\tilde{\varepsilon}}}}{\sum_{\hat{R}_i \in \Lambda} e^{\overline{V}_{t\hat{R}_i}/\sigma_{\tilde{\varepsilon}}}}, \tag{5}$$

where $\overline{V}_{tR_i} \equiv V_{tR_i} - \tilde{\varepsilon}_{itR_i}$, is the expected value of searching a subset of retailers R_i net of the shock $\tilde{\varepsilon}_{itR_i}$, with V_{tR_i} given by equation (3); Λ is the powerset of all retailers; and the equality follows the well-known logit choice probability.

Choice Probabilities and Market Shares. The unconditional choice probability of consumer type i for product j in market t is:

$$\mathbb{P}_{ijt} = \sum_{R'_i \in \Lambda} \mathbb{P}_{ijt|R'_i} \times \mathbb{P}_{R'_i}, \tag{6a}$$

$$= \sum_{R'_i \in \Lambda} \underbrace{\mathbb{P}_{ijt|gR'_i} \times \mathbb{P}_{igt|R'_i}}_{\mathbb{P}_{ijt|R'_i}} \times \mathbb{P}_{R'_i}, \tag{6b}$$

$$= \sum_{R'_i \in \Lambda} \underbrace{\underbrace{\frac{\exp(I_{igR'_i})}{\exp(I_{gR'_i})}}_{\mathbb{P}_{ijt|gR'_i}} \times \underbrace{\frac{\exp\left(\frac{\overline{U}_{ijt}}{1-\lambda}\right)}{\exp\left(\frac{I_{igR'_i}}{1-\lambda}\right)}}_{\mathbb{P}_{igt|R'_i}}}_{\mathbb{P}_{ijt|R'_i}} \times \underbrace{\frac{e^{\overline{V}_{tR'_i}/\sigma_{\tilde{\varepsilon}}}}{\sum_{\hat{R}_i \in \Lambda} e^{\overline{V}_{t\hat{R}_i}/\sigma_{\tilde{\varepsilon}}}}}_{\mathbb{P}_{R'_i}}, \tag{6c}$$

[29] The scale parameter, $\sigma_{\tilde{\varepsilon}}$, is identified because we have already normalized the scale of the ordinal utility of the consumer. The latter was done by normalizing the scale parameter of the stochastic term $\hat{\varepsilon}_{ijt}$ in equation (1) to $\sigma_{\hat{\varepsilon}} = 1$. We make the assumption that the shocks are *i.i.d.* across consideration sets of retailers due to the nature of our data that is aggregated at the market level. In Appendix A we extend the search model to allow for unobserved search-cost heterogeneity. may counterfactuals. The cumulative distribution function for the shocks $\tilde{\varepsilon}_{itR_i}$ is: $F(\tilde{\varepsilon}_{ijt}) = e^{-e^{-\tilde{\varepsilon}_{ijt}/\sigma_{\tilde{\varepsilon}}}}$.

$$i = 1, \ldots, I_t, \qquad j \in J_t, \qquad g \in \{0, 1, 2\}, \qquad t = 1, \ldots, T,$$

where the equality in (6a) follows from the law of total probability; the equality in (6b) follows from equation (2a); and the equality in (6c) follows by replacing the expressions for $\mathbb{P}_{i\hat{j}t|\hat{g}R_i}$ and $\mathbb{P}_{i\hat{g}t|R_i}$ by equation (2b) (purchase step), and by replacing the expression for $\mathbb{P}_{R_i'}$ by equation (5) (search step).

Intuitively, equation (6) says that the unconditional probability that consumer type i chooses product j in market t is the weighted average of the conditional choice probability of each consideration set, where the weight of each consideration set is given by the unconditional probability that the consumer finds it optimal to sample that subset of retailers, $\mathbb{P}_{R_i'}$. This weighted average of probabilities (equation 6a) can be written as the product of three standard logit formulas that are linked (equation 6c): (i) the conditional probability of choosing product j given that it belongs to group g and is sold by the subset of searched retailers R_i ($\mathbb{P}_{ijt|gR_i'}$); (ii) the conditional probability of choosing a product in group g given that it is sold by the subset of searched retailers ($\mathbb{P}_{igt|R_i'}$); and (iii) the unconditional probability that the consumer finds optimal to sample the subset of retailers ($\mathbb{P}_{R_i'}$). The probabilities in (i) and (ii) are linked through the inclusive value I_{igR_i}. This inclusive value is the expected utility of consumer i from choosing a product among the ones in nest g. When $\lambda = 0$, the probabilities in (i) and (ii) collapse to a standard random-coefficient logit model. Similarly, these probabilities are linked to the probability in (iii) through the consideration sets. These subsets of retailers, R_i', enter into the value $\overline{V}_{tR_i'}$, and in the inclusive values $I_{igR_i'}$ and $I_{gR_i'}$. The parameters in the search costs, $SC_{itR_i'}$, determine the probability that the consumer finds it optimal to search R_i' retailers. When all search costs are zero, the consumer searches all retailers with probability one and $\mathbb{P}_{R_i'} = 0$ for any other subset R_i' of retailers. Equation (6) therefore collapses to $\mathbb{P}_{ijt} = \mathbb{P}_{ijt|g} \times \mathbb{P}_{igt}$, a standard random-coefficient nested-logit model without search.[30]

The market share function for product j in market t, denoted by s_{jt}, is obtained by integrating over the distribution of consumer types:

$$s_{jt} = \int_{\nu_i} \mathbb{P}_{ijt} \, \mathrm{d}P_\nu(\nu_i), \tag{7}$$

where $\mathbb{P}_{ijt}$ is given by equation (6); and $P_\nu(\cdot)$ is a parametric distribution assumed to be a standardized Normal, $\mathcal{N}(0, 1)$, for the estimation.

In Appendix A, we generalize the search model by allowing correlation between the stochastic shocks to the consideration sets of retailers, R_i.

3.2 Manufacturers and Retailers

The supply-side model has two main characteristics. First, the industry consists of two layers of activity that are related vertically. Second, there are two distribution channels (or retailers' types),

[30] If the nesting, price heterogeneity, and search-cost parameters equal zero (*i.e.*, if $\lambda = \sigma_\nu = \bar{S}_t = s^D_{rt} = 0$ for all D, t), then the demand model collapses to a standard logit model, and $\mathbb{P}_{ijt} = e^{\delta_{jt}} / \sum_{\hat{j}=0}^{J_t} e^{\delta_{\hat{j}t}}$ in equation (6). Similarly, our random-coefficient nested-logit model with search collapses to the nested-logit model if $\sigma_\nu = \bar{S}_t = s^D_{rt} = 0$ for all D, t.

where consumers can buy advertising: the direct sales channel (DSC) and the vertical sales channel (VSC). The game unfolds in two stages. In the first stage, manufacturers and VSC retailers bargain over wholesale prices through Nash bargaining). In the second stage, VSC and DSC retailers set retail prices to consumers through Bertrand competition.

Consider an industry with a two-layered vertical structure, the manufacturer layer and the retail layer. In the manufacturer layer, multi-product firms, called *manufacturers*, produce basic production factors, called display formats, that they sell either to the VSC retailers or directly to the consumers if they have a DSC channel. A production factor (display format) from a given manufacturer sold to different VSC retailers generates different *manufacturer products*. In the retail layer, multi-product firms, called *VSC retailers*, combine manufacturer products with their retail production factors to produce *retail products*, also called display formats, that they sell to final consumers. Retailers have free access to all the information regarding the products that they carry in their portfolios.

There are $d = 1, \ldots, \mathcal{D}$ basic production factors, $m = m_1, \ldots, m_{\mathcal{M}}$ manufacturers, and $r = r_1, \ldots, r_{\mathcal{R}}$ retailers. Each manufacturer may sell their product through one of the retailers or directly to the final consumer. There are potentially $\mathcal{J} = \mathcal{D} \times \mathcal{M} \times (\mathcal{R} + 1)$ final products.[31] Not all the manufacturers have a DSC channel. It is therefore convenient to divide them into *pure* manufacturers (those who sell only in the VSC) and *hybrid* manufacturers (those who sell in both the VSC and DSC). Denote by Ω_m^V the set of products that manufacturer m sells to VSC retailers and by Ω_m^D the set of products that manufacturer m sells to consumers directly. Denote by Ω_r the set of products that retailer r sells to the final consumers. Denote by ω_j the wholesale price of manufacturer product j, by ω the $\mathcal{J} \times 1$ vector of manufacturer wholesale prices, by c_j^m the marginal cost of manufacturer product j, and by $\mathbf{c^m}$ the $\mathcal{J} \times 1$ vector of manufacturer marginal costs. Denote by p_j the price of retail product j, by $\mathbf{p}$ the $\mathcal{J} \times 1$ vector of retail prices, by c_j^r the marginal cost of retail product j, and by $\mathbf{c^r}$ the $\mathcal{J} \times 1$ vector of retail marginal costs. The profit function of hybrid manufacturers contains two terms: the profits from selling the products in the VSC and the DSC. For the profit of hybrid manufacturers in the DSC, we assume that the marginal cost is the manufacturer cost plus a retail cost: $c_j^m + c_j^r$. Denote by M the market size, by $s_j(\mathbf{p})$ the market share of product j given by equation (7), and by $\mathbf{s}(\mathbf{p})$ the $\mathcal{J} \times 1$ share vector.[32]

The profit of a VSC retailer r is:

$$\Pi_r = \sum\nolimits_{j \in \Omega_r} \left(p_j - \omega_j - c_j^r\right) M s_j(\mathbf{p}).$$

The profit of a pure manufacturer m is:

$$\Pi_m^{pure} = \sum\nolimits_{j \in \Omega_m^V} \left(\omega_j - c_j^m\right) M s_j(\mathbf{p}).$$

The profit of an hybrid manufacturer m is:

$$\Pi_m^{hyb} = \sum\nolimits_{j \in \Omega_m^V} \left(\omega_j - c_j^m\right) M s_j(\mathbf{p}) + \sum\nolimits_{j \in \Omega_m^D} \left(p_j - c_j^m - c_j^r\right) M s_j(\mathbf{p}),$$

[31] Some of these products may not be offered because some VSC retailers may not carry the products of all manufacturers. The total number of inside products in our data is 57 and the total number of possible products in the market is 81.

[32] We omit the market subscript, t, for the variables in this subsection to simplify the notation.

where we allow that the manufacturer's marginal costs to differ depending on whether it is sold to the consumer or to a VSC retailer (*i.e.*, we allow for $c_j^r > 0$ for $j \in \Omega_m^V$).

Our model allows for economies of scale because a product is a combination of display format, manufacturer, and retailer and because retailers have different marginal costs; that is, larger retailers may have lower marginal costs than smaller ones.

To account for the dual channel, but keep the equations compact, we define $\widetilde{\omega}_k$ as:

$$\widetilde{\omega}_k = \begin{cases} \omega_k, & k \in \Omega_m^V, \\ p_k - c_k^r, & k \in \Omega_m^D. \end{cases}$$

Then, the profit of manufacturers (pure or hybrid) can be written as:

$$\Pi_m = \sum\nolimits_{j \in \Omega_m} \left(\widetilde{\omega}_j - c_j^m\right) M s_j(\mathbf{p}),$$

where $\Omega_m = \Omega_m^V$ for pure manufacturers, and $\Omega_m = \Omega_m^V \cup \Omega_m^D$ for hybrid manufacturers.

3.3 Equilibrium

We construct the equilibrium by working backward. The game unfolds in two stages. In the first stage, manufacturers and VSC retailers bargain over manufacturer prices (*i.e.*, wholesale prices of display formats), in a Nash bargaining game. The equilibrium concept is Nash equilibrium in Nash bargains. We call this the *manufacturer game.* In the second stage, VSC and DSC retailers set retail prices to the consumers, through a Nash Bertrand game. We call this the *retail game.* The equilibrium concept is subgame perfect equilibrium (henceforth, equilibrium). We solve for the equilibrium by backward induction, starting with the retail game. Equilibrium prices are denoted with asterisks.[33]

3.4 Stage 2: The Retail Game

The standard equilibrium first-order necessary conditions for p_j are:

$$s_j(\mathbf{p}^*) + \sum\nolimits_{k \in \Omega_r} (p_k^* - \omega_k - c_k^r) \frac{\partial s_k(\mathbf{p}^*)}{\partial p_j} = 0, \tag{8a}$$

$$\sum\nolimits_{k \in \Omega_m^V} (\omega_k - c_k^m) \frac{\partial s_k(\mathbf{p}^*)}{\partial p_j} + s_j(\mathbf{p}^*) + \sum\nolimits_{k \in \Omega_m^D} (p_k^* - c_k^m - c_k^r) \frac{\partial s_k(\mathbf{p}^*)}{\partial p_j} = 0. \tag{8b}$$

The system of equations (8) defines retail prices implicitly as a function of wholesale prices, $\mathbf{p}^* = \mathcal{P}(\omega)$ by applying the implicit function theorem to (8).

3.5 Stage 1: The Manufacturer Game

Manufacturers and VSC retailers bargain bilaterally and simultaneously over wholesale prices, ω_j, as in Horn and Wolinsky (1988). The equilibrium concept is Nash equilibrium in Nash bargains: no manufacturer-retailer pair would like change their agreement given all other agreements.[34] Motivated by our empirical setting, where VSC retailers negotiate with manufacturers each display format separately, we assume that all manufacturer-retailer pairs negotiate each wholesale price separately, as in Draganska, Klapper, and Villas-Boas (2010) and Bonnet, Bouamra-Mechemache,

[33] Retailers do account for the impact of their retail price choices on the wholesale price negotiations. Given any wholesale prices, retailers independently choose retail prices. At a Nash equilibrium of the second stage game, each retailer's strategy is the best response to the rivals' strategies. Anticipating the equilibrium of the second stage game, retailers and manufacturers bargain over wholesale prices.

[34] Each pair of players maximizes the bilateral gains from trade, modeled by an asymmetric Nash bargaining solution, given the strategies of all others pairs.

and Molina (2016).[35] If the negotiations over ω_j fail, manufacturer and retail products j are not sold. If the negotiations over ω_j succeed, the profit of manufacturer m from manufacturer product j is $\Pi_{mj}(\omega) = \left(\omega_j - c_j^m\right) Ms_j(\mathcal{P}(\omega))$, and the profit of retailer r from retail product j is $\Pi_{rj}(\omega) = \left(p_j^* - \omega_j - c_j^r\right) Ms_j(\mathcal{P}(\omega))$. Denote by $\Pi_{r,-j}$ and $\Pi_{m,-j}$ the disagreements payoffs of retailer r and manufacturer m, respectively, when they bargain over ω_j. Denote by ν_{rmj} the bargaining weight of retailer r when it bargains with manufacturer m over ω_j and define $\delta^S_{rmj} \equiv \frac{(1-\nu_{rmj})}{\nu_{rmj}}$. The Nash product of manufacturer m and retailer r for ω_j is:

$$\mathcal{N}_{rmj} \equiv \left[\sum_{k\in\Omega_r} \left(p_k^* - \omega_k - c_k^r\right) Ms_k(\mathcal{P}(\omega)) - \Pi_{r,-j}\right]^{\nu_{rmj}} \left[\sum_{k\in\Omega_m} \left(\widetilde{\omega}_k - c_k^m\right) Ms_k(\mathcal{P}(\omega)) - \Pi_{m,-j}\right]^{1-\nu_{rmj}}. \tag{9}$$

Denote by $\Omega_x \backslash \{j\}$, $x = r, m$, the set of products that firm x sells without product j. Denote by ω_{-j} the $(\mathcal{J} - 1) \times 1$ vector of manufacturer prices without element ω_j. Denote by $\Delta s_k^{-j}(\mathcal{P}(\omega_{-j}))$ the change in the market share of product k if product j is not offered. We assume that the disagreement profits for manufacturer m and retailer r when they bargain over ω_j are the maximum profits each could earn if product j were not offered, where the parties assume that other contracts would not be renegotiated if they did not reach an agreement. The disagreements payoffs are: $\Pi_{r,-j} \sum_{k\in\Omega_r\backslash\{j\}} \left(p_k - \omega_k - c_k^r\right) Ms_k^{-j}(\mathcal{P}(\omega_{-j}))$ and $\Pi_{m,-j} \sum_{k\in\Omega_m\backslash\{j\}} \left(\widetilde{\omega}_k - c_k^m\right) Ms_k^{-j}(\mathcal{P}(\omega_{-j}))$. The bargaining game takes place only over products that are sold in the VSC. However, when hybrid manufacturers bargain with retailers, the Nash product expression includes profits from both the VSC and DSC because a change in the wholesale price that the parties negotiate also affects sales in the DSC channel.

The first-order necessary equilibrium conditions for ω_j with $j = 1, ..., \mathcal{J}$ are:

$$\nu_{rmj} \left[\Pi_r(\omega^*) - \Pi_{r,-j}\right]^{\nu_{rmj}-1} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{1-\nu_{rmj}} \frac{\partial \Pi_r(\omega^*)}{\partial \omega_j} + (1-\nu_{rmj}) \left[\Pi_r(\omega^*) - \Pi_{r,-j}\right]^{\nu_{rmj}} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{-\nu_{rmj}} \frac{\partial \Pi_m(\omega^*)}{\partial \omega_j} = 0. \tag{10}$$

4 Demand: Identification and Estimation

Demand and search-cost parameters enter the purchase probability in different ways. To identify the price coefficient and the heterogeneity parameters we rely on instruments with the exclusion restrictions discussed below. We identify the value to consumers of the services provided by the VSC retailers by using the model and comparing instances where the same combination of display format and manufacturer is sold by DSC and VSC retailers. We describe a procedure where we use ratios of searched retailers that do not depend on the demand parameters. Then we show that certain ratios of Google searches can be used to estimate the ratios of probabilities. We estimate the demand and search-cost parameters by GMM without using the supply-side model. For the estimation, we use an adapted version of the procedure proposed by Moraga-González, Sándor, and Wildenbeest (2015) with the modifications described below.[36] We then construct micro moments using the ratios of Google searches and incorporate them into the GMM objective.

[35] An alternative assumption, followed by Bonnet, Bouamra-Mechemache, and Molina (2016), is that each pair of manufacturer-retailer negotiate all their products jointly.

[36] They provide conditions under which a combination of aggregate and consumer search data can identify these parameters. Their main insight is to use certain ratios of choice probabilities that do not depend on the search-cost parameters.

4.1 Identification of Demand Parameters

We rely on instruments with exclusion restrictions to identify the price coefficient and the heterogeneity parameters. Identification of these parameters requires at least one instrument for price and each heterogeneity parameter.

Price parameter, α. At least one instrument is needed to identify α due to price endogeneity concerns (*e.g.*, Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2001). The error term may be correlated with prices because retailers make their pricing decisions with knowledge about the valuations of the consumers in each market, conditional on the search step. In our case, the error term is the unobserved month-specific deviation from the overall mean valuation of the product. The supply-side model assumes that retailers in the industry observe this deviation. It enters into the market-specific markup term in the pricing equation, thus introducing a bias in the estimate of the price sensitivity, α. To address price endogeneity, we use prices of the same product in other markets as instruments for the price of the product in the current market (*e.g.*, Hausman 1996; Nevo 2001).[37] The identifying assumption is that month-specific valuations for a product are independent across time after accounting for display format, manufacturer, retailer, and months fixed effects. The prices of the same product are correlated across months due to the common marginal cost. They are uncorrelated with month-specific valuations due to the exclusion restriction. We use average retail and average wholesale prices in all months (excluding in both cases the price of the product in the month being instrumented) and lagged wholesale prices.

Heterogeneity parameters, σ_ν and λ. The parameter σ_ν governs the distribution of the random coefficients (or heterogeneity in consumer preferences) for price. An instrument is needed to identify this parameter due to the endogeneity problem arising from the unknown parameter σ_ν interacting with the endogenous variables, (s_{jt}, p_{jt}). We use a variation of the differentiation instruments proposed by Gandhi and Houde (2019). We construct instruments defined by a proximity measure counting the number of competitors located within one standard deviation of product j. We use the count of other products whose predicted prices lie within five Euros of the own price and the interaction of this variable with product and manufacturer dummy variables.[38]

The nested-logit parameter, λ, governs the substitution within and between subgroups of products (or nests) sold by the retailers in the DSC, VSC, and the outside product. An instrument is needed due to the unknown parameter, λ, interacting with the endogenous within-group share. We use the number of products in the market within each distribution channel as an instrument. The identifying assumption is that the error term is uncorrelated with the number of products in the

[37] In the setting studied, a market is a month and a product is a combination of display format, manufacturer, and retailer.

[38] We use predicted prices instead of the potentially endogenous prices as follows. We run a regression of prices on characteristics and predict prices using the estimated parameters from this regression. Then we use the predicted prices to count the number of products within the 5-Euro band. Using such predicted prices generates a valid instrument (even if prices are endogenous) because the characteristics used in the preliminary regression are exogenous. Such regression generates an unbiased estimate of prices in which shocks are removed. The characteristics included in the preliminary regression explain over 90 percent of the price variation in the data (adjusted $R^2 = 0.927$). We have also experimented with a band of ten Euros and obtained similar results.

market within each distribution channel. The power of the instrument comes from the number of products in the market within each distribution channel being negatively correlated with the share of the products within that distribution channel.

Value of VSC Retailers. The identification problem arises due to the non-existence of a counterfactual scenario without the VSC retailers. We evaluate the performance of the market without the VSC retailers by constructing such a counterfactual scenario using our model and the fact that, in the outdoor advertising industry, goods can be purchased by the final consumer from either VSC or DSC retailers. We compare instances where the same combination of display format and manufacturer is sold by a DSC and a VSC retailer and compute the counterfactual value that the consumer would have obtained had the purchase been made in a distribution channel different from the one used. Consider consumer i and suppose that a given combination of display format and manufacturer is sold by a DSC and a VSC retailer in a given market and that both types of retailers are part of the consideration set of the consumer. The value of a VSC retailer to consumer i is determined by the extent to which the consumer purchases from a VSC retailer rather than from a DSC retailer. There are three non-mutually exclusive channels for such consumer decision according to the model. The first is that the access to quantity discounts by the VSC retailer may bring its retail prices down relative to where they would have been if those quantity discounts were not present. The second is that the VSC retailer reduced the search costs to the consumer due to its access to the display formats of multiple manufacturers (search services). The third is that the gross utility to the consumer of purchasing from a VSC retailer is larger than the gross utility of purchasing from a DSC retailer (consulting services). The model decomposes the value of VSC retailers to consumer i into the three channels by constructing counterfactual scenarios where we remove each of these channels at a time.

4.2 Identification of Search-Cost Parameters

To identify search-cost parameters we rely on an exogenous variation of product availability across markets within retailers in the VSC, the search-cost specification in our setting, and availability of search data with information about ratios of the subset of searched retailers. We show that the search-cost parameters can be written as a function of the ratios of subset searched retailers using equation (5). Then, we show under which assumptions one can use the Google-search data to construct sample analogs of these ratios. Intuitively, if the search costs are high, consumers search only for the more preferred retailers. Thus, the prices of the products sold by the less preferred retailers would likely not affect the market shares of the products sold by the more preferred retailers because the consumers are not aware of possible lower prices from the less preferred retailers. In contrast, price reductions of less preferred retailers can affect the market shares of most preferred retailers when search costs are low. In general, consumers have more incentives to search, the larger is the variance from the distribution of prices of the inside products available in the market, denoted by $\tilde{F}_p(p)$ in the model, which is known by the consumers *ex ante*. Thus, the correlation between prices of less preferred retailers and market shares of more preferred retailers is larger when this variance is large.

We proceed in four steps. First, we present the three assumptions that we use to identify the search-cost parameters. Second, we present the main identification argument assuming that search data is available (assumption 3a). Third, we extend the previous argument to the case in our setting with Google-search data (assumption 3b). In Online Appendix C.4 we discuss the validity of the assumptions in our empirical setting. See Appendix A for a generalization of the search model allowing for correlation between the stochastic shocks to the consideration sets of retailers.

We use the following assumptions to identify the search-cost parameters:

Assumption 1 (Exogeneity and Full Support). *There is an exogenous variation of product availability across markets within retailers in the VSC with full support conditional on the other variables.*

Assumption 2 (Search-Cost Specification). *Consumers search for retailers but pay a search cost for each manufacturer sold by the retailer.*

Assumption 3a (Search Data). *There is availability of search data with the ratios of probabilities of the searched retailers for any pair of retailers.*

Assumption 3b (Google-Search Data). *The ratio of Google searches of two retailers converges in probability to the ratio of consumers who searched the retailers for any pair of retailers such that the denominator is positive.*

Assumption 1 says that the number of products offered by each retailer varies exogenously across markets. The main restriction from assumption 2 is that consumers search for retailers but pay a search cost for each manufacturer sold by the retailer. For the estimation, we use the linear specification of search costs in equation (4).[39] There are two alternative versions of assumption 3. Assumption 3a simply says that there is availability of data about ratios of the subset of searched retailers. We use assumption 3a to show the economic argument to identify the search-cost parameters and how the argument can be generalized by relaxing assumptions 1 and 2. Assumption 3b shows how we use readily available Google-search data to identify search-cost parameters.

We start discussing identification of the search-cost parameters using assumptions 1, 2, and 3a. Consider a consumer type who bought a given product $j \in (\hat{g} \cap \hat{J}_{\tilde{t}} \setminus \{0\})$ in $\tilde{t} \in \{t, t'\}$. Denote by $R_{\tilde{t}}$ the subset of retailers searched by this consumer in $\tilde{t} \in \{t, t'\}$ and by $\hat{r}$ the retailer who sold product j. Choose t such that $R_t = \{\hat{r}\}$ is singleton and that retailer $\hat{r}$ has only availability of products from a single manufacturer. Such choice is always possible due to assumption 1 and observability of products available in a given market. For example, using the full support variation from assumption 1, pick t such that only the products of retailer $\hat{r}$ are available and $\hat{r}$ has only products from the manufacturer of j. We focus on the case where $R_t = \{\hat{r}\}$ is singleton to ease the exposition. Recall from Section 3, that search is costly and consumers know the products available in the market in

[39] We focus on the linear specification because is the specification used for the estimation in our application. The linearity of search costs, however, can be relaxed, as we discuss below.

the search step. The argument can be extended to the case where $\hat{r}$ is the only retailer in the VSC channel. In such case, one can use a weaker version of assumption 1: exogenous variation of product availability across markets within distribution channels with full support conditional on the other variables. Note that $R_{\tilde{t}} = \{\hat{r}\}$ does not imply that the consideration set, $\hat{J}_{\tilde{t}}$, is singleton, because $\hat{r}$ may sell multiple products from the same manufacturer. Similarly, choose t' such that product $j \in (\hat{g} \cap \hat{J}_{t'} \setminus \{0\})$ is available, $R_{t'} = \{\hat{r}\}$ is singleton, and that retailer $\hat{r}$ has availability of products from two manufacturers. Then, using equation (5):

$$\log\left(\frac{\mathbb{P}_{R_t}}{\mathbb{P}_{R_{t'}}}\right) = \frac{\overline{V}_{R_t} - \overline{V}_{R_{t'}}}{\sigma_{\tilde{\varepsilon}}},$$

$$= \frac{SC_{tR_t} - SC_{t'R_{t'}}}{\sigma_{\tilde{\varepsilon}}}, \tag{11a}$$

$$= -\frac{\bar{S}}{\sigma_{\tilde{\varepsilon}}}, \tag{11b}$$

where (11a) follows from $\int \log\left(1 + \sum_{\hat{g}=1}^{2} e^{I_{\hat{g}R_{ti}}}\right) \mathrm{d}\tilde{F}_{pt}(p) = \int \log\left(1 + \sum_{\hat{g}=1}^{2} e^{I_{\hat{g}R_{t'i}}}\right) \mathrm{d}\tilde{F}_{pt'}(p)$, due to $\operatorname{argmax}_{j \in \hat{J}_t} U_{ijt|R_{ti}} = \operatorname{argmax}_{j \in \hat{J}_{t'}} U_{ijt'|R_{t'i}}$ and (11b) follows from assumption 2 using the search-cost specification in (4). The key restriction for the last step is that consumers search for VSC retailers but pay search cost for each manufacturer.

Similarly, by choosing t'' such that product $j \in (\hat{g} \cap \hat{J}_{t''} \setminus \{0\})$ is available, $R_{t''} = \{\hat{r}\}$ is singleton, and that retailer $\hat{r}$ has availability of products from three manufacturers:

$$\log\left(\frac{\mathbb{P}_{R_t}}{\mathbb{P}_{R_{t''}}}\right) = -\frac{2\bar{S}}{\sigma_{\tilde{\varepsilon}}}. \tag{12}$$

Using assumption 3a, the left hand side in the equations in (11) and (12) is observed. Thus, these equations jointly identify the search-cost parameters, $\bar{S}$ and $\sigma_{\tilde{\epsilon}}$. Assumption 2 and equation (4) posit linearity for the SC. Such linearity can be generalized by positing, *e.g.*, a polynomial function. In the case of a polynomial function of degree two with two parameters, one can use a similar argument as above with an additional ratio of probabilities in t''' to jointly identify the two parameters of the second-degree polynomial function and $\sigma_{\tilde{\epsilon}}$ using a system of three equations. It is straightforward to generalize the argument to allow for additional parameters. We suspect that this argument may also be used to non-parametrically identify the curvature of the search costs under certain assumptions although we have not proved it.

For the remaining of analysis in this subsection, denote with a hat "$\widehat{\ }$" variables that are not function of model parameters (*i.e.*, data). Let $\widehat{G}_{rt}$ be number of google searches for retailer r in t, $\widehat{M}_{rt}$ be the number of consumers who searched for retailer r in t, $\widehat{M}_t$ be the size of the market, and $\widehat{\mathbb{P}}_{rt} \equiv \widehat{M}_{rt}/\widehat{M}_t \in (0,1)$ be the share of consumers who searched for retailer r in t. For the estimation, we are interested in $\widehat{\mathbb{P}}_{rt}$. An identification problem arises because we observe $\widehat{G}_{rt}$ not $\widehat{M}_{rt}$ nor the ratio of probabilities in assumption 3a. We provide conditions under which $\widehat{G}_{rt}$ can be used as proxy for $\widehat{M}_{rt}$ to compute the ratios of probabilities $\widehat{\mathbb{P}}_{rt}$.

Denote by $\mathbb{P}_{rt}$, without hat, the prediction of the model for the share of consumers who searched for retailer r in t. This variable is calculated from the model and is a function of the parameters. Define the set of consumers who searched for retailer r in t as $A_{rt} = \{(\zeta_{igt}, \varepsilon_{ijt}, \nu_i, \tilde{\varepsilon}_{itR_t}) : r \in R_{it}\}$, where R_{it} is the set of retailers searched by consumer i in t, and ζ_{igt}, ε_{ijt}, ν_i, and $\tilde{\varepsilon}_{itR_t}$ are defined in Section 3. Then:

$$\mathbb{P}_{rt} = \int_{A_{rt}} \mathrm{d}P(\zeta_{igt}, \varepsilon_{ijt}, \nu_i, \tilde{\varepsilon}_{itR_t}).$$

where $P(\cdot)$ denotes the population distribution function.

Then, for any retailers r and k with $\mathbb{P}_{kt} > 0$:

$$\underset{t\to\infty}{\text{p-lim}} \quad \underbrace{\left(\frac{\widehat{G}_{rt}}{\widehat{G}_{kt}}\right)}_{\text{Observed in the data}} \quad = \quad \underbrace{\left(\frac{\mathbb{P}_{rt}}{\mathbb{P}_{kt}}\right)}_{\text{Prediction of the model}}, \tag{13}$$

where the equality follows from assumption 3b.

Finally, $R_{\tilde{t}}$, with $\tilde{t} \in \{t, t', t''\}$, is singleton in equations (11) and (12). With the Google-search data we proceed in similar form as before. Choose t such that $R_t = \{\hat{r}\}$ is singleton. For example, pick t such that the only products available in the market are the products sold by retailer $\hat{r}$ from a single manufacturer, the manufacturer of j. Again, the exogeneity and full support variation from assumption 1 ensures this is always possible. Thus, $\mathbb{P}_{R_{\tilde{t}}} = \mathbb{P}_{r\tilde{t}}$ and the ratio of Google searches in (13) can be replaced in the left-hand side in equations (11) and (12), provided $\mathbb{P}_{kt} > 0$.

See Online Appendix C.4 for a discussion of assumptions 1 to 3.

4.3 Estimation

We estimate the demand model adapting the procedure used by Moraga-González, Sándor, and Wildenbeest (2015, MSW). The procedure by MSW adapts the nested fixed algorithm used by Berry, Levinsohn, and Pakes (1995, BLP) by allowing for an endogenous choice set for each consumer type i, which is the outcome of the search step. There are four major differences in our procedure relative to the one by MSW. First, due to our research question, we account for consumers' preferences for the two distribution channels. The additional distribution channel introduces the multiplicative term, $\mathbb{P}_{igt|R_i'}$, to the choice probability in equation (6c), which enters into the market-share equation (7). Second, we estimate the parameters on the demand side without specifying a functional form for the supply side, while the estimation in MSW relies on the functional form of a supply equation, similar to BLP. Third, we use micro moments to identify the search parameters. Finally, the instruments and identifying assumptions are different due to the previous points.

The model is estimated by GMM and relies on the moment condition $\mathbb{E}[Z' \cdot \omega(\theta^*)] = 0$, where Z is a matrix of instruments, $\omega(\cdot)$ is an error term defined below, and $\theta^* = (\alpha, \sigma_\nu, \lambda, \Psi)$ is the true value of the parameters. The GMM estimate is:

$$\hat{\theta} = \arg\min_{\theta} \left[\omega(\theta)' Z A^{-1} Z' \omega(\theta)\right], \tag{14}$$

where A is a consistent estimate of $\mathbb{E}(Z'\omega\omega' Z)$ described below.

For each candidate parameter vector, we use equation (7) with the choice probability in equation (6c) to compute the market shares as a function of the parameters.[40] We define the error term as the unobserved products' characteristics and compute it by solving for the mean utility level, δ_{jt} that equates:

[40]The main difference relative to BLP is that the choice probability and, hence, the market share function incorporates the search step (this is the last term in equation 6c, denoted by $\mathbb{P}_{R_i'}$). Once the market share function is computed, the estimation procedure resembles BLP.

$$s_{jt}(p_{jt}, x_{jt}, \delta_{jt}; \sigma_\nu, \lambda, \Psi) = S_{jt}, \tag{15}$$

where $s_{jt}(\cdot)$ is the market share function given by equation (7) and S_{jt} are the observed market shares obtained from the data. We use a contraction mapping to solve for the implicit system of equations in (15) and identify the vector of mean utility levels. After solving this system of equations, the error term is defined as $\omega \equiv \delta_{jt}(p, x, S; \sigma_\nu, \lambda, \Psi) + \alpha p_{jt}$. For the estimation, we concentrate the linear price parameter, α, out of the optimization problem to reduce the dimensionality of the nonlinear search.

Google Search Micro Moments. For the estimation with Google search micro moments, we add one additional moment condition defined as follows.[41] First, for each retailer $r = 1, \ldots, R$ we compute the difference between the ratio of probabilities across consecutive months predicted by the model and the Google search measure observed in the data, $\frac{\mathbb{P}_{rt}(\theta)}{\mathbb{P}_{r,t+1}(\theta)} - \frac{\widehat{G}_{rt}}{\widehat{G}_{r,t+1}}$, where $\mathbb{P}_{rt}(\theta)$ is the model's prediction of the share of consumers who searched for retailer r in t and $\widehat{G}_{rt}$ is the number of searches for retailer r in t from the Google-search data. We define by $\mathcal{P}_t(\theta)$ the $(R \times 1)$ row-vector with such differences, one for each retailer. Finally, we define the micro moment as $m(\theta^*) \equiv \mathbb{E}\left[\mathcal{P}_t(\theta^*)'\mathcal{P}_t(\theta^*)\right] = 0$. For the estimation, we use its empirical analog:

$$\hat{m}(\theta) = \frac{1}{T}\sum_{t=1}^{T} \mathcal{P}_t(\theta)'\mathcal{P}_t(\theta). \tag{16}$$

We add the moment condition in (16) to the GMM objective in (14) and use the inverse of the sample variance of the empirical moments as the weighting matrix. We compute the standard errors for the estimates using the standard procedures (*e.g.*, Hansen 1982, Newey and McFadden 1994), correcting them to account that the simulation draws are the same for all of the observations in a market.

5 Supply: Identification and Estimation

5.1 Identification

The parameters from the supply side are the vector of retail marginal costs, $\mathbf{c^r}$, the vector of manufacturer marginal costs, $\mathbf{c^m}$, and the vector of bargaining weights, δ^S. We observe the vector of retail prices, $\mathbf{p}^*$, the vector of wholesale prices, ω^*, the vector of market shares, $\mathbf{s}$, and size of the market, M. Using the previously described procedure, we have an estimate of the demand system, $(\mathbf{s}(\mathbf{p}^*), \nabla_p \mathbf{s}, \bar{s})$.

The first-order conditions from the retail game in equation (8) provide a system of $\mathcal{J}$ equations that just identifies the $\mathcal{J}$-vector of retail marginal costs, $\mathbf{c^r}$. The first-order conditions from the manufacturer game in equation (10) also provide a system of $\mathcal{J}$ equations. Thus, in general, without additional restrictions, equation (10) cannot be used to identify both, the vector of vector of manufacturer marginal costs, $\mathbf{c^m}$, and bargaining weights, δ^S, which jointly has dimension $2 \times \mathcal{J}$.

We obtain these additional restrictions using the vertical structure in our empirical setting. Namely, that manufacturers sell the same display format to both, consumers (charging DSC prices)

[41] See Table A2 in the Online Appendix for a comparison using alternative price beliefs.

and VSC retailers (charging wholesale prices). A natural set of restrictions justified by this structure is that the manufacturer marginal cost of a given display format in a given month is the same whether it is sold to the consumer or to a VSC retailer. In terms of the model, this implies that the manufacturer marginal costs, $\mathbf{c^m}$, could be recovered using the first-order conditions from the retail game (system in equation 8), without using the first-order conditions from the manufacturer game (system in equation 10), because the manufacturers are DSC retailers. Therefore, in the first step, we use the first-order conditions from the retail game in equation (8) to identify the vector of retail *and* manufacturer marginal costs using that manufacturer marginal costs are the same for a display format sold to a VSC retailer and the consumer. In other words, $\mathbf{c^m}$ is contained in $\mathbf{c^r}$. Then, in the second step, we use the first-order conditions from the manufacturer game in equation (10) to identify the bargaining weights. The $\mathcal{J}$-vector of bargaining weights, δ^S, is just identified using the system in equation (10) conditional on the estimated manufacturer marginal costs, $\mathbf{c^r}$, from the retailer game. Our identification arguments exploit the vertical structure in our empirical setting and, thus, are different from the ones used previously in the literature (*e.g.*, Draganska, Klapper, and Villas-Boas 2010; Grennan 2013).[42]

5.2 Estimation of Marginal Costs and Bargaining weights

To estimate the vector of marginal costs, we need to compute the element $\frac{\partial s_{kt}(\mathbf{p}*)}{\partial p_{jt}}$ in the matrix $[\nabla_p \mathbf{s}]'$ in the retail-game equation (8), which is:

$$\begin{aligned} \frac{\partial s_{kt}(\mathbf{p}*)}{\partial p_{jt}} &= \int_i \frac{\partial s_{ijt}(\mathbf{p}*)}{\partial p_{jt}} \mathrm{d}v_i, \\ &= \int_i \left(\sum_{R'_i \in \Lambda} \frac{\partial s_{ijt|R'_i}}{\partial p_{jt}} \times s_{R'_i} \right) \mathrm{d}v_i. \end{aligned}$$

From Grigolon and Verboven (2014, p. 934), the last derivative is:

$$\frac{\partial s_{ijt|R'_i}}{\partial p_{kt}} = \begin{cases} \alpha_i \left(s_{ijt} + \frac{\lambda}{1-\lambda} s_{ijt|g} - \frac{1}{1-\lambda} \right) s_{ijt} & \text{if } j = k, \\ \alpha_i \left(s_{ikt} + \frac{\lambda}{1-\lambda} s_{ikt|g} \right) s_{ijt} & \text{if } j, k \text{ are in the same nest } g, \\ \alpha_i s_{ikt} s_{ijt} & \text{if } j, k \text{ are in different nests,} \end{cases}$$

where $\alpha_i > 0$.

Applying the envelope theorem and simplifying the first-order conditions from the manufacturer game in (10), we obtain the following expression used to recover the bargaining weights (see Online Appendix D):

$$\mathbf{c^m} = \omega^* - \delta^S \left(\Lambda^{\mathcal{M}} \odot \overline{s} \right)^{-1} \left(\Lambda^{\mathcal{R}} \odot \overline{s} \right) (\mathbf{p}^* - \omega^* - \mathbf{c^r}), \tag{18}$$

[42] For example, Draganska, Klapper, and Villas-Boas (2010) use observed prices and quantities to estimate demand parameters. In addition, they have cost data, which they use to estimate marginal costs. Finally, they use the first-order conditions to estimate the bargaining parameters. Grennan (2013) also uses observed prices and quantities to estimate demand parameters. However, he does not have cost data and cannot estimate all the bargaining and marginal cost parameters. Hence, he imposes restrictions on marginal cost parameters and then uses first-order conditions to estimate bargaining parameters. We use a somewhat different approach. Prior knowledge of the industry structure allows us to reduce the dimension of the marginal costs parameters (so that manufacturer marginal costs can be estimated with the retailer marginal costs). Then, we use the first-order conditions from the bargaining game to estimate the bargaining parameters alone.

where:

$$\overline{s} \equiv \begin{bmatrix} s_1 & -\Delta s_2^{-1} & \cdots & -\Delta s_{\mathcal{J}}^{-1} \\ -\Delta s_1^{-2} & s_2 & \cdots & -\Delta s_{\mathcal{J}}^{-2} \\ \vdots & \vdots & \ddots & \vdots \\ -\Delta s_1^{-\mathcal{J}} & -\Delta s_2^{-\mathcal{J}} & \cdots & s_J \end{bmatrix},$$

is the matrix of shares and changes in shares in Draganska, Klapper, and Villas-Boas (2010, p. 62, first matrix) with $\Delta s_k^{-j} \equiv s_k^{-j}(\mathcal{P}(\omega)) - s_k(\mathcal{P}(\omega))$ denoting the difference between the market share of product k if product j is offered and if it is not and δ^S is the vector of bargaining weights defined above.

We parameterize the manufacturers' marginal costs, c_{jt}^m, as:

$$c_{jt}^m = \gamma_0 + \gamma_d^S + \gamma_m^S + \gamma_t^S + \hat{\epsilon}_{jt}, \tag{19}$$

where γ_0 is a constant; γ_d^S, γ_m^S, and γ_t^S capture marginal cost for display format d, manufacturer m, and month of the year t, using fixed dummy variables for display format, manufacturer, and monthly seasonal effects in market t, respectively; and $\hat{\epsilon}_{jt}$ is an unobservable error term. Denote by $\gamma \equiv (\gamma_0, \gamma_d^S, \gamma_m^S, \gamma_t^S)$.

Rearranging terms, write the supply unobservable error term as:

$$\hat{\epsilon}(\gamma, \mathbf{c^r}, \delta^S) = \omega^* - \gamma_0 - \gamma_d^S - \gamma_m^S - \gamma_t^S - \delta^S \left(\Lambda^{\mathcal{M}} \odot \overline{s}\right)^{-1} \left(\Lambda^{\mathcal{R}} \odot \overline{s}\right) (\mathbf{p}^* - \omega^* - \mathbf{c^r}). \tag{20}$$

For the estimation, we assume that the unobservable determinants of costs are $i.i.d$ across products, j and markets, t. We set the retailers' marginal cost to zero, $c_{jt}^r = 0 \ \forall \ (j,t)$. We believe these are sensible assumptions in our empirical setting for two reasons. First, because manufacturers and retailers' marginal costs are quite low in this industry and vary little across markets (Table 7 discussed in next section). Second, because our interest in the supply-side parameters is as inputs for counterfactual scenarios without intermediaries' services in Subsection 7.2.[43] We perform the estimation by choosing the value of the parameters, $(\gamma, \mathbf{c^r}, \delta^S)$, that minimize the sum of squared errors given by equation (20), subject to the demand estimates, $c_{jt}^m \in [0, p_{mjt}]$, $c_{jt}^r = 0$, and $\delta^S \in (0,1)$.

6 Estimation Results

6.1 Demand Estimates

Table 5 displays estimates from the following specifications of the model. (1) A simple logit model (without random coefficients for the price, without channel-specific preferences, without search). (2) A mixed logit model (without channel-specific preferences and without search). (3) A mixed logit model with channel-specific preferences (without search). (4) A mixed logit model with channel-specific preferences and with costly search. The latter specification corresponds to the full model described Subsection 3.1. Model 4 uses the additional Google micro moments implemented using equation (16). All the specifications include a set of dummy variables for manufacturers, retailers,

[43] Alternatively, one can perform the estimation by using the supply-side moment condition $\mathbb{E}[Z^S \cdot \hat{\epsilon}(\gamma^*, \mathbf{c^{r}}^*, \delta^{S^*})] = 0$, where Z^S is a matrix of supply-side instruments, $\hat{\epsilon}(\cdot)$ is the error term defined in equation (20), and $(\gamma^*, \mathbf{c^{r}}^*, \delta^{S^*})$ is the true value of the supply parameters. We have also performed the estimation using an expression analog to equation (19) for retailers' marginal costs with no unobservable determinants and obtained retailers' marginal costs that were very close to zero.

display formats, and months fixed effects. The instruments used in the GMM specifications are described in Subsection 4.

We apply the estimation procedure from Subsection 4 with the obvious modifications. For example, for the simple logit, model 1, the error term in the system of equations (15) has a closed-form expression, the search step in Section 3 is skipped, and the model is estimated by OLS. For models 2 and 3, we solve for the error term using the contraction mapping and skip the search step. The demand estimates do not impose the equilibrium conditions from the supply side.

The estimated parameters have the expected signs and are sensible in magnitude. Three conclusions emerge from this table. First, by comparing the estimates from models 1 and 2, one can see the role of accounting for price endogeneity and unobserved price heterogeneity. The estimated mean price coefficient in model 2 is three times higher in absolute terms than the one in model 1 ($^{0.168}/_{0.050}$). The coefficient for the standard deviation of the random coefficients for the price is statistically different from zero. Consumer heterogeneity is important in this industry. Not accounting for these features may bias the estimated absolute-value mean price elasticity downwards.

Second, by comparing the estimates from models 2 and 3, one can see the role of accounting for preference heterogeneity for the distribution channels. Model 3 allows for such preference heterogeneity. The null hypothesis that there is no preference heterogeneity for the distribution channels, $\hat{\lambda} = 0$, is rejected. Model 2 precludes correlation in consumer preferences for the products in the same distribution channel. In model 3, consumers self-select into the distribution channels based on their preferences. They are less responsive (lower α in absolute value) and more homogeneous (lower σ_ν) in their taste for price for products in the same channel, relative to model 2. Overall, these results indicate that ignoring channel-specific preferences may overestimate price sensitivity and price heterogeneity.

Finally, by comparing the estimates from models 3 and 4, one can see the role of accounting for consumer search. The search-cost parameters, $\bar{S}$ and $\sigma_{\tilde{\varepsilon}}$, are precisely estimated. The estimate of the search-cost parameter, $\bar{S}$, implies that the cost of searching one additional retailer is 1.54 Euros on average ($^{0.182}/_{0.118}$). This search cost represents 8 percent of the mean price paid by consumers across all display formats in the setting ($^{1.54}/_{19.64}$, where 19.64 Euros is the mean price of all display formats across both distribution channels in Table 3). For 2 m^2 panels, the most popular product in the industry, with 56 percent of the sales, the cost of searching one additional retailer represents 12 percent of the mean price ($^{1.54}/_{13.09}$). The estimate of the scale parameter of the consideration sets, $\sigma_{\tilde{\varepsilon}}$, is about 9 times smaller than the scale parameter of the utility function shock, which is normalized to 1 ($^{1}/_{0.116}$). This result indicates that unobserved factors affecting consumer choice of the consideration sets, although statistically different from zero, play a relatively small role in the empirical setting studied. The estimated search-cost parameters imply that consumers search, on average, for 5.8 retailers to collect information about their prices, p_{jt}, and the realization of their random shocks, $\hat{\varepsilon}_{ijt}$, associated with their products. In other words, consumers sample approximately 60 percent of the subset of all retailers available in the market when performing their search ($^{5.77}/_{9} = 0.64$). This finding indicates that the restriction to consumers' consideration sets is substantial due to search costs: around 40 percent of the overall retailers do not belong to the consideration set of a given consumer.

Next, compare the price sensitivity of the models with and without search. Table 6 presents the consumer-level, own-price elasticities. The last column shows the ratio of elasticities computed from the model without search (model 3) relative to the elasticity of the model with search (model 4). For the median elasticity, the ratio is 0.5. Consumers are more sensitive to price in model 4 with search. These results are consistent with prior findings in Draganska and Klapper (2011) and De los Santos, Hortaçsu, and Wildenbeest (2012). They indicate that ignoring consumer search (*i.e.*, incorrectly assuming that consumers have full information), may bias the estimated absolute-value price elasticities downwards. The explanation is simple, as emphasized by De los Santos, Hortaçsu, and Wildenbeest (2012, p. 2977): "[...] the price changes we—as econometricians—observe in the data are not observed by consumers who sample only a subset of the stores. A full information [...] model assumes that all prices are observed, thus ascribing unresponsiveness to price changes to low price elasticity." Finally, compare the ratio of elasticities between DSC and VSC retailers. For DSC retailers, the ratio ranges between 0.5 and 0.8; for VSC retailers, it ranges between 0.2 and 0.7. In other words, the bias is larger for VSC retailers. By allowing consumers to have access to multiple manufacturers, VSC retailers decrease consumer search costs relative to DSC retailers. Ignoring search generates a greater bias in the estimated price elasticities of VSC retailers than the ones of DSC retailers because VSC retailers provide better search services. These demand elasticities are important by themselves, as they directly translate into price-cost margins and affect merger simulations.[44]

The demand estimates in Table 5 and the elasticities in Table 6 show that consumer search plays a relatively large role in the empirical setting studied. By facilitating search, intermediaries increase consumer welfare, a result that will be reflected in the counterfactual analysis.

6.2 Supply Estimates

Table 7, Panel A displays the estimates of selected parameters of the manufacturers' marginal cost from equation (19). Panel B displays summary statistics of the distribution of manufacturers' marginal costs. Panel C displays the mean bargaining weights.

The estimated parameters are sensible in magnitude. Two patterns stand out. First, panel B shows that manufacturers' marginal costs are relatively low in this industry, consistent with expert industry reports as in, *e.g.*, U.K. Office of Fair Trading (2011). For example, for 2 m^2 panels, the median wholesale price is 8.34 Euros per square meter (Table 2) and the median estimated marginal cost is 1.30 Euros per square meter ($0.877 + 0.431$). Marginal costs vary little across firms, display formats, and markets. The coefficient of variation is 0.4 ($^{0.353}/_{0.872}$). Second, panel C shows that the VSC retailers have relatively low bargaining power, 0.24 on average, compared to

[44] Our estimates imply that the price-cost margins computed from the model without search are substantially lower than those computed from the model with search (50 percent or more) with a greater bias for VSC retailers. Estimates from a model without search tend to underestimate the effects of a merger because they tend to underestimate the substitution among products. The bias is greater for mergers encompassing VSC retailers that provide better search services.

the bargaining power of the manufacturers, 0.76 on average. These numbers are consistent with the large concentration at the manufacturer level and the low retail margins in the empirical setting. The largest manufacturer, m_2, has nearly 50 percent of the sales. VSC retailers have little bargaining power when negotiating with manufacturer m_2. Retail margins for the VSC retailers are low. The median (mean) margin of the VSC retailers is 0.57 (1.72) Euros per square meter.[45]

We use the supply-side parameters to simulate the counterfactual scenarios in Subsection 7.2.

6.3 Robustness

We performed several robustness tests of our model. First, in Table 5 we performed the estimation of the demand model using different specifications, where we build up the full demand model starting from a simple logit model. We also tested different specifications of the supply model, as discussed in footnote 43. Second, we tested for different information structures for the specification of the empirical distributions of prices, $\tilde{F}_p(p)$, in Table A2 in the Online Appendix, discussed in footnote 28. Third, in unreported results, we tested for different specifications of the Google search micro moments using ratios of probabilities of different retailers in a given market (instead of ratios of probabilities of the same retailer in different markets as implemented in Table 5) and using the same specifications of the micro moment as in Table 5 but with the different definitions of Google searches in Online Appendix B.2.2. Fourth, also in unreported results, we estimated the model using different instruments (using a different definition of the differentiation instruments as discussed in footnote 38, using wholesale prices or lagged wholesale prices to address price endogeneity, and using interactions of the latter variables with product availability in the previous months). Sixth, we tested for different functional form specifications of the search cost in the demand model (*e.g.*, using an exponential function) and the counterfactual (see Section 7). Seventh, we tested increasing/decreasing the market size (to, respectively, 50 and 10 percent greater than the maximum observed total monthly sales). Finally, we tested using different nonlinear programming solvers, starting values, number of simulated consumers, and seeds to control the generation of random numbers. The estimated parameters did vary sometimes across some of these robustness tests. However, the implications discussed in subsections 6.1, 6.2, and 7.3 are robust in the cases examined.

7 Welfare

7.1 Welfare Measures

The expected consumer surplus, in Euros, for consumer type i is given by (see Online Appendix C.5):

$$\mathbb{E}(CS_i) = \frac{1}{\alpha_i}\sigma_{\tilde{\varepsilon}} \log \left\{ \sum_{R_i' \in \Lambda} \exp \frac{1}{\sigma_{\tilde{\varepsilon}}} \left[\log \left(1 + \sum_{\hat{g}=1}^{2} e^{I_{\hat{g}R_i}} \right) - SC_{R_i} \right] \right\} + C, \tag{21}$$

[45]The estimated bargaining weights also show that direct-to-consumer sales increase the bargaining power of manufacturers when negotiating with retailers. In this paper, our main focus is the demand side. We use the supply model to compute the counterfactual prices to investigate the welfare effects to consumers of the services provided by the intermediaries. See Donna, Pereira, Trindade, and Yoshida (2021) for a supply-side investigation about the impact of direct-to-consumer sales on the bargaining power of the manufacturers and the implications for vertical mergers.

where $\mathbb{E}(\cdot)$ denotes the expectation operator taken over both random shocks $\hat{\varepsilon}_{ijt}$ and $\tilde{\varepsilon}_{ijR_i}$, the inclusive value, $I_{\hat{g}R_i}$, is given in Online Appendix C.3, and C is a constant.[46]

Consumer welfare for type i is defined as the change in the consumer surplus, or compensating variation, CV, that results from a change in the services offered by the retailers. We compute the difference between the consumer surplus before and after such change. We consider four changes in the services offered by the retailers that described in Subsection 7.2. We compute the total consumer surplus calculated as the weighted sum of $\mathbb{E}(CS_i)$ using the weights reflecting the number of consumers who face the same representative utilities as the sampled consumer. That is:

$$\mathbb{E}(CV) = \int_{\nu_i} \left[\mathbb{E}(CS_i^1) - \mathbb{E}(CS_i^0)\right] \, \mathrm{d}P_\nu(\nu_i), \tag{22}$$

where $\mathbb{E}(CV)$ denotes the weighted sum across types of consumers of the compensating variation, the superscripts 0 and 1 refer, respectively, to before and after the counterfactual change in the services offered by the retailers, and $\mathbb{E}(CS_i)$ is given by equation (21).

7.2 Counterfactual Scenarios

Three channels through which VSC retailers affect consumers' welfare are by providing consulting, search, and purchase-aggregation services. We consider three counterfactual scenarios where we turn off each of these channels and an additional one where we turn off all three simultaneously. For each counterfactual scenario we compute the compensating variation using equation (22).

For each scenario, we follow the following three steps. First, we compute the optimal prices by solving the system of retail and bargaining equations using the initial matrix of elasticities. Second, we use the vector of prices from the supply side to form the consumer's price expectations. We do this step by taking multiple draws with replacement from the optimal price vector and integrating them numerically. This step guarantees that the price expectations are rational. Finally, we solve the consumer-demand problem using the price expectations.

No Consulting Services. In this scenario, consumers may use the VSC but VSC retailers do not offer consulting services, defined as the gross utility of a given display format from the retailer. In Subsection 3.1, the gross utility of the consumer of purchasing a display format from a given manufacturer differed according to whether it was purchased through the VSC or DSC. We define the difference in gross utilities between the VSC and DSC retailers as the consulting services provided by the VSC retailers.

We implement this counterfactual by imposing that the gross utility of consuming a display format from a given manufacturer (purchased through the VSC) to be the gross utility of consuming the same display format of the same manufacturer purchased through the DSC. According to equation (1), the gross utility for display format d, produced by manufacturer m, and sold by retailer r, in market t, is given by $\tau_{dmrt} \equiv \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D$. The no-consulting-service scenario, denoted with the superscript c_1, is implemented by changing each component of the vector that corresponds

[46]The constant indicates that the absolute level of utility cannot be measured.

to purchases made trough the VSC, such that: $\tau^{c_1}_{dmrt} = \tau_{dmmt}$, for every m, r and t.[47]

No Search Services. In this scenario, consumers may use the VSC but VSC retailers do not offer search services. According to our model, VSC retailers reduce consumers' cost of searching. We implement this counterfactual by increasing the search cost of consumers as follows. In equation (4), consumers pay $\bar{S}$ for each manufacturer sold by the searched retailer. In this counterfactual, consumers pay $\bar{S}$ for each retailer-manufacturer combination carried by the retailer searched.[48]

This counterfactual leaves constant the number of "stores" and display formats. It only eliminates the search-cost advantage of buying through a retailer instead of a manufacturer. We then simulate the choice outcomes predicted by the demand model.

No Purchase-Aggregation Services. In this scenario, we recompute the equilibrium prices using the supply side. According to the model, the initial observed prices were set following, first, the bargaining game and, then, the retail (or Nash Bertrand) game. In this counterfactual, we use the estimated supply parameters to remove the purchase-aggregation services by recomputing prices assuming that they are generated by two successive Nash Bertrand. We follow the following four steps. First, we compute the optimal retail-price function (as a function of any wholesale price) given by equation (8). Second, we use the result from step 1 to solve numerically for the pass-through matrix defined by ${}^{\partial p_k}/_{\partial \omega_r}$ for all k, r, similar to equation (9) in Villas-Boas (2007, p. 634). Third, we solve for the optimal wholesale prices in the two-margin model using equation (10) with $\nu_{rmj} = 0$ and step 2 to get $\nabla_w \mathbf{s} \equiv {}^{\partial \mathbf{s}}/_{\partial \omega'} = {}^{\partial \mathbf{s}}/_{\partial \mathbf{p}} \times {}^{\partial \mathbf{p}}/_{\partial \omega}$. Finally, we solve for the optimal wholesale prices, ω, using equation (10) from step 3, which is similar to equation (9) in Draganska, Klapper, and Villas-Boas (2010, p. 62). This procedure gives an expression that is a function of ω and $\mathbf{p}$ that can be solved for ω using the implicit function theorem applied to (10) because $\mathbf{p}^* = \mathcal{P}(\omega)$. We then use the new price vector and the estimated demand system to recompute the purchase decisions of the consumers.

No Intermediaries' Services. In this scenario, both VSC and DSC retailers operate but VSC retailers do not offer either consulting, search, nor purchase-aggregation services, as defined above. We implement it by simulating a new counterfactual where implement the three previous counterfactuals simultaneously. To evaluate the welfare under the different scenarios we simulate the choice outcomes predicted by the demand model.

7.3 Counterfactual Results

Table 8 reports the results from the counterfactual scenarios above. Columns 1 to 4 compare the results relative to the baseline predictions (model 4 in Table 5 labeled as baseline). We report the following outcome variables: the inside share (fraction of the market with purchases of inside

[47] The value τ_{dmrt} represents the gross utility of a display format d, produced by manufacturer m, and sold to consumers by retailer r. In this counterfactual scenario, that product has the gross utility of a display format d, produced by manufacturer m, and sold to consumers by manufacturer m (*i.e.*, a DSC retailer), τ_{dmmt}.

[48] For example, if the VSC retailer carries products of only 1=one manufacturer, consumers' search costs do not change in the counterfactual. If the VSC retailer carries products of two (three) manufacturers, consumers' search costs increase by $\bar{S}$ ($2\bar{S}$). With this specification, the resulting increase in search costs is small. The key insight of this counterfactual is that search costs increase without VSC retailers.

products), DSC as fraction of inside (fraction of inside purchases made through the DSC), mean posted prices, mean paid prices (mean posted prices weighted by the quantities purchased), number of retailers searched, count paid of search costs (number of times that a search cost was paid), and the total change in the consumer surplus.

In column 1 we remove the consulting-service differential between the VSC and the DSC. We observe a small decrease in the total purchases. There is an increase in the sales fraction from the DSC. The number of searched retailers exhibits little variation. This finding is consistent with the search costs not being affected in this counterfactual. The total consumer surplus decreases by one Euro per square meter. These results reflect the estimated demand system, which shows a larger gross utility for purchases in the VSC. It is consistent with intermediaries providing additional services besides the advertising space, such as assistance with the advertising design and brand recognition for intermediaries.

In column 2 we remove intermediaries' search services. The cost of searching increases for consumers. There is a decrease in the amount purchased of inside products. The increase in search costs decreases the number of retailers searched by 5 percent ($^{5.47}/_{5.77} - 1$). The overall cost of the search increases substantially, by 35 percent ($^{7.79}/_{5.77} - 1$), even when the overall level of prices is similar to the baseline. That is, removing the intermediaries' search-cost advantage results in consumers paying substantially higher search costs: now consumers pay the search cost for each retailer-manufacturer combination carried by the searched retailer relative to paying such cost for each manufacturer sold by the searched retailer. Although the increase in the search cost decreases the number of searched retailers, the total amount spent on searching increases. In sum, consumers search less, pay more search costs, buy less inside products, and pay similar prices relative to the benchmark. The consequence is a large decrease in the total consumer surplus, 12 Euros per square meter. This number is 33 percent higher than the mean paid price in the baseline ($^{11.6}/_{8.73} - 1$). These outcomes reflect the estimates of the search parameters in the demand system. Search frictions are substantial. Intermediaries reduce them by providing consumers access to the display formats of multiple manufacturers. The removal of the intermediaries' search advantage generates a decrease in the consumer surplus comparable to a large increase in the market power.

In column 3 we remove the intermediaries' purchase-aggregation services. Wholesale prices paid by the VSC retailers increase due to the elimination of the intermediaries' bargaining power, thus partially transferring the increase to the consumers. Prices to the consumers increase by 42 percent ($^{11.81}/_{8.29} - 1$). This increase reflects the rise of VSC prices. DSC prices decrease. The increase in relative VSC prices induces consumers to substitute away from the intermediaries to the DSC retailers. It also generates a decrease in the amount purchased of inside products. These two effects mitigate the large increase in VSC prices. As a consequence, total consumer surplus decreases only two Euros per square meter.

In column 4 we simultaneously remove all services provided by the VSC retailers. There is a relatively large increase in prices, 45 percent on average ($^{12.03}/_{8.29} - 1$). This increase is driven by the rise in DSC prices due to the removal of the purchase-aggregation services of the VSC retailers. On the one hand, higher prices induce consumers to search more and to substitute to the DSC retailers, as in column 3. On the other, the higher search costs induce them to search less and to pay more search costs, as in column 2. Column 4 shows that the net effect is a decrease in the number of searched retailers and an increase in the fraction of DSC purchases by 53 percent ($^{28.0}/_{18.2} - 1$). There is also a decrease in the total purchases of inside products by 12 percent ($^{62.0}/_{76.6} - 1$). The consumer surplus decreases by a large amount, 14 Euros per square meter.[49] The decrease in the consumer surplus is 64 percent higher than the mean paid price in the baseline ($^{14.28}/_{8.73} - 1$). The decrease in the consumer surplus can be decomposed in terms of the contribution of the services provided by the intermediaries. The consulting services explain approximately 7 percent of the raw decrease in the consumer surplus in column 4 ($^{-0.93}/_{-14.28}$), while the search services explain approximately 81 percent ($^{-11.58}/_{-14.28}$), and the purchase-aggregation services explain the remaining 12 percent ($^{-1.77}/_{-14.28}$). In other words, providing search services is the most prominent mechanism for intermediaries' welfare enhancement in the empirical setting studied, followed by purchase-aggregation and consulting services. We interpret the welfare results from column 4 as the impact that VSC retailers have on consumer welfare, holding constant the market structure. In column 4 we remove the three channels through which the VSC retailers (intermediaries) affect consumers' welfare without affecting the downstream level of competition or the vertical structure in the marketplace: VSC and DSC retailers continue to operate but VSC retailers do not offer consulting, search, nor purchase-aggregation services.[50]

8 Concluding Remarks

We proposed an empirical framework to quantify the welfare effects due to intermediation. We employ structural econometric techniques in demand and supply estimation to isolate the channels through which intermediaries affect welfare. We apply our empirical framework to the outdoor advertising industry, recover the primitives of the industry, and simulate counterfactual scenarios to quantify the welfare of the services offered by the retailers. The presence of intermediaries increases the welfare in this industry. The value of their services outweighs the additional margin charged.

Our model combines features that are typical of a vertical industry. These features include consumers who have unobserved preferences that are specific to the distribution channel and engage in costly search on the demand side, and two layers of activity—where manufacturers and intermediaries bargain over wholesale prices—with two distribution channels—that compete on downstream prices—on the supply side. The empirical setting studied, outdoor advertising, looks similar to other vertical markets in several dimensions. Recent examples in the U.S. include disputes between

[49]The change in the consumer surplus in column 4 does not correspond to the sum of the changes in consumer surpluses in columns 1, 2, and 3. The difference is due to interactions between these effects in the counterfactual in column 4, as explained in this paragraph.

[50]See Donna, Pereira, Trindade, and Yoshida (2021) for an investigation of the impact of direct-to-consumer sales on welfare and the implications for market power and merger evaluation.

Tesla and Automobile Dealer Association, and the proposed merger between Aetna and CVS.[51] Our framework may be used to evaluate the implications of vertical mergers when intermediaries, or retailers, offer additional services relative to the ones of the manufacturers.

Two main conclusions arise from our analysis. First, the presence of intermediaries increases welfare. This finding is not surprising because consumers made 85 percent of the purchases through the intermediaries in the setting studied. However, similar canals to the ones analyzed here may be present in other industries and sectors, where the counterfactual scenario without intermediaries may not be observable; that is, where consumers do not buy directly from the manufacturers. Measuring the welfare of intermediaries for merger evaluation, for example, may also require quantifying the value of the services provided by the intermediaries to consumers. In such cases, our framework may provide new insights for regulators, competition authorities, and antitrust agencies. Ignoring the retailers' search-cost advantage or the resulting increase in final prices due to the removal of the retailers' bargaining advantage may generate effects comparable to a large increase in the market power with significant consequences for horizontal- and vertical-merger evaluation. Second, we find that the three services considered provide value to consumers, with search playing a prominent role. This finding is, no doubt, specific to the empirical setting investigated. However, our approach shows the importance of specifying a flexible model that may allow for such quantification. It is well known that vertical integration often eliminates double marginalization and may generate efficiencies gains.[52] Our analysis complements such literature. It helps to explain why intermediaries are ubiquitous in modern economies despite the double marginalization, a subject that has received little empirical work.

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[51] Regarding the U.S. car industry, in 48 states franchise laws prohibit/limit auto manufacturers from selling directly to consumers. They require the intermediation of car dealers. It has resulted in disputes between Tesla Inc. and state auto dealer associations (Sibilla 2017). Regarding the proposed merger between Aetna and CVS, one of the arguments in its favor is that the merged CVS-Aetna would not need CVS/Caremark as an intermediary, thus benefiting consumers from the elimination of the intermediaries' markup (Frakt 2017).

[52] See, *e.g.*, Motta (2004, chapter 6) and the references therein.

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Appendix

A Search Model with Correlated Consideration Sets of Retailers

We extend the search model to allow for unobserved search-cost heterogeneity. We generalize the search model in step 1 by allowing correlation between the stochastic shocks to the consideration sets of retailers, R_i. The idiosyncratic unobserved search costs may be correlated between the consideration sets of DSC and VSC retailers. For instance, a consumer i who has a idiosyncratic search cost that makes it more likely to search the subset of VSC retailers $R_i = \{r_4^v, r_5^v, r_6^v\}$, may be more likely to search for the subset of VSC retailers $R_i' = \{r_4^v, r_5^v\}$ than the subset of DSC retailers $R_i'' = \{r_1^d, r_2^d\}$. In the baseline search model, the idiosyncratic shocks to the consideration sets are independent across R_i, R_i', and R_i''. We now extend the baseline model to allow for correlation between the shocks to R_i and R_i'; that is, between the shocks to the consideration sets of retailers in the same distribution channel.

We allow consumers to have search-costs shocks that are specific to consideration sets of retailers in the same distribution channel and consideration sets with retailers in both distribution channels and the no-search option. We capture this correlation by decomposing the stochastic term, $\tilde{\varepsilon}_{itR_i}$ in equation (3) using the distributional assumptions of the nested logit. It is straightforward to extend the approach using other distributions. For example, one can also obtained closed-form solutions for the search probabilities using the generalized extreme value (GEV) distribution. Let $\vartheta \in \{0, 1, 2\}$ define three groups (or nests) of nonoverlapping consideration set of retailers for: (i) consideration sets with retailers in both distribution channels and the no-search option denoted by $\vartheta = 0$ (henceforth, mixed consideration sets), (ii) consideration sets with retailers in the DSC denoted by $\vartheta = 1$ (henceforth, DSC consideration sets), and (iii) consideration sets with retailers in the VSC denoted by $\vartheta = 2$ (henceforth, VSC consideration sets). Let $\varkappa$ be a nesting parameter, such that $0 \leq \varkappa < 1$. A larger value of $\varkappa$ corresponds to a greater correlation in idiosyncratic search costs for consideration sets in DSC, VSC, and mixed consideration sets. A larger value of $\varkappa$ is therefore associated with less search for consideration sets in DSC, VSC, and mixed consideration sets. When $\varkappa = 0$ the search model collapses to the baseline search model with no search-cost heterogeneity for consideration sets of retailers. Consumer i chooses the subset of searched retailers, R_i, that maximizes the expected net benefit of searching, V_{tR_i}. The probability that consumer i finds optimal to sample the subset of retailers $\hat{R}_i$ in market t, $\mathbb{P}_{\hat{R}_i}$ in equation (5), is:

$$\mathbb{P}_{\hat{R}_i} = \frac{\exp\left(\frac{\overline{V}_{t\hat{R}_i}}{\sigma_{\tilde{\varepsilon}}(1-\varkappa)}\right)\left[\sum_{\tilde{R}_i \in \vartheta} \exp\left(\frac{\overline{V}_{t\tilde{R}_i}}{\sigma_{\tilde{\varepsilon}}(1-\varkappa)}\right)\right]^{-\varkappa}}{\sum_{\tilde{\vartheta}=0}^{2}\left[\sum_{\tilde{R}_i \in \tilde{\vartheta}} \exp\left(\frac{\overline{V}_{t\tilde{R}_i}}{\sigma_{\tilde{\varepsilon}}(1-\varkappa)}\right)\right]^{1-\varkappa}}, \tag{23}$$

$$i = 1, \ldots, I_t, \qquad \hat{R}_i \in \hat{\vartheta}, \qquad \hat{\vartheta} \in \{0, 1, 2\}, \qquad t = 1, \ldots, T,$$

where the derivation is similar as the one in in Online Appendix C.

The unconditional choice probability of consumer type i for product j in market t is:

$$
\begin{aligned}
\mathbb{P}_{ijt} &= \sum_{R_i' \in \Lambda} \mathbb{P}_{ijt|R_i'} \times \mathbb{P}_{R_i'}, && \text{(24a)}\\
&= \sum_{R_i' \in \Lambda} \underbrace{\mathbb{P}_{ijt|gR_i'} \times \mathbb{P}_{igt|R_i'}}_{\mathbb{P}_{ijt|R_i'}} \times \mathbb{P}_{R_i'}, && \text{(24b)}\\
&= \sum_{R_i' \in \Lambda} \underbrace{\underbrace{\frac{\exp(I_{igR_i'})}{\exp(I_{gR_i'})}}_{\mathbb{P}_{ijt|gR_i'}} \times \underbrace{\frac{\exp\left(\frac{\overline{U}_{ijt}}{1-\lambda}\right)}{\exp\left(\frac{I_{igR_i'}}{1-\lambda}\right)}}_{\mathbb{P}_{igt|R_i'}}}_{\mathbb{P}_{ijt|R_i'}} \times \underbrace{\frac{\exp\left(\frac{\overline{V}_{tR_i'}}{\sigma_{\bar{\varepsilon}}(1-\varkappa)}\right)\left[\sum_{\tilde{R}_i \in \vartheta} \exp\left(\frac{\overline{V}_{t\tilde{R}_i}}{\sigma_{\bar{\varepsilon}}(1-\varkappa)}\right)\right]^{-\varkappa}}{\sum_{\tilde{\vartheta}=0}^{2}\left[\sum_{\tilde{R}_i \in \tilde{\vartheta}} \exp\left(\frac{\overline{V}_{t\tilde{R}_i}}{\sigma_{\bar{\varepsilon}}(1-\varkappa)}\right)\right]^{1-\varkappa}}}_{\mathbb{P}_{R_i'}}, && \text{(24c)}
\end{aligned}
$$

$$
i = 1, \dots, I_t, \qquad j \in J_t, \qquad g \in \{0, 1, 2\}, \qquad \vartheta \in \{0, 1, 2\} \qquad t = 1, \dots, T,
$$

where Λ is the powerset of all retailers and we followed the same derivation as in equation (6) with $\mathbb{P}_{R_i'}$ given by equation (23). Then, equation (24) can be replaced in the market share function (7).

Allowing for the unobserved search-cost heterogeneity discussed in this subsection adds an additional search parameter to the estimation routine, $\varkappa$. The demand nesting parameter, λ, and the search nesting parameter, $\varkappa$, enter the unconditional choice probability, $\mathbb{P}_{ijt}$ in equation (24), in different ways through the net indirect utility, $\overline{U}_{ijt}$, and the net expected value of searching, $\overline{V}_{tR_i}$, respectively. Under assumptions 1, 2, and 3b in Subsection 4.2, the parameter $\varkappa$ is identified using an additional ratio of probabilities in t''' yielding to a system of three equations in $\bar{S}$, $\sigma_{\bar{\epsilon}}$, and $\varkappa$.

Table 1: Sales Percentage to Consumers by Manufacturer, Retailer, and Product.

Panel A: Sales to Consumers by Manufacturer and Retailer (as percentage of total sales)

	Seller	Manufacturer m_1	m_2	m_3	m_4	Total
VSC Retailers	r_4^v	1.06	2.34	0.63	2.34	6.36
	r_5^v	0.54	1.24	0.66	0.96	3.41
	r_6^v	3.31	5.35	1.26	5.32	15.25
	r_7^v	1.43	4.61	1.68	13.53	21.25
	r_8^v	0.18	1.36	0.37	–	1.91
	r_9^v	6.97	23.86	5.86	0.30	37.00
DSC Retailers	r_1^d	1.51	–	–	–	1.51
	r_2^d	–	8.79	–	–	8.79
	r_3^d	–	–	4.52	–	4.52
Total		15.01	47.56	14.98	22.45	100.00

Panel B: Sales to Consumers by Manufacturer, Retailer, and Display Type (as percentage of total sales)

	Seller	2 m^2 panel				Senior				Other				Total 3	Total 4
		m_1	m_2	m_3	m_4	m_1	m_2	m_3	m_4	m_1	m_2	m_3	m_4		
VSC Retailers	r_4^v	1.06	0.94	0.24	–	–	1.40	0.10	–	–	–	0.29	2.34	6.36	85.18
	r_5^v	0.54	1.10	0.28	–	–	0.14	0.22	0.17	–	–	0.16	0.79	3.41	
	r_6^v	3.31	3.20	0.97	1.39	–	2.15	0.19	–	–	–	0.10	3.93	15.25	
	r_7^v	1.43	3.42	0.68	0.28	–	1.06	0.45	–	–	0.13	0.55	13.25	21.25	
	r_8^v	0.18	0.22	–	–	–	1.10	0.16	–	–	0.04	0.21	–	1.91	
	r_9^v	6.93	17.55	3.79	0.10	0.03	5.82	0.53	0.15	0.01	0.49	1.55	0.06	37.01	
DSC Retailers	r_1^d	1.51	–	–	–	–	–	–	–	–	–	–	–	1.51	14.83
	r_2^d	–	5.10	–	–	–	3.49	–	–	–	0.21	–	–	8.80	
	r_3^d	–	–	1.61	–	–	–	0.21	–	–	–	2.70	–	4.52	
Total 1		14.97	31.54	7.56	1.77	0.03	15.17	1.86	0.32	0.01	0.87	5.56	20.36	100	
Total 2		55.84				17.37				26.80					100

Notes: Each cell in Panels A and B corresponds to the percentage of sales to consumers (relative to the total sales' volume to consumers sold in year 2013 in the whole sample) by the corresponding combination of: (1) Manufacturer and Seller in Panel A and (2) Manufacturer, Seller, and Display Format in Panel B. Thus, in each panel, all the numbers sum to 100 (excluding the rows and columns labeled as "Total"). A cell displays the symbol "–" when no sales are observed for such combination. In Panel B, there are a total of 57 cells with positive sales (*i.e* without the symbol "–'), that corresponds to the 57 inside products (see footnote 16). In panel B, "Total 1" refers to the total sum by manufacturer m_i, $i = 1, \ldots, 4$, "Total 2" refers to the total by display format (2 m^2 panel, Senior, and Other), "Total 3" refers to the total sum by retailer r_j^v, $j = 4, \ldots, 9$ and r_j^d, $j = 1, 2, 3$, "Total 4" refers to the total by VSC Retailers (*i.e.*, sum over r_j^v, $j = 1, \ldots, 6$) and by DSC Retailers (*i.e.*, sum over r_j^d, $j = 1, 2, 3$). "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 for definitions of prices and vertical relations in the industry.

Table 2: Wholesale and Retail Prices in the VSC.

Panel A: All Manufacturers and All VSC Retailers

Display Format	Wholesale Price					VSC Price (Retail Price)				
	Median	Mean	SD	Min	Max	Median	Mean	SD	Min	Max
2 m^2 panel	8.34	12.05	12.75	0.81	93.38	9.05	13.14	13.94	0.86	99.39
Senior	12.93	17.23	18.21	0.81	158.06	13.71	18.30	19.46	0.83	165.80
Other	24.79	28.67	26.07	0.34	148.60	27.04	31.76	29.52	0.37	171.99

Panel B: By Manufacturer and All VSC Retailers

Display Format	Manu- facturer	Wholesale Price					VSC Price (Retail Price)				
		Median	Mean	SD	Min	Max	Median	Mean	SD	Min	Max
2 m^2 panel	m_1	8.11	9.39	7.35	1.42	51.64	8.75	10.61	8.26	1.50	56.18
	m_2	10.50	11.99	9.52	2.33	64.80	11.31	13.06	11.33	2.41	83.22
	m_3	6.26	8.64	11.74	1.04	79.45	6.79	9.40	12.73	1.09	81.52
	m_4	12.38	19.80	18.88	0.81	93.38	13.29	21.10	20.22	0.86	99.39
Senior	m_1	16.09	14.95	4.39	9.07	24.13	16.78	15.67	4.49	9.46	25.17
	m_2	6.27	10.77	14.22	0.81	98.39	6.42	11.12	14.59	0.83	100.57
	m_3	9.01	21.76	27.55	2.09	158.06	10.06	23.95	29.69	2.17	165.80
	m_4	18.71	21.07	10.25	6.11	46.45	19.40	22.03	10.85	6.49	53.85
Other	m_1	48.69	42.41	24.94	3.61	83.26	52.58	48.05	29.76	5.09	106.60
	m_2	34.39	37.18	17.99	0.34	117.09	37.97	39.31	18.77	0.37	120.03
	m_3	12.98	28.50	33.93	0.45	148.60	14.66	32.55	39.33	0.64	171.99
	m_4	13.48	15.44	14.73	0.38	57.28	14.44	17.59	16.88	0.41	66.93

Notes: Panel A reports summary statistics of wholesale and VSC prices (*i.e.*, retail prices) for each display format (2 m^2 panel, Senior, and Other) across manufacturers (m_1, m_2, m_3, and m_4) and VSC retailers ($r_4^v, r_5^v, \ldots, r_9^v$), respectively. Panel B reports summary statistics of wholesale and VSC prices across all VSC retailers for each combination of display format and manufacturer. See Table A1 in the Online Appendix for a comparison of summary statistics of wholesale and VSC prices by manufacturer and by VSC retailer for the display format 2 m^2 panel. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 for definitions of prices and vertical relations in the industry.

Table 3: Price Paid by Consumers to in the DSC and VSC.

Panel A: By Display Format, All Manufacturers

Display Format	Sales Channel	Median	Mean	SD	Min	Max
2 m^2 panel	DSC	10.16	12.79	12.29	1.67	66.90
	VSC	9.05	13.14	13.94	0.86	99.39
Senior	DSC	13.61	13.38	4.54	6.30	22.98
	VSC	13.71	18.30	19.46	0.83	165.80
Other	DSC	9.15	14.81	16.36	1.36	63.62
	VSC	27.04	31.76	29.52	0.37	171.99

Panel B: By Display Format and by Manufacturer

Display Format	Manu-facturer	Sales Channel	Median	Mean	SD	Min	Max
2 m^2 panel	m_1	DSC	11.71	12.28	2.88	9.19	19.04
		VSC	8.75	10.61	8.26	1.50	56.18
	m_2	DSC	14.71	19.41	19.07	1.67	66.90
		VSC	11.31	13.06	11.33	2.41	83.22
	m_3	DSC	6.85	6.64	2.23	2.67	10.16
		VSC	6.79	9.40	12.73	1.09	81.52
Senior	m_1	DSC	14.64	14.61	2.65	11.84	19.04
		VSC	16.78	15.67	4.49	9.46	25.17
	m_2	DSC	14.68	14.56	3.93	7.87	21.31
		VSC	6.42	11.12	14.59	0.83	100.57
	m_3	DSC	9.80	11.32	5.52	6.30	22.98
		VSC	10.06	23.95	29.69	2.17	165.80
Other	m_2	DSC	15.84	22.89	20.57	1.36	63.62
		VSC	37.97	39.31	18.77	0.37	120.03
	m_3	DSC	5.46	7.31	4.36	1.87	16.58
		VSC	14.66	32.55	39.33	0.64	171.99

Notes: The table reports summary statistics of the price paid by consumers on sales made in the DSC and in the VSC (column labeled "Sale's Channel"). Panel A reports the summary statistics by display format (2 m^2 panel, Senior, and Other). DSC prices refer to the prices over all sales from manufacturers to consumers in that display format. VSC prices refer to the prices over all sales from retailers that are not manufacturers for that display format. Panel B reports the summary statistics by display format and by the manufacturer. DSC prices in Panel B refer to the manufacturer in each cell (*i.e.*, there is only one manufacturer in each of these cells). VSC prices refer to the prices over all sales from retailers that are not manufacturers for the display format and manufacturer in the relevant cell. Manufacturer m_4, that corresponds to the additional manufacturer that aggregates smaller manufacturers, is not included because it does not perform any sale to the consumers directly (*i.e.*, manufacturer m_4 does not participate in the DSC). Similarly, manufacturer m_1 is not included for the display format "Other" because it does not perform any sale to the consumers directly. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 for definitions of prices and vertical relations in the industry.

Table 4: Quantity Discounts in the VSC but not in the DSC.

Price paid by consumers per m^2	(1)	(2)	(3)	(4)
$\text{Log}(m^2)$	-7.0708***	-1.8348	-6.9948***	-1.5502
	(0.4472)	(1.2105)	(0.4511)	(1.1810)
$\text{Log}(m^2) \times$ VSC		-6.0297***		-6.2510***
		(1.2990)		(1.2576)
Manufacturers Fixed Effects	Yes	Yes	Yes	Yes
Retailers Fixed Effects	Yes	Yes	Yes	Yes
Display Formats Fixed Effects	No	No	Yes	Yes
Months Fixed Effects	No	No	Yes	Yes
Adjusted R^2	0.4081	0.4291	0.4493	0.4723
Number of Observations	570	570	570	570

Notes: All regressions are OLS specifications. The sample is the same sample used for the structural estimation. It corresponds to all purchases of all display formats made by the consumers in the industry. The dependent variable is the price paid by consumers per square meter of advertising in a given month, labeled as "Price paid by consumers per m^2." The variable "$\text{Log}(m^2)$" corresponds to the total square meters of advertising purchased by consumers in that month on a logarithmic scale. The variable "VSC" is a dummy variable that equals 1 if the consumer performed the purchase through a VSC retailer and 0 if the consumer performed the purchase through the DSC retailer. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. Standard errors are in parentheses. *p<0.10; **p<0.05; ***p<0.01.

Table 5: Demand Estimates.

	Logit (1)		Mixed logit (2)		Mixed logit with channel-specific preferences (3)		Mixed logit with channel-specific preferences and costly search (4)	
	Coefficient	St. error	Coefficient	St. error	Coefficient	St. error	Coefficient	St. error
Price:								
- Mean (α)	0.050	(0.001)	0.168	(0.004)	0.057	(0.001)	0.118	(0.002)
- St. dev. (σ_ν)			0.071	(5.8e-05)	0.024	(0.007)	0.057	(0.002)
Firm dummy variables:								
- Manufacturer 1	-0.672	(0.117)	-0.416	(0.198)	-0.142	(0.076)	-0.275	(0.134)
- Manufacturer 2	0.930	(0.103)	1.005	(0.169)	0.336	(0.065)	0.609	(0.115)
- Manufacturer 3	-0.382	(0.096)	-0.493	(0.162)	-0.147	(0.062)	-0.338	(0.110)
- Retailer 1	0.193	(0.257)	0.459	(0.437)	-0.683	(0.168)	0.063	(0.297)
- Retailer 2	-0.659	(0.117)	-0.836	(0.196)	-0.262	(0.075)	0.008	(0.133)
- Retailer 3	-0.909	(0.107)	-0.541	(0.181)	-0.224	(0.069)	0.314	(0.123)
- Retailer 4	2.728	(0.119)	0.128	(0.267)	-0.784	(0.103)	-0.291	(0.182)
- Retailer 5	-0.424	(0.113)	-0.874	(0.186)	-0.257	(0.072)	-0.106	(0.126)
- Retailer 6	0.242	(0.161)	0.129	(0.272)	-0.877	(0.105)	-0.228	(0.185)
- Retailer 7	-0.505	(0.109)	-0.494	(0.179)	-0.164	(0.069)	-0.360	(0.121)
- Retailer 8	-1.867	(0.118)	-1.603	(0.203)	-0.456	(0.078)	-0.525	(0.138)
Product dummy variables:								
- 2 m^2 panel	0.911	(0.085)	0.336	(0.143)	0.156	(0.055)	0.270	(0.097)
- Senior	-0.652	(0.086)	-0.848	(0.145)	-0.194	(0.056)	-0.406	(0.099)
Channel-specific preferences:								
- Nesting parameter (λ)					0.495	(0.002)	0.373	(0.025)
Search parameters:								
- Search cost ($\bar{S}$)							0.182	(0.021)
- Scale of $\tilde{\varepsilon}$ ($\sigma_{\tilde{\varepsilon}}$)							0.116	(0.023)
Model specification:								
- OLS	Yes		No		No		No	
- GMM	No		Yes		Yes		Yes	
- Random coefficients for price	No		Yes		Yes		Yes	
- Channel-specific preferences	No		No		Yes		Yes	
- Costly search	No		No		No		Yes	
- Google search micro moments	No		No		No		Yes	
Value of GMM Objective:	–		26.762		4.800		29.375	
Number of observations:	570		570		570		570	

Notes: Estimates of selected parameters from the structural demand model. All specifications include dummy variables for manufacturers, retailers, display format, and months fixed effects. The model with search uses the following information structure for $\tilde{F}_p(p)$: consumers know two distributions of prices, the distribution of prices for the DSC retailers and the distribution of prices for the VSC retailers (see footnote 16). See Subsection 2.2 for details about the data used in the estimation. A description of the demand model is in Subsection 4. Details about the estimation procedure are in Subsection 3.1. See Subsection 6.1 for details about the specifications of the models in the different panels. The Google search micro moment is implemented using equation 16. See Subsection 4.2 for details. Standard errors are in parenthesis.

Table 6: Consumer-Level Own-Price Elasticities.

Break-out	**Statistic**	**No Search Model** Mixed logit with channel-specific preferences (3)	**Full Model** Mixed logit with channel-specific preferences and costly search (4)	**Ratio** (No Search/Full) (5)
Panel A: All retailers, manufacturers, display formats, and markets				
All pooled	25th Percentile	-3.49	-11.08	0.31
	50th Percentile	-1.04	-2.12	0.49
	75th Percentile	-0.35	-0.87	0.40
Panel B: By DSC retailers (all manufacturers, display formats, and markets)				
- r_1^d	50th Percentile	-0.70	-0.87	0.80
- r_2^d		-0.81	-1.62	0.50
- r_3^d		-1.80	-3.56	0.51
Panel C: By VSC retailers (all manufacturers, display formats, and markets)				
- r_4^v	50th Percentile	-0.89	-1.49	0.59
- r_5^v		-0.51	-1.10	0.46
- r_6^v		-0.84	-1.22	0.68
- r_7^v		-1.04	-2.25	0.46
- r_8^v		-2.66	-12.77	0.21
- r_9^v		-1.28	-3.31	0.39
Panel D: By manufacturer (all DSC and VSC retailers, display formats, and markets)				
- m_1	50th Percentile	-0.95	-1.93	0.49
- m_2		-1.13	-1.76	0.64
- m_3		-0.83	-2.08	0.40
- m_4		-1.58	-3.53	0.45

Notes: Consumer-level, own-price elasticities from the structural model. Models 3 (mixed logit with channel-specific preferences) and 4 (mixed logit with channel-specific preferences and costly search) correspond to models 3 and 4 in Table 5, respectively. The table presents the consumer-level, own-price elasticities across all display formats and markets disaggregated by type of retailer or manufacturer. The elasticities for all models and panels are the percent change in market share of the product j with a 1 percent change in the price of product j. Panel A displays 25th, 50th, and 75th percentiles of the elasticities across all manufacturers, VSC and DSC retailers, display formats, and markets. Panel B displays 50th percentile of the elasticities for the DSC retailers across all manufacturers, display formats, and markets. Panel C displays 50th percentile of the elasticities for the VSC retailers across all manufacturers, display formats, and markets. Panel D displays 50th percentile of the elasticities by manufacturer across all VSC and DSC retailers, display formats, and markets. The last column shows the ratio of elasticities computed from the model without search (model 3) relative to the elasticity of the model with search (model 4). "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel.

Table 7: Supply Estimates.

	Estimate
Panel A: Marginal costs estimates	
Manufacturers:	
- Constant (γ_0)	0.383
- 2 m^2 panel	0.431
- Senior	0.127
- Manufacturer 1	0.604
- Manufacturer 2	0.508
- Manufacturer 3	0.063
Retailers:	
- Constant	0
Panel B: Distribution of manufacturers' marginal costs	
Mean	0.872
St. dev.	0.353
Min.	0.383
Median	0.877
Max.	1.418
Panel C: Bargaining weight estimates (mean)	
Bargaining weight retailers ($\bar{\nu}_{rmj}$)	0.240
Bargaining weight manufacturers (1-$\bar{\nu}_{rmj}$)	0.760
$\bar{\delta}^S_{rmj}$	0.806

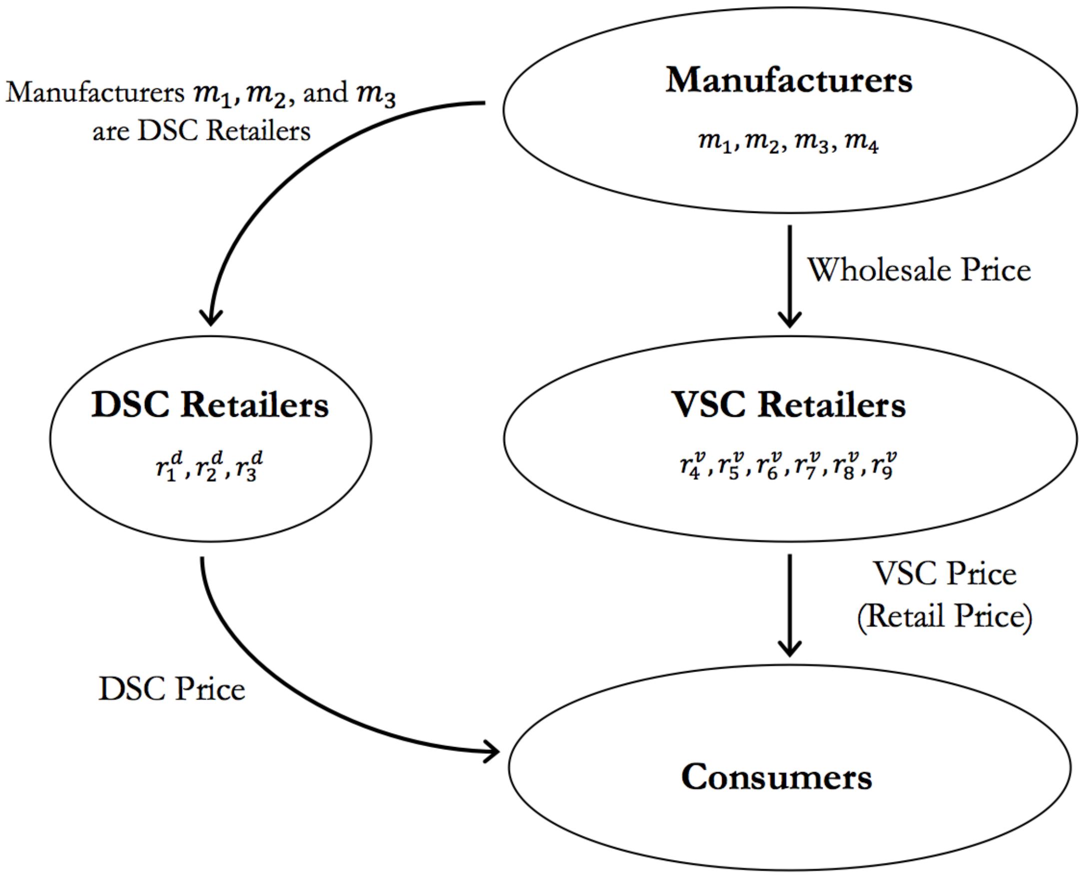
Notes: Estimates of selected parameters from the structural supply model. The supply estimates use the estimated demand model 4 from Table 5. A description of the supply model is in Subsection 3.2. Details about the estimation procedure for the supply model are in Subsection 5. See Subsection 6.2 for details about the estimates. The estimates in panel C refer to the mean (across retailers, manufacturers, and display formats) of the variables as defined in subsections 3.2 and 6.2 and are denoted with upper bars.

Table 8: Counterfactual Results.

Outcome variables	**Baseline**	**Intermediaries do not provide:** Consulting services (1)	Search services (2)	Purchase-aggregation services (3)	Consulting, search, nor purchase-aggregation services (4)
Inside share (percentage)	70.63	69.61	67.45	65.33	61.98
DSC sales as a fraction of inside sales (percentage)	18.25	19.91	18.31	25.92	28.01
Mean posted price (Euros per square meter)	8.29	8.47	8.28	11.81	12.03
Mean paid price (Euros per square meter)	8.73	8.71	8.73	10.98	11.01
Number of retailers searched	5.77	5.79	5.47	5.74	5.50
Count of search costs	5.77	5.79	7.79	5.74	7.77
Change in consumer surplus (Euros per square meter)	–	-0.95	-11.60	-1.79	-14.28

Notes: Counterfactual results using model 4 from Table 5 and the supply estimates from Table 7. The row labeled "Inside share" reports the fraction of the total potential size of the market that resulted in purchases of the inside products. The row labeled "DSC as fraction of inside" reports the fraction of those purchases of the inside products made through the Direct Sales Channel (DSC). The row labeled "Mean posted price" reports the mean price posted for the inside products. The row labeled "Mean paid price" reports the mean price weighted by the quantity purchased. The row labeled "Number of retailers searched" reports the mean number of retailers searched by the consumers (both in the DSC and VSC). The last row labeled "Change in consumer surplus" reports the change in the total consumer surplus of each column, relative to the baseline, computed using the weighted sum across types of consumers of the compensating variation using equation 22. The column labeled "Baseline" reports the previous measures for the baseline model 5 from Table 5. Columns 1 to 4 reports the previous measures for each of the counterfactual scenarios defined in Subsection 7.2. In column 4, the change in consumer surplus is computed by simulating simultaneously the counterfactuals in columns 1, 2, and 3, which is not equivalent to the sum of the change in consumer surplus in these columns. See Section 7 for details.

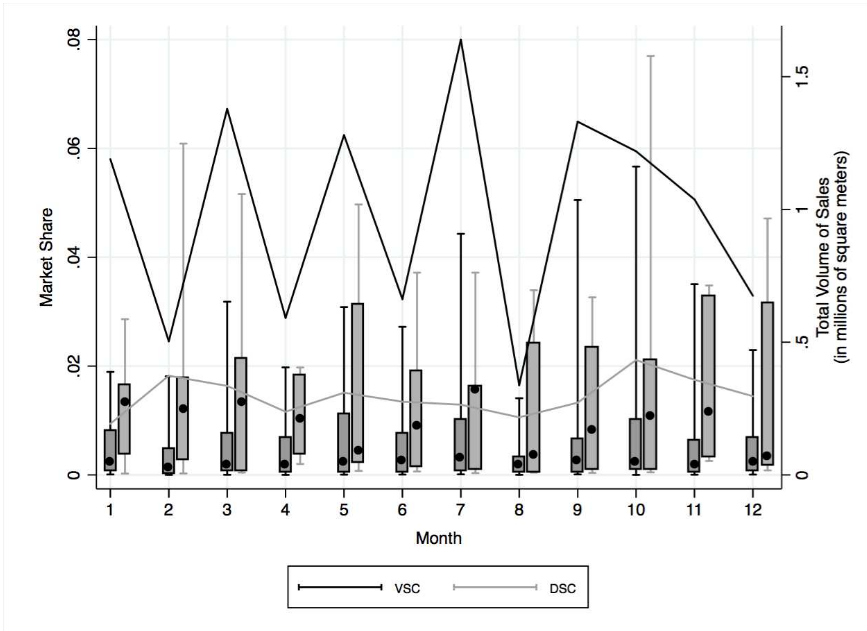
Figure 1: The Portuguese Outdoor Advertising Industry.



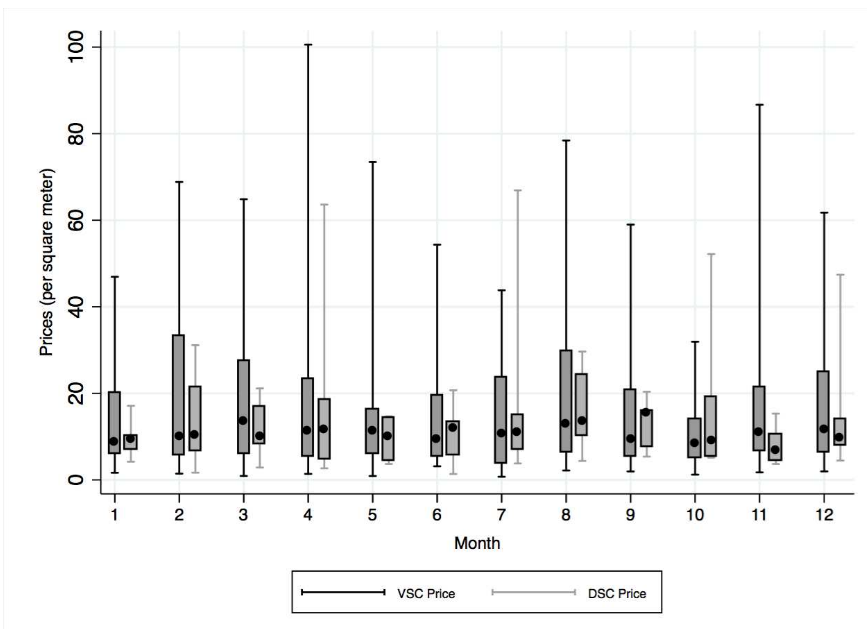
Notes: The figure displays the vertical relations in the Portuguese outdoor advertising industry. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. The manufacturers $(m_1, \ldots, m_4)$ sell their products to the VSC retailers $(r_4^v, \ldots, r_9^v)$ charging wholesale prices. The VSC retailers sell to consumers, charging VSC prices (or retail prices). The three main manufacturers (m_1, m_2, m_3) also sell directly to the consumers through the DSC. This feature is captured in the diagram by the DSC retailers (r_1^d, r_2^d, r_3^d), which correspond to the large manufacturers charging a DSC prices to the consumers.

Figure 2: Market Shares, Total Volume, and Prices by Month.

Market Shares and Total Volume



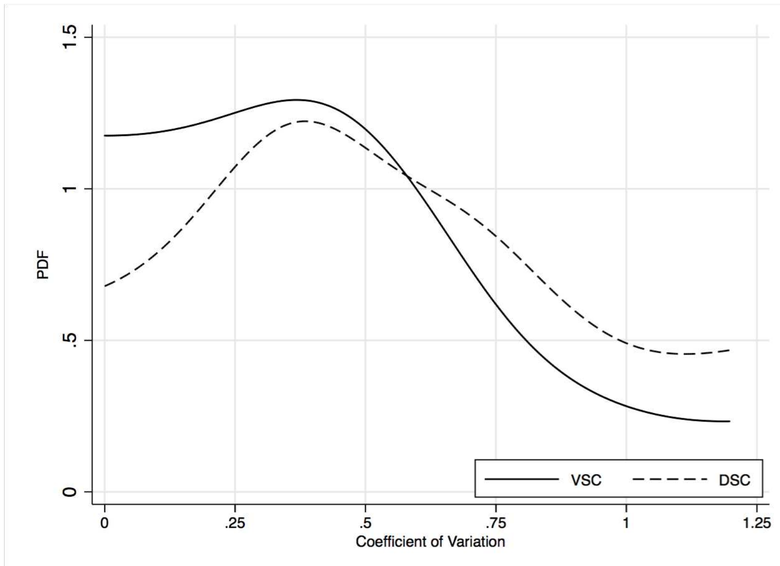
Prices



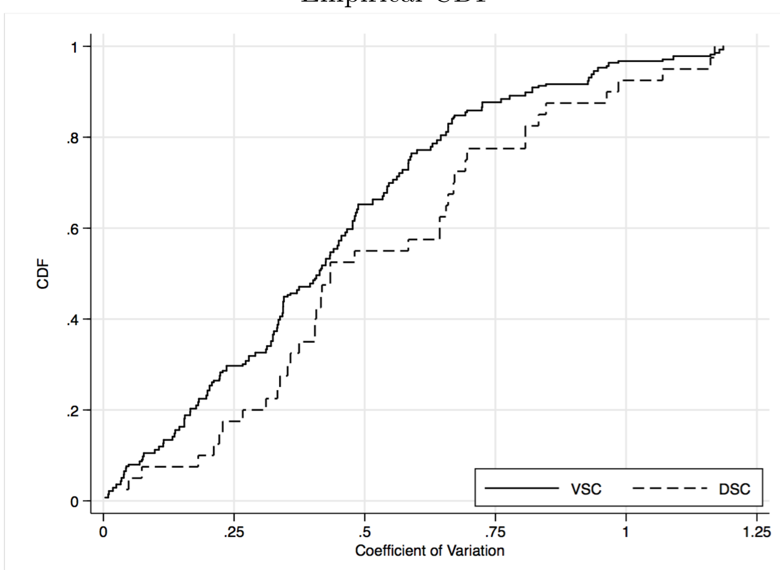
Notes: The top panel displays the distribution of market shares and total volume by month. The left vertical axis shows the distribution of market shares each month, distinguishing the sales to consumers in the VSC and DSC. The right vertical axis shows the total sales volume from each month (horizontal series) distinguishing the sales to consumers in the VSC and DSC. The bottom panel displays the distribution of prices (per square meter) each month, distinguishing the sales to consumers in the VSC and DSC. Each vertical box displays the 95th percentile (upper whisker), 75th percentile (upper hinge), median (black circle marker), 25th percentile (lower hinge), and 5th percentile (lower whisker). The maximum market share by month are as follows (the first number refers to the sales on the VSC and the second number refers to the sales in the DSC): January (0.188, 0.029), February (0.028, 0.061), March (0.218, 0.052), April (0.024, 0.020), May (0.142, 0.050), June (0.032, 0.037) July (0.164, 0.037), August (0.016, 0.034), September (0.139, 0.033), October (0.066, 0.077), November (0.139, 0.035), December (0.038, 0.047). "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 for definitions of prices and vertical relations in the industry.

Figure 3: Distribution of Coefficient of Variation.

Density Estimate



Empirical CDF



Notes: The figure displays the kernel density estimate (top panel) and empirical cumulative distribution (bottom panel) of coefficient of variation of prices (CV) for sales to consumers in the VSC and DSC, conditional on quantity discounts. To perform the estimation we proceed in three steps. First, we define the unit of analysis as a tuple (Display Format, Month, Volume Percentile), where "Display Format" are the display formats as defined in Subsection 2.1, "Month" are the months of the year, and "Volume Percentile" are the percentiles in the volume variable that account for quantity discounts. Second, for each unit of analysis (*i.e.* tuple as defined above) we compute the CV (*i.e.*, the variation of prices is within tuple). Third, we estimate the kernel density and empirical cumulative distribution as follows. Let cv denote realized CV in each tuple $j \in \{1, \ldots, J\}$. We estimate the probability density function for sales made to consumers through retailers and manufacturers, $f\left(cv\right)$, as: $\hat{f}_K\left(cv; h\right) = \frac{1}{J\,h}\sum_{j=1}^{J} K\left(\frac{cv - cv(j)}{h}\right)$, where $K\left(z\right)$ is a standard univariate gaussian kernel function, h is the bandwidth that we choose by cross validation, and $cv(j)\,, j = 1, \ldots, J$ are the CV in each tuple. Given that the price distribution has its domain bounded we use a renormalization method to deal with the boundaries when estimating the probability density function of CV. We estimate the empirical cumulative distribution of CV, $F\left(cv\right)$, as: $\hat{F}_J\left(cv\right) = \frac{1}{J}\sum_{j=1}^{J} \mathbf{1}\left\{cv(j) \leq cv\right\}$, where $\mathbf{1}\left\{A\right\}$ is the indicator function of the event A. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 for definitions of prices and vertical relations in the industry.

Online Appendix to:
Measuring the Welfare of Intermediaries

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Appendix

Contents

B Additional Details Regarding the Industry, Data, and Analysis

B.1 Additional Description of the Industry

Differentiation. Retailers sell advertising space and other services, such as consulting. Display formats from a given, specific manufacturer sold through different retailers are differentiated products. Manufacturers are not necessarily present at the same locations at all times. They do not have identical networks. Manufacturers also offer differentiated products. Finally, some combinations of display formats, manufacturers, and retailers may not be available at a given time. Consumers ought to consider not only the attributes of the advertising space they require but also the characteristics of the retailers and manufacturers when searching among retailers and manufacturers.

Payment Schedules. Contracts and payment schedules between manufacturers and VSC retailers are negotiated because all participants in the industry are firms. Manufacturers charge a price schedule that consists of a linear price and quantity discounts as a function of the total sales. Consumers' purchases in the DSC exhibit no quantity discounts (Table 4 in the article). However, when consumers purchase in the VSC, the quantity discounts that VSC retailers obtain from manufacturers are partially transferred to the consumers. Payment schedules between (VSC or DSC) retailers and consumers are posted prices from the consumers' perspective.

Productive Capacity. In the short run, the productive capacity of each manufacturer and, thus, of the industry is fixed. The capacity is measured by the installed equipment available for outdoor advertising. To operate, manufacturers must first obtain the right to use the space where the display equipment is installed, either through a public tender or direct contracting. This right is obtained from the *site owners*, which are the landlords of the physical space where the display equipment is installed. Site owners include transit authorities, airports, supermarkets, malls, and other public/private landlords. The rights between manufacturers and site owners are set by long-run contracts that last up to 20 years. We focus on the year 2013. The productive capacity is therefore fixed. Inspection of our data on manufacturers' installed capacity and monthly usage indicates that capacity limits are never attained in our sample for any of the manufacturers. That is, manufacturers always operate below capacity.

Market Concentration. The Portuguese outdoor advertising market is quite concentrated both at the manufacturer and retail levels. At the manufacturer level there are three large national firms, m_1, m_2, and m_3. They are responsible of 77.6 percent of the sales in the market (Panel A in Table 1 in the article). The other small local manufacturers are responsible of the reminder of the sales. Manufacturer m_2 is the largest manufacturer with 47.6 percent of the sales. At the retail level, the five largest VSC retailers, retailers $r_4^v, \ldots, r_8^v$, are responsible of 48.2 percent of the sales. Retailer r_7^v is the largest retailer with 21.2 percent of the sales. It is larger than the DSC retailers. The most popular display format are 2 m^2 panels. They encompass 55.8 percent of the sales (Panel B in Table 1 in the article). The largest manufacturer, m_2, is responsible of 56.5 percent of the sales of 2 m^2 panels in the market ($^{31.5}/_{55.8}$). The largest VSC retailer, r_7^v, is responsible of 10.4 percent of the sales of 2 m^2 panels ($^{(1.4+3.4+0.7+0.3)}/_{55.8}$). There is no cross-ownership between manufacturers, nor between retailers, nor between manufacturers and retailers.

B.2 Additional Description of the Data

B.2.1 Procedures to Collect and Clean the Main Data

The data were collected directly from the VSC retailers and manufacturers. The information collected from the VSC retailers includes, for each product and each month of the year 2013: the sales values, the quantity sold in the number of advertising faces and m^2, the cost of the products transacted, the commissions, fees, and quantity discounts received and paid.

Retailer data are complemented with information of direct sales of manufacturers (*i.e.*, sales of manufacturers to consumers) and sales of manufacturers to VSC retailers other than the 5 main VSC retailers. This information was obtained from a survey to the 3 main manufacturers, J.C. Decaux, Cemusa, and Mop, and includes the same information previously described for the VSC retailers.

We exclude observations with a ratio of median absolute deviation (MAD) of m^2 sold in natural logarithm (logs) to the standard deviation larger than 3 (11 observations dropped),[1] with a ratio of MAD of wholesale price in logs to the standard deviation larger than 3 (12 observations dropped), with a ratio of MAD of the retail price in logs to standard deviation larger than 3 (6 observations dropped), panels sold in airports (9 observations dropped).[2] We further aggregate all monthly sales through groups that are not the ones that we surveyed in a single product (54 observations collapsed).

B.2.2 Google-Search Data

We use Google-search data to generate micro moments used to identify the search parameters on the demand side. The Google-search data were obtained directly from Google Trends Portugal from the link below, and accessed on August 30, 2017:

https://trends.google.com/trends/explore?date=2013-01-01%202013-12-31&geo=PT

The raw Google-search data correspond to weekly searches for the period under study in Google Portugal (https://www.google.pt/) of the names of the retailers spelled as follows: cemusa, havas, ipg, jcdecaux, mop, omnicom, pmg, and wpp. These retailers correspond, respectively, to the following retailers in the data: Cemusa, Havas, Megameios, JCDecaux, Mop, Opusopera, Powermedia, and Group M. For robustness, we performed the search in Google Portugal for each of these retailers with the names spelled as above. In all cases, the first result displayed by Google Portugal was the webpage of the retailer. We use these raw data to generate the variables defined next. For the micro moments in Section 6 in the article, we use the mean weekly searches for the previous 3 months.

[1] The median and standard deviation are always specific to each display format.

[2] Panels at airports are typically negotiated on a case-by-case basis and are substantially more expensive.

Google-Search Variables Definitions

- Mean weekly searches previous month. Mean per month of weakly searches using the previous month.

- Mean weekly searches previous 3 months. Mean per month of weakly searches using the mean over the previous 3 months.

- Mean weekly searches previous 6 months. Mean per month of weakly searches using the mean over the previous 6 months.

- Mean weekly searches moving average. Mean per month of weakly searches using a three-period moving average.

- Total searches previous month. Total searches per month using the previous month.

- Total searches previous 3 months. Total searches per month using the mean of the previous 3 months.

- Total searches previous 6 months. Total searches per month using the mean of the previous 6 months.

- Total searches moving average. Total searches per month using a three-period moving average.

The idea behind the variables using moving averages is to capture an adaptive expectation of the searches based on information on these lags. That is, they are a proxy for what could consumers forecast for the current visibility of a retailer based on the past values, using the fixed weighting scheme determined by the moving average.

The measures of price dispersion and Google searches are positively correlated. The pairwise correlation between the level of Google searches and the level of retail prices is 0.2805. The coefficient of a regression of the level of retail prices on the level on Google searches plus fixed effects is 0.184, statistically different from zero at the 1 percent level (similarly for the next coefficients). Using the standard deviation (for both retail prices and Google searches), the pairwise correlation and regression coefficients are 0.320 and 0.344, respectively. Using the coefficient of variation (for both retail prices and Google searches), the pairwise correlation and regression coefficients are 0.161 and 0.077, respectively.

We interpret the Google searches as a proxy for the visibility of the retailer not necessarily as a proxy for price dispersion itself nor a reduced-form measure of the observed price dispersion. Of course, price levels and price dispersion are determined by the extent of search frictions in the market and, in particular, retailer visibility, as explained in Section 4 in the article. The reported reduced-form measures can be thought of as an approximate measure of the level of frictions in the marketplace.

B.2.3 Additional Summary Statistics

Table A1: Wholesale and Retail Prices in the VSC: By Manufacturer and by VSC Retailer, Display Format: 2 m^2 panel.

Manu-facturer	VSC Retailer	Wholesale Price Median	Mean	SD	Min	Max	VSC Price (Retail Price) Median	Mean	SD	Min	Max
m_1	r_4^v	8.01	7.75	1.02	5.68	9.41	8.40	8.30	1.11	6.11	10.27
	r_5^v	9.84	9.29	2.77	3.36	13.97	11.13	11.06	2.35	7.42	15.40
	r_6^v	2.94	3.72	1.89	1.42	7.25	3.20	4.01	2.05	1.50	8.19
	r_7^v	5.92	6.00	1.31	3.51	8.29	6.20	6.27	1.35	3.64	8.61
	r_8^v	10.50	11.58	2.92	8.10	16.27	11.54	12.94	3.46	8.94	19.42
	r_9^v	12.68	18.29	13.08	5.55	51.64	19.11	21.36	13.89	7.38	56.18
m_2	r_4^v	11.95	11.60	2.71	6.92	16.23	12.28	11.97	2.77	7.31	16.70
	r_5^v	11.62	12.70	5.58	5.76	29.02	11.94	13.42	5.51	7.02	29.92
	r_6^v	5.10	5.59	2.76	2.33	11.34	5.28	5.77	2.82	2.41	11.62
	r_7^v	8.64	9.64	4.17	4.79	20.64	9.01	10.02	4.27	4.94	21.19
	r_8^v	9.54	17.05	17.52	3.79	55.53	10.59	18.34	18.77	3.92	60.76
	r_9^v	14.21	19.99	16.30	8.19	64.80	16.96	23.92	20.32	10.97	83.22
m_3	r_4^v	7.07	7.50	1.14	6.47	9.93	7.28	7.71	1.15	6.79	10.28
	r_5^v	6.07	7.99	5.44	4.20	22.56	7.32	8.92	5.65	4.88	24.28
	r_6^v	3.42	3.78	2.30	1.04	8.79	3.58	4.02	2.41	1.09	9.34
	r_7^v	6.29	14.64	22.20	2.96	79.45	6.49	15.14	22.74	3.17	81.52
	r_8^v	4.51	5.28	2.24	3.57	11.16	4.94	5.72	2.29	4.05	11.63
	r_9^v	6.97	12.86	15.85	5.24	51.92	9.44	15.63	19.78	5.49	64.36
m_4	r_4^v	11.48	21.56	20.72	5.29	61.70	11.60	22.35	21.71	5.34	61.65
	r_5^v	40.44	34.72	14.47	18.48	56.84	43.47	37.48	16.88	18.92	64.88
	r_6^v	3.42	3.17	1.68	0.81	6.04	3.52	3.27	1.72	0.86	6.20
	r_7^v	11.42	12.41	3.32	7.43	18.40	11.98	13.29	3.75	7.94	19.94
	r_9^v	30.91	31.17	23.52	9.94	93.38	33.10	33.42	24.67	11.91	99.39

Notes: The table reports summary statistics of wholesale and VSC prices (*i.e.*, retail prices) in the VSC for the display format 2 m^2 panel for each combination of manufacturer (m_1, m_2, m_3, and m_4) and VSC retailer ($r_4^v, r_5^v, \ldots, r_9^v$) across months of the year. This table corresponds to Table 2, Panel B, sub-panel 2 m^2 panel in the article, disaggregated by retailer that is not manufacturer. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 in the article for definitions of prices and vertical relations in the industry.

B.3 Additional Preliminary Analysis

B.3.1 Seasonalities and Monthly Variation

Market Shares and Quantities. The top panel in Figure 2 in the article shows monthly seasonal variations in total volume and market shares within the month. The top panel shows the total volume sold each month (right vertical axis) distinguishing the sales to consumers in the VSC and DSC. The total volume purchased in the Portuguese advertising industry increases during the summer. Total volume varies substantially by month, reflecting the monthly variation in the purchases made in the VSC. The figure also shows the distribution of products' market shares (left vertical axis) for each month distinguishing sales to consumers in the VSC and DSC. There is a large variation in market shares both in the VSC and DSC.

Seasonal variations in the Portuguese advertising industry have two main components. First, a deterministic component, whereby the demand for advertising increases during certain months of the year (*e.g.*, summer vacation). Second, a non-deterministic component, whereby individual firms make specific advertising decisions on certain months of the year based on their needs (firms launching a new product in September, advertising in December before Christmas, *etc.*). The deterministic component explains the increase in advertising during the summer. The non-deterministic component explains the monthly volatility.

Differentiation in the application studied primarily arises due to the location of the display formats. A given manufacturer provides formats to one VSC retailer in one location and other VSC retailers in a different location. The locations are *ex ante* unknown to the consumers. They vary from month to month due to the availability of the formats in the manufacturers' network.

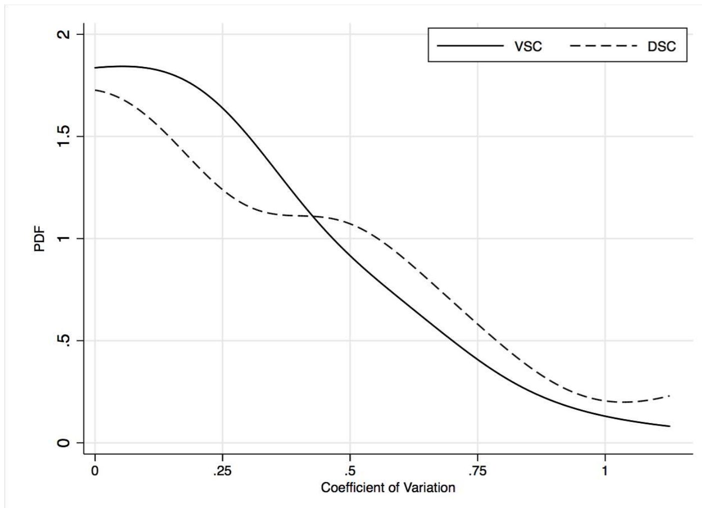
Prices. The bottom panel in Figure 2 in the article shows that the within monthly variation in prices is larger than the variation across months. The bottom panel displays the distribution of prices paid by consumers each month distinguishing sales to consumers in the VSC and DSC. The distribution of prices of sales made in the VSC is more disperse than the one in the DSC. It is due to the presence of quantity discounts on the sales made in the VSC that are not present in the DSC (table 4 in the article). Conditional on quantity discounts, the distribution of prices of sales made in the VSC is less disperse as discussed in the paper.

B.3.2 Price Dispersion and Returns to Consumer Search

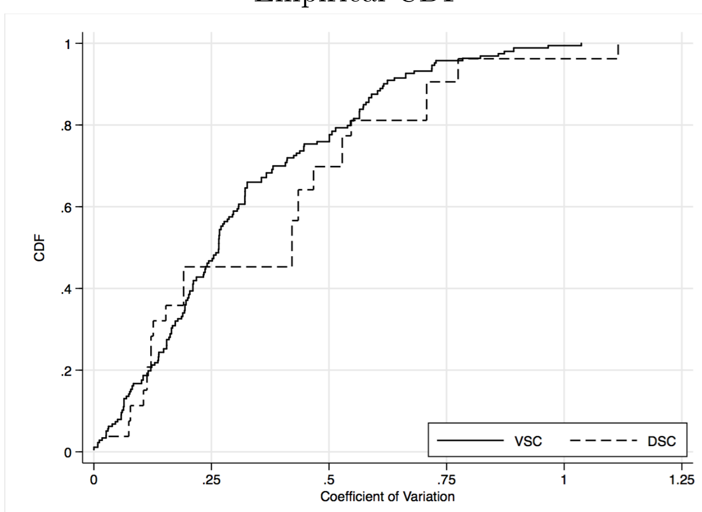
One can also measure the variation in prices across identical goods sold by the same retailer holding constant the manufacturer, the month of the year (seasonal effects), and the volume percentile (quantity discounts). We cannot hold constant, however, both the retailer-manufacturer and the month of the year due to the nature of our data. We do not observe the individual transactions of the consumers, only the total transactions per month per product and per retailer-manufacturer. Figure 3 in the article measures price dispersion across retailers holding constant the display format, the month of the year, and the volume percentile (quantity discounts). Figure A1 below measures price dispersion across months holding constant the display format, the manufacturer, the retailer, and the volume percentile. Similar results are obtained.

Figure A1: Distribution of Coefficient of Variation.

Density Estimate



Empirical CDF



Notes: The figure displays the kernel density estimate (top panel) and empirical cumulative distribution (bottom panel) of coefficient of variation of prices (CV) for sales made to consumers through retailers and manufacturers, conditional on quantity discounts. To perform the estimation we proceed in three steps. First, we define the unit of analysis as a tuple (Display Format, Manufacturer, Retailer, Volume Percentile), where "Display format" are the display formats as defined in Subsection 2.1 in the article, " Manufacturer" are the manufacturers of the product ($M_1, \ldots, M_4$), "Retailer" are the VSC retailers ($r_4^v, \ldots, r_9^v$) and DSC retailers (r_1^d, r_2^d, r_3^d), and "Volume Percentile" are the percentiles in the volume variable (to account for quantity discounts). Second, for each unit of analysis (*i.e.*, tuple as defined above) we compute the CV (*i.e.*, the variation of prices is within tuple). Third, we estimate the kernel density and empirical cumulative distribution as follows. Let cv denote realized CV in each tuple $j \in \{1, \ldots, J\}$. We estimate the probability density function for sales made to consumers through retailers and manufacturers, $f(cv)$, as: $\hat{f}_K(cv; h) = \frac{1}{J\,h} \sum_{j=1}^{J} K\left(\frac{cv - cv(j)}{h}\right)$, where $K(z)$ is a standard univariate gaussian kernel function, h is the bandwidth that we choose by cross validation, and $cv(j)$, $j = 1, \ldots, J$ are the CV in each tuple. Given that the price distribution has its domain bounded we use a renormalization method to deal with the boundaries when estimating the probability density function of CV. We estimate the empirical cumulative distribution of CV, $F(cv)$, as: $\hat{F}_J(cv) = \frac{1}{J} \sum_{j=1}^{J} \mathbf{1}\{cv(j) \leq cv\}$, where $\mathbf{1}\{A\}$ is the indicator function of the event A. "DSC" stands for Direct Sales Channel. "VSC" stands for Vertical Sales Channel. See Figure 1 in the article for definitions of prices and vertical relations in the industry.

C Random-Coefficient Nested-Logit Model with Search

In this appendix, we compute the choice probabilities, maximum expected value, and welfare for the nested-logit random-coefficient model with search. To facilitate the reading we repeat the notation of the model in Subsection C.1.

C.1 Notation Overview

The indirect utility of consumer i for inside product j in market t conditional on the set of retailers searched, R_i, is:

$$U_{ijt|R_i} = -\alpha_i p_{jt} + x_{jt}\beta + \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D + \xi_{jt} + \hat{\varepsilon}_{ijt},$$

$$i = 1, \ldots, I_t, \qquad j \in \hat{J}_{tR_i} = \{\hat{j} : \hat{j} \in J_t \text{ is sold by retailer } r \in R_i\} \cup \{0\}, \qquad t = 1, \ldots, T,$$

where R_i denotes the subset of retailers searched; $\hat{J}_{tR_i}$ is the consideration set of consumer i, given by the subset of products sold by all the searched retailers and the outside product; p_{jt} is the price of product j in market t; x_{jt} is a S-dimensional row vector of observable characteristics of product j in market t; τ_d^D, τ_m^D, τ_r^D, and τ_t^D capture the preferences for display format d, manufacturer m, retailer r, and monthly seasonal effects in market t, using fixed dummy variables for display format, manufacturer, retailer, and monthly seasonal effects, respectively; ξ_{jt} is the valuation of unobserved by the econometrician characteristics of product j in market t; $\hat{\varepsilon}_{ijt} = \zeta_{igt} + (1-\lambda)\varepsilon_{ijt}$, is a stochastic term; $g \in \{0, 1, 2\}$ define three groups (or nests) of nonoverlapping products for the outside product (denoted $g = 0$ with only one product), the products sold by the DSC retailers (denoted $g = 1$), and the products sold by the VSC retailers (denoted $g = 2$); ζ_{igt} has a unique distribution such that $\hat{\varepsilon}_{ijt}$ is extreme value; λ is a nesting parameter such that $0 \leq \lambda < 1$; $\alpha_i = \alpha + \sigma_\nu \nu_i$, $\nu_i \sim P_\nu(\nu_i) = \mathcal{N}(0, 1)$, are individual-specific parameters that capture consumers' preferences for price; and β is a S-dimensional vector of parameters. In each market t, we normalize the characteristics of the outside product, $j = 0$, such that $p_{0kt} = x_{0t} = \tau_0^D = \tau_0^D = \tau_0^D = \tau_t^D = \xi_{0t} = 0$ for all t. Denote by $\overline{U}_{ijt} \equiv -\alpha_i p_{jt} + x_{\hat{q}t}\beta + \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D + \xi_{jt}$ and by $\delta_{jt} \equiv -\alpha p_{jt} + x_{jt}\beta + \tau_d^D + \tau_m^D + \tau_r^D + \tau_t^D + \xi_{jt}$. Then $\overline{U}_{ijt} = \delta_{jt} - \sigma_\nu \nu_i p_{jt}$.

C.2 Choice Probabilities

The probability that consumer i chooses product $\hat{j}$ in group $\hat{g}$ conditional on the searched retailers, R_i, denoted by $P_{i\hat{j}t|R_i}$, is given by:

$$
\begin{aligned}
\mathbb{P}_{i\hat{j}t|R_i} &= \frac{\exp\left(\frac{\overline{U}_{i\hat{j}t}}{(1-\lambda)}\right)\left[\sum_{\tilde{j}\in g}\exp\left(\frac{\overline{U}_{i\tilde{j}t}}{1-\lambda}\right)\right]^{-\lambda}}{\sum_{\tilde{g}=0}^{2}\left[\sum_{\tilde{j}\in\tilde{g}}\exp\left(\frac{\overline{U}_{i\tilde{j}t}}{1-\lambda}\right)\right]^{1-\lambda}}, && \text{(C.1a)}\\
&= \frac{\exp\left(\frac{\overline{U}_{i\hat{j}t}}{1-\lambda}\right)}{\exp\left\{\log\left[\sum_{\hat{j}\in\hat{g}}\exp\left(\frac{\overline{U}_{i\hat{j}t}}{(1-\lambda)}\right)\right]\right\}} \times \frac{\exp\left\{\log\left[\sum_{\hat{j}\in\hat{g}}\exp\left(\frac{\overline{U}_{i\hat{j}t}}{(1-\lambda)}\right)\right]^{1-\lambda}\right\}}{\exp\left\{log\left[\sum_{\hat{g}=0}^{2}\exp\left(\log\left\{\sum_{\tilde{j}\in\tilde{g}}\exp\left[\frac{\overline{U}_{i\tilde{j}t}}{(1-\lambda)}\right]\right\}^{1-\lambda}\right)\right]\right\}},\\
&= \frac{\exp\left(\frac{\overline{U}_{i\hat{j}t}}{1-\lambda}\right)}{\exp\left\{\log\left[\sum_{\hat{j}\in\hat{g}}\exp\left(\frac{\overline{U}_{i\hat{j}t}}{(1-\lambda)}\right)\right]\right\}} \times \frac{\exp\left\{(1-\lambda)\log\left[\sum_{\hat{j}\in\hat{g}}\exp\left(\frac{\overline{U}_{i\hat{j}t}}{(1-\lambda)}\right)\right]\right\}}{\exp\left\{log\left[\sum_{\hat{g}=0}^{2}\exp\left((1-\lambda)\log\left\{\sum_{\tilde{j}\in\tilde{g}}\exp\left[\frac{\overline{U}_{i\tilde{j}t}}{(1-\lambda)}\right]\right\}\right)\right]\right\}},\\
&= \frac{\exp\left(\frac{\overline{U}_{i\hat{j}t}}{1-\lambda}\right)}{\exp\left(\frac{I_{i\hat{g}R_i}}{1-\lambda}\right)} \times \frac{\exp(I_{i\hat{g}R_i})}{\exp(I_{\hat{g}R_i})}, && \text{(C.1b)}\\
&= \quad \mathbb{P}_{i\hat{g}t|R_i} \quad \times \quad \mathbb{P}_{i\hat{j}t|\hat{g}R_i}, && \text{(C.1c)}
\end{aligned}
$$

$$
i = 1, \ldots, I_t, \qquad \hat{j} \in (\hat{g} \cap \hat{J}_{tR_i}), \qquad \hat{g} \in \{0, 1, 2\}, \qquad t = 1, \ldots, T,
$$

where:

$$
\begin{aligned}
I_{i\hat{g}R_i} &\equiv (1-\lambda)\mathbb{E}\left[\max_{j\in(\hat{g}\cap\hat{J}_{tR_i})} U_{ijt|R_i}\right],\\
&= (1-\lambda)\log\sum_{j\in(\hat{g}\cap\hat{J}_{tR_i})} e^{\overline{U}_{ijt}/(1-\lambda)}, && \text{(C.2a)}\\
I_{\hat{g}R_i} &\equiv \log\left(1 + \sum_{g=1}^{2} e^{I_{i\hat{g}R_i}}\right), && \text{(C.2b)}
\end{aligned}
$$

and where the first equality in (C.1a) follows from the nested-logit choice probability (*e.g.*, McFadden 1978, equation 18); the equality in (C.1b) follows from replacing the definitions of the *inclusive values*, $I_{i\hat{g}R_i}$ and $I_{\hat{g}R_i}$, given by equations (C.2a) and (C.2b), respectively;[3] and where $\mathbb{P}_{i\hat{g}t|R_i}$ is the marginal conditional probability of choosing a product in group $\hat{g}$ given that the product is in the consideration set $\hat{J}_{tR_i}$, and $\mathbb{P}_{i\hat{j}t|\hat{g}R_i}$ is the conditional probability of choosing product $\hat{j}$ given that the product is in group $\hat{g}$ and in the consideration set $\hat{J}_{tR_i}$.

C.3 Maximum Expected Value

Following McFadden (1978),[4] the expected maximum utility conditional on the set of retailers R_i searched is:[5]

$$\mathbb{E}\left[\max_{j\in\hat{J}_t}\left(\overline{U}_{ijt}+\hat{\varepsilon}_{ijt}\right)\right] = \log \sum_{\tilde{g}=0}^{2}\left[\sum_{\tilde{j}\in\tilde{g}}\left(e^{\overline{U}_{i\tilde{j}t}}\right)^{1/1-\lambda}\right]^{1-\lambda} + \hat{\gamma},$$

where $\mathbb{E}(\cdot)$ is the expectation operator taken over $\hat{\varepsilon}_{ijt}$; $\log(\cdot)$ denotes the natural logarithm function; and $\hat{\gamma} = 0.5772$ is the Euler's constant.

Denote by $I_{\hat{g}R_i}$ the *inclusive value* of the set of products from the searched retailers that belong to subset $\hat{g}$ excluding the outside product:

$$I_{\hat{g}R_i} \equiv (1-\lambda)\log \sum_{j\in(\hat{g}\cap\hat{J}_{tR_i}\setminus\{0\})} e^{\overline{U}_{ijt}/(1-\lambda)}, \quad \hat{g}\in\{1,2\}. \tag{C.3}$$

[3] As before, $\mathbb{E}(\cdot)$ is the expectation operator taken over the *i.i.d.* shocks within group $\hat{g}$; the equation (C.2a) follows from the maximum expected value of the logit model (*i.e.*, within group $\hat{g}$) (see, *e.g.*, footnote 5); and equation (C.2b) follows because the inclusive value of the outside product is equal to zero.

[4] Corollary to theorem 1 on pages 82-3, equations (14) and (17).

[5] For the case of the logit model, where ε_{ijt} is a standardized type I extreme value, this expression specializes to $\mathbb{E}\left[\max_{j\in\hat{J}_t}\left(\overline{U}_{ijt}+\varepsilon_{ijt}\right)\right] = \log\sum_{j\in\hat{J}_i} e^{\overline{U}_{ijt}}$, a well-known result.

Then:

$$
\begin{aligned}
\mathbb{E}\left[\max_{j\in\hat{J}_t}\left(\overline{U}_{ijt}+\hat{\varepsilon}_{ijt}\right)\right] &= \log\ \sum_{\tilde{g}=0}^{2}\left[\sum_{j\in\tilde{g}}\left(e^{\overline{U}_{ijt}}\right)^{1/1-\lambda}\right]^{1-\lambda}+\hat{\gamma},\\
&= \log\ \sum_{\tilde{g}=0}^{2}\left[e^{log\left(\sum_{j\in\tilde{g}}e^{\overline{U}_{ijt/1-\lambda}}\right)}\right]^{1-\lambda}+\hat{\gamma},\\
&= \log\ \sum_{\tilde{g}=0}^{2}e^{I_{\tilde{g}R_i}}+\hat{\gamma},\\
&= \log\ \left(1+\sum_{\hat{g}=1}^{2}e^{I_{\hat{g}R_i}}\right)+\hat{\gamma},
\end{aligned}
\tag{C.4}
$$

where the last equality follows because the inclusive value of the outside product is equal to zero.

Then, the expected net value for consumer i of searching a subset of retailers R_i in market t is:

$$
\begin{aligned}
V_{tR_i} = \int \max_{j\in\hat{J}_i}\ U_{ijt}\ \mathrm{d}F_{\hat{\varepsilon}}(\hat{\varepsilon})\ \mathrm{d}F_p(p) - SC_{R_i} + \tilde{\varepsilon}_{itR_i} = \\
\int \log\ \left(1+\sum_{\hat{g}=1}^{2}e^{I_{\hat{g}R_i}}\right)\ \mathrm{d}F_p(p) + \hat{\gamma} - SC_{R_i} + \tilde{\varepsilon}_{itR_i},
\end{aligned}
$$

where SC_{R_i} is the cost of searching the subset of retailers R_i; $\tilde{\varepsilon}_{itR_i}$ is a random shock to the subset of searched retailers that is drawn *i.i.d.* from a type I extreme value distribution with location parameter $\mu_{\tilde{\varepsilon}} = 0$ and scale parameter $\sigma_{\tilde{\varepsilon}} > 0$; and the last equality follows from equation (C.4) with the inclusive value, $I_{\hat{g}R_i}$, defined by equation (C.3).

C.4 Additional Discussion about Identification of Search-Cost Parameters

Assumptions 1 to 3 in the article merit further discussion. The main hypothesis in assumption 1 is that product availability varies exogenously within retailers across markets. This hypothesis is necessary for identification. It is non-testable. We believe it is reasonable in our empirical setting for two reasons. First, manufacturers have limited capacity. Thus, it is not unusual for a given VSC retailer not to have availability of a particular display format from a given manufacturer based on past sales, even if the manufacturer's capacity limit is not reached because the manufacturer may have additional formats to sell directly to consumers or through other VSC retailers. Second, because we observe substantial empirical variation across markets in the number of products available within retailers in the VSC. Such variation occurs because a given manufacturer sells display formats to multiple VSC retailers *and* to consumers. Assumption 1 also presumes full support variation, which is seldom observed in the data. For the estimation in Subsection 4.3 in the article, we propose using several differences of ratios for each retailer across months to incorporate variation in product availability. We compute, for each retailer, the difference between the ratio of probabilities across consecutive months predicted by the model and the Google search measure observed in the data. There is a reasonable variation in these differences for a given retailer across months in the setting studied. We believe that the observed empirical variation is sensible given our linear specification. With a larger number of periods/markets, one may be able to obtain information about the curvature of the search costs.

The key restriction for assumption 2 is that consumers search for VSC retailers but pay search costs for the product of each manufacturer sold by the VSC retailer. We interpret it as the consumers interacting with the different managers within the VSC retailer, who are responsible for the display formats of different manufacturers. If a consumer wants to collect information about the prices of the display formats of the manufacturers carried by the retailer, the consumer needs to contact the various managers. It is a reasonable practice in the outdoor advertising industry studied.

The main insight about using Google searches in assumption 3b is that they capture the visibility of retailers and manufacturers. We do not posit that the search cost is the cost of a Google-search click. If a consumer decides to search for a retailer, then the consumer may Google search such retailer with a certain probability to, *e.g.*, find the retailer's email, phone number, address, *etc.* The consumer incurs the *actual* search cost by gathering such information. For example, by scheduling/having a meeting or sending several emails, the consumer incurs a search cost and learns about the retailer's offerings (*e.g.*, prices, locations of the billboard, *etc.*). One way to rationalize assumption 3b is to assume that the total number of Google searches, $\widehat{G}_{rt}$, and the number of consumers who searched for retailer r, $\widehat{M}_{rt}$, are related as follows:

$$\widehat{G}_{rt} = \kappa \widehat{M}_{rt} + \Xi_{rt}, \tag{C.5}$$

where κ is a scalar, and Ξ_{rt} denote mean zero random variables that are *i.i.d.* across r and t.

With this interpretation, there are two main assumptions in equation (C.5). The first is that Ξ_{rt} are *i.i.d.* across retailers and markets (periods). This assumption would be violated if a significant number of consumers would search more for $\widehat{G}_{1t}$ than $\widehat{G}_{2t}$ because, for example, the name of retailer r_1 coincides (or is similar) to other search queries unrelated to r_1. This effect would confound the Google search for retailer r_1 with the unrelated search query. For example, in an English-speaking country, Google searches for the retailer "Mop" may be confounded with Google searches for the article for cleaning floors. For Google searches in Portugal during the period under analysis, we did not find any confounding searches for any of the names of the retailers. We find that, for *all* retailers and manufacturers, the first result displayed by Google Portugal was the webpage of the corresponding retailer/manufacturer, after performing a search query in Google Portugal with the name of the retailer/manufacturer used to construct the variable.[6] Consumers who performed such searches in Google Portugal are predominantly searching for information about the retailers. We interpret this fact as evidence that these confounding factors do not play a major role in our setting. The second is that the scalar κ is the same across retailers. This assumption would be violated if, for example, consumers would search for retailer r_1 distinctively more online than for retailer r_2, relative to non-online searches (*e.g.*, Yellow-page searches). There are no substantial differences across retailers in

[6]We believe this is a sufficient condition to argue that confounding factors do not bias the Google searches used for the estimation. See Appendix B.2.2 for details about the Google-search data and the names of the retailers.

online searches by consumers in the setting studied. Google searches are a good proxy for searches in our setting because our data include all meaningful transactions in the industry and consumers search for these retailers/manufacturers predominantly online. For these reasons, we believe that the specification in equation (C.5) is sensible in our empirical setting.

C.5 Welfare Measures

The expected consumer surplus, in Euros, for consumer i is given by:

$$\begin{aligned}
\mathbb{E}(CS_i) &= \frac{1}{\alpha_i}\ \mathbb{E}\left\{\max_{R_i'\in\Lambda}\left[\max_{j\in\hat{J}_i}\left(\overline{U}_{ijt}+\hat{\varepsilon}_{ijt}\right)-SC_{R_i}+\tilde{\varepsilon}_{itR_i}\right]\right\}, \\
&= \frac{1}{\alpha_i}\int_{\tilde{\varepsilon}_{ijt}}\left\{\max_{R_i'\in\Lambda}\left[\int_{\hat{\varepsilon}_{ijt}}\left(\max_{j\in\hat{J}_i}\left\{\overline{U}_{ijt}+\hat{\varepsilon}_{ijt}\right\}\ \mathrm{d}F_{\hat{\varepsilon}_{itR_i}}(\hat{\varepsilon}_{itR_i})\right)-SC_{R_i}+\tilde{\varepsilon}_{itR_i}\right]\right\}\mathrm{d}F_{\tilde{\varepsilon}_{itR_i}}(\tilde{\varepsilon}_{itR_i}), \\
&= \frac{1}{\alpha_i}\int_{\tilde{\varepsilon}_{ijt}}\left\{\max_{R_i'\in\Lambda}\left[\log\left(1+\sum_{\hat{g}=1}^{2}e^{I_{\hat{g}R_i}}\right)-SC_{R_i}+\tilde{\varepsilon}_{itR_i}\right]\right\}\ \mathrm{d}F_{\tilde{\varepsilon}_{itR_i}}(\tilde{\varepsilon}_{itR_i})+C_1, \\
&= \frac{1}{\alpha_i}\sigma_{\tilde{\varepsilon}}\log\left\{\sum_{R_i'\in\Lambda}\exp\frac{1}{\sigma_{\tilde{\varepsilon}}}\left[\log\left(1+\sum_{\hat{g}=1}^{2}e^{I_{\hat{g}R_i}}\right)-SC_{R_i}\right]\right\}+C_2,
\end{aligned} \tag{C.6}$$

where the expectation in the first line is taken over both random shocks, $\hat{\varepsilon}_{ijt}$ and $\tilde{\varepsilon}_{ijR_i}$; the third equality follows by computing the maximum expected utility over the shocks $\hat{\varepsilon}_{ijt}$ using equation (C.4) with the inclusive value, $I_{\hat{g}R_i}$, defined by equation (C.3); the fourth equality follows by computing the maximum expected utility over the shocks $\tilde{\varepsilon}_{itR_i}$ (*e.g.*, Ben-Akiva and Lerman 1985, p. 105) with $\sigma_{\tilde{\varepsilon}}$ being the scale parameter of these shocks; and C_1 and C_2 are constants.

D Details About the Supply

D.1 Derivation of the Estimating Equation for the Bargaining Weights.

In this subsection, we compute the equations that we use for the estimation in the supply side. We derive the first-order necessary conditions from the bargaining problem and transform them into an expression that we use to recover the bargaining weights.

Next equation repeats the objective problem to facilitate the reading:

$$
\begin{aligned}
\mathcal{N}_{rmj} &\equiv \left[\sum_{k\in\Omega_r} \left(p_k^* - \omega_k - c_k^r\right) M s_k(\mathcal{P}(\omega)) - \Pi_{r,-j}^{\text{Dist}}\right]^{\nu_{rmj}} \left[\sum_{k\in\Omega_w} \left(\omega_k - c_k^m\right) M s_k(\mathcal{P}(\omega)) - \Pi_{m,-j}^{\text{Dist}}\right]^{1-\nu_{rmj}}, \\
&\equiv \left[\Pi_r^{\text{Dist}}(\omega^*) - \Pi_{r,-j}^{\text{Dist}}\right]^{\nu_{rmj}} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{1-\nu_{rmj}}. \qquad \text{(D.1)}
\end{aligned}
$$

The first-order necessary conditions for ω_j from equation (D.1) are:

$$
\begin{aligned}
&\nu_{rmj} \left[\Pi_r^{\text{Dist}}(\omega^*) - \Pi_{r,-j}^{\text{Dist}}\right]^{\nu_{rmj}-1} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{1-\nu_{rmj}} \frac{\partial \Pi_{rj}^{\text{Dist}}(\omega^*)}{\partial \omega_j} + \\
&\quad (1-\nu_{rmj}) \left[\Pi_r^{\text{Dist}}(\omega^*) - \Pi_{r,-j}^{\text{Dist}}\right]^{\nu_{rmj}} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{-\nu_{rmj}} \frac{\partial \Pi_{mj}(\omega^*)}{\partial \omega_j} = 0. \qquad \text{(D.2)}
\end{aligned}
$$

From the envelope theorem, $\frac{\partial \Pi_m(\omega^*)}{\partial \omega_j} = -\frac{\partial \Pi_m^{\text{Dist}}(\omega^*)}{\partial \omega_j} = M s_j(\mathcal{P}(\omega))$, which means that equation (D.2) simplifies to:

$$
\begin{aligned}
&\nu_{rmj} \left[\Pi_r^{\text{Dist}}(\omega^*) - \Pi_{r,-j}^{\text{Dist}}\right]^{\nu_{rmj}-1} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{1-\nu_{rmj}} - \\
&\quad (1-\nu_{rmj}) \left[\Pi_r^{\text{Dist}}(\omega^*) - \Pi_{r,-j}^{\text{Dist}}\right]^{\nu_{rmj}} \left[\Pi_m(\omega^*) - \Pi_{m,-j}\right]^{-\nu_{rmj}} = 0. \qquad \text{(D.3)}
\end{aligned}
$$

Simplifying equation (D.3):

$$\begin{aligned}\nu_{rmj}\left[\Pi_m(\omega^*)-\Pi_{m,-j}\right]^{1-\nu_{rmj}}-\left(1-\nu_{rmj}\right)\left[\Pi_r^{\text{Dist}}(\omega^*)-\Pi_{r,-j}^{\text{Dist}}\right]\left[\Pi_m(\omega^*)-\Pi_{m,-j}\right]^{-\nu_{rmj}}&=0,\\ \nu_{rmj}\left[\Pi_m(\omega^*)-\Pi_{m,-j}\right]-\left(1-\nu_{rmj}\right)\left[\Pi_r^{\text{Dist}}(\omega^*)-\Pi_{r,-j}^{\text{Dist}}\right]&=0,\\ \left[\Pi_m(\omega^*)-\Pi_{m,-j}\right]-\frac{\left(1-\nu_{rmj}\right)}{\nu_{rmj}}\left[\Pi_r^{\text{Dist}}(\omega^*)-\Pi_{r,-j}^{\text{Dist}}\right]&=0,\\ \left[\Pi_m(\omega^*)-\Pi_{m,-j}\right]-\delta_{rmj}^S\left[\Pi_r^{\text{Dist}}(\omega^*)-\Pi_{r,-j}^{\text{Dist}}\right]&=0,\end{aligned} \tag{D.4}$$

where $\delta_{rmj}^S \equiv \frac{(1-\nu_{rmj})}{\nu_{rmj}} \in (0,1)$.

Now look at the components in equation (D.4), namely, the difference between the profits with agreement and disagreement:

$$\begin{aligned}\Pi_m(\omega^*)-\Pi_{m,-j}&=\sum_{k\in\Omega_m}\left(p_k^*-\omega_k-c_k^r\right)Ms_k(\mathcal{P}(\omega))-\sum_{k\in\Omega_m\backslash j}\left(p_k^*-\omega_k-c_k^r\right)Ms_k^{-j}(\mathcal{P}(\omega)),\\ &=\left(p_j^*-\omega_j-c_j^r\right)Ms_j(\mathcal{P}(\omega))-\sum_{k\in\Omega_m\backslash j}\left(p_k^*-\omega_k-c_k^r\right)M\underbrace{\left[s_k^{-j}(\mathcal{P}(\omega))-s_k(\mathcal{P}(\omega))\right]}_{\Delta s_k^{-j}},\\ &=\left(p_j^*-\omega_j-c_j^r\right)Ms_j(\mathcal{P}(\omega))-\sum_{k\in\Omega_m\backslash j}\left(p_k^*-\omega_k-c_k^r\right)M\Delta s_k^{-j}.\end{aligned} \tag{D.5}$$

where $\Delta s_k^{-j} \equiv s_k^{-j}(\mathcal{P}(\omega)) - s_k(\mathcal{P}(\omega))$ denotes the difference between the market share of product k if product j is offered and if it is not. This expression corresponds to equation (9) in Draganska, Klapper, and Villas-Boas (2010, p. 62). In our case, does not has closed-form solution. It corresponds to the proportion of the market share of product j that is allocated to the other products carried by the retailer or manufacturer. Similarly, for the difference in retail profits, an expression analog to the one in (D.5) is obtained.

Next, replace expression (D.5) and its analog for the the difference in retail profits into (D.4) and divide by M:

$$\left[\left(p_j^* - \omega_j - c_j^r\right) s_j - \sum_{k \in \Omega_m \setminus j} \left(p_k^* - \omega_k - c_k^r\right) \Delta s_k^{-j}\right] - \delta_{rmj}^S \left[\left(p_j^* - \omega_j - c_j^r\right) s_j - \sum_{k \in \Omega_r \setminus j} \left(p_k^* - \omega_k - c_k^r\right) \Delta s_k^{-j}\right] = 0. \tag{D.6}$$

Denote that matrix of shares and changes in shares by:

$$\overline{s} \equiv \begin{bmatrix} s_1 & -\Delta s_2^{-1} & \cdots & -\Delta s_{\mathcal{J}}^{-1} \\ -\Delta s_1^{-2} & s_2 & \cdots & -\Delta s_{\mathcal{J}}^{-2} \\ \vdots & \vdots & \ddots & \vdots \\ -\Delta s_1^{-\mathcal{J}} & -\Delta s_2^{-\mathcal{J}} & \cdots & s_J \end{bmatrix}. \tag{D.7}$$

Finally, rewrite equation (D.6) in matrix form using (D.7):

$$\begin{aligned} \left(\Lambda^{\mathcal{M}} \odot \overline{s}\right) \left(\omega^* - \mathbf{c^m}\right) - \delta^S \left(\Lambda^{\mathcal{R}} \odot \overline{s}\right) \left(\mathbf{p}^* - \omega^* - \mathbf{c^r}\right) = 0, \\ \mathbf{c^m} = \omega^* - \delta^S \left(\Lambda^{\mathcal{M}} \odot \overline{s}\right)^{-1} \left(\Lambda^{\mathcal{R}} \odot \overline{s}\right) \left(\mathbf{p}^* - \omega^* - \mathbf{c^r}\right). \end{aligned} \tag{D.8}$$

We use expression (D.8) for the estimation of the supply side.

E Robustness Analysis: Demand Estimates using Alternative Price Beliefs

Table A2: Demand Estimates using Alternative Price Beliefs.

	Baseline		**Less Information**		**More information**	
	Mixed logit with channel-specific preferences and costly search		Mixed logit with channel-specific preferences and costly search		Mixed logit with channel-specific preferences and costly search	
	(1)		(2)		(3)	
	Coefficient	St. error	Coefficient	St. error	Coefficient	St. error
Price:						
- Mean (α)	0.118	(0.002)	0.095	(0.002)	0.100	(0.002)
- St. dev. (σ_ν)	0.057	(0.002)	0.043	(0.001)	0.046	(0.008)
Firm dummy variables:						
- Manufacturer 1	-0.275	(0.134)	-0.245	(0.130)	-0.263	(0.126)
- Manufacturer 2	0.609	(0.115)	0.575	(0.110)	0.604	(0.107)
- Manufacturer 3	-0.338	(0.110)	-0.274	(0.106)	-0.300	(0.103)
- Retailer 1	0.063	(0.297)	-0.184	(0.286)	-0.044	(0.278)
- Retailer 2	0.008	(0.133)	-0.082	(0.128)	-0.130	(0.124)
- Retailer 3	0.314	(0.123)	0.244	(0.118)	-0.038	(0.115)
- Retailer 4	-0.291	(0.182)	-0.390	(0.175)	-0.276	(0.170)
- Retailer 5	-0.106	(0.126)	-0.190	(0.122)	-0.147	(0.118)
- Retailer 6	-0.228	(0.185)	-0.367	(0.178)	-0.202	(0.173)
- Retailer 7	-0.360	(0.121)	-0.154	(0.117)	0.013	(0.114)
- Retailer 8	-0.525	(0.138)	-0.470	(0.133)	-0.546	(0.129)
Product dummy variables:						
- 2 m^2 panel	0.270	(0.097)	0.230	(0.093)	0.241	(0.091)
- Senior	-0.406	(0.099)	-0.413	(0.095)	-0.442	(0.092)
Channel-specific preferences:						
- Nesting parameter (λ)	0.373	(0.025)	0.409	(0.007)	0.375	(0.017)
Search parameters:						
- Search cost ($\bar{S}$)	0.182	(0.021)	0.051	(0.013)	0.087	(0.107)
- Scale of $\tilde{\varepsilon}$ ($\sigma_{\tilde{\varepsilon}}$)	0.116	(0.023)	0.115	(0.005)	0.113	(0.022)
Model specification:						
- OLS	No		No		No	
- GMM	Yes		Yes		Yes	
- Random coefficients for price	Yes		Yes		Yes	
- Channel-specific preferences	Yes		Yes		Yes	
- Search	Yes		Yes		Yes	
- Google search micro moments	Yes		Yes		Yes	
Price Information Structure:						
- Consumers' beliefs about prices	Two distributions: prices in VSC and DSC		One distribution: with all prices		57 distributions: prices by product	
Value of GMM Objective:	29.375		30.927		32.552	
Number of observations:	570		570		570	

Notes: Estimates of selected parameters from the structural demand model. All specifications include dummy variables for manufacturers, retailers, display format, and months fixed effects. Model 1 is the same as model 4 in Table 5 in the article and is presented to facilitate the comparison. Information structure for $\tilde{F}_p(p)$ in model 1: consumers know two distributions of prices, the distribution of prices for the VSC retailers and the distribution of prices for the DSC retailers. Information structure for $\tilde{F}_p(p)$ in model 2: consumers only know one distribution with the prices for all the products in the market. Information structure for $\tilde{F}_p(p)$ in model 3: consumers know 57 distributions of prices, corresponding to the 57 inside products in the sample. See Subsection 2.2 in the article, and footnotes 16 and 28 in the article for details. See Subsection 2.2 in the article for details about the data used in the estimation. A description of the demand model is in Subsection 4 in the article. Details about the estimation procedure are in Subsection 3.1 in the article. The Google search micro moment is implemented using equation 16 in the article; see Subsection 4.2 in the article for details. Standard errors are in parenthesis.

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