The Value of Online Interactions for Store Execution

Felipe Caro[1] • Victor Martínez-de-Albéniz[2] • Borja Apaolaza[3]

Abstract

Problem definition: Omnichannel retailers interact with customers both online and offline. So far, they have used this richer information to optimize the sales process by designing the right channel and supply chain structures, and by personalizing offer, pricing and promotions. We advance an additional dimension of omnichannel value: retailers can use online clickstreams to better understand customer needs, and optimize store layouts to maximize conversion. ***Methodology/results:*** We develop a model where in-store purchases depend on the customer's shopping list, and the effort required to locate and reach the products within the store. Category location in the store thus drives conversion. We then apply our model to a large home improvement retailer and find that shoppers' preferences are revealed by nearby online traffic, and hard-to-reach locations lead to lower conversion. Finally, we optimize category-location assignments using our demand model and find that putting higher-interest and higher-price items in the most effective locations can increase revenues by about 2% in comparison with models that ignore online clicks. ***Managerial implications:*** We show how using online clickstream information for optimizing offline operations can create significant value. More fundamentally, our results provide a word of caution that in some retail segments like home improvement, longer in-store paths might not necessarily be better.

Keywords: Shopping lists, shopping baskets, clickstream, webrooming, demand estimation, layout

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1. Introduction

Suppose that you manage a home improvement store. You have noticed that a prime location of the store is being used by the "smart-home connectivity" category – which consists of devices that connect remote sensors to monitor the status of a house – but you are thinking that the space is underutilized because the sales of that category are meager. Then, the question is what else to place in that prime location. If you only have access to store sales, then you might consider placing a steady seller such as the locks category. However, if you also had access to clickstream data from shoppers living nearby, you might be able to detect categories that are "punching below their weight", such as laminated flooring in our case study. That is the purpose of this paper.

In the last decade, omnichannel has become a dominating retail strategy in which retailers do not see online and offline as independent channels, but manage them jointly (Gallino and Moreno 2019, Caro et al. 2020). Omnichannel delivers value on multiple dimensions, because it allows customers to learn about the product in one channel, and fulfill the demand in another (Bell et al. 2014). This flexibility implies that retailers are no longer constrained to run a single-channel sales

[1]UCLA Anderson School of Management, Los Angeles, CA 90095, felipe.caro@anderson.ucla.edu
[2]IESE Business School, University of Navarra, Av. Pearson 21, 08034 Barcelona, Spain, valbeniz@iese.edu.
[3]The Wharton School, University of Pennsylvania, Philadelphia, PA 19104, apaolaza@upenn.edu.

process, and have more freedom to optimize the funnel from need to purchase (Wiesel et al. 2011). The additional flexibility requires closer coordination of the operations and marketing functions (Bijmolt et al. 2021), but has the potential to groom more effective interactions with the customer, increasing their satisfaction and delivering higher profits to the retailer.

The literature has identified different ways to extract value from omnichannel. On the one hand, traditional marketing actions can be refined with more precise customer histories, such as targeted advertising or promotions (Goic and Olivares 2019). On the other hand, many decisions in the operational realm have been improved. The design of channels can be optimized by better understanding how offline and online affect each other (Bell et al. 2017, 2020, Kumar et al. 2019, Bar-Gill and Reichman 2020). Information provision can drive the channel choices of the consumers (Gallino and Moreno 2014). Information from online sources can also help predict demand better so inventory levels can be optimized (Huang and Van Mieghem 2014, Cui et al. 2018). Finally, fulfillment flexibility allows firms to better run their supply networks (Hübner et al. 2019).

Most of the strategies described above are effective for firms that have a large online sales channel, but it is less clear how offline-heavy retailers can take advantage of an omnichannel strategy. Moreover, despite the increase of online shopping, retailers keep investing in stores as these remain the primary channel to interact with consumers (Schaverien 2018, Dowsett 2019). According to Bell et al. (2014), the value can be obtained by providing better information online, in a webrooming model. In this paper, we intend to uncover one additional value creation strategy available to omnichannel retailers, which is especially important under webrooming: one can leverage online interactions to detect (true) customer needs at the category level and analyze the determinants of store effectiveness. Namely, we are interested in conversion, measured as the number of sales in the category divided by the number of potential customers that showed interest online in the store vicinity. Note that this definition is different from the common metric used by retailers, who divide sales by footfall, which is problematic because footfall need not be made of shoppers with an interest in the product. In contrast, our definition accounts for such interest, while ignoring the actual number of store visitors.

The conversion process is complex, as visitors' initial shopping intention must translate into store visit first, then into exposure to the wanted products (and others), then into consideration sets, and finally, into purchase. It involves time and effort from the consumers. As a result, a well-engineered layout can help them access their desired products quicker, and they might end up buying with a higher probability (Underhill 2009). Indeed, convenience increases the chances that customers buy: more formally, time pressure and higher search costs decrease sales (Hui et al. 2009b, Brynjolfsson et al. 2011). This is the reason why impulse items such as chocolates are often located near the check-out line, and Amazon has patented the One-Click button to reduce cart abandonment (Wagner and Jeitschko 2017). Unfortunately, the understanding of the relationship between layouts and conversion is limited. While richer displays are known to increase conversion (Boada-Collado and Martínez-de-Albéniz 2020), there is a lack of empirical evidence linking product position in the store with sales. Causal evidence of this kind is hard to obtain, because retailers generally do not know the store visitor's shopping list, and hence they only observe sales performance of a particular store area but not how effective it was in capturing potential purchase intentions. A rare exception is Hui et al. (2013) who collect the planned shopping list of 275 shoppers across 99 categories, and subsequently show that longer in-store paths increase unplanned spending. However, this type of effort is hard to scale. As Goic and Olivares (2019) put it, "In contrast [to online channels], data regarding browsing behavior in retail stores have been, for the most part, nonexistent. Studies that seek to measure the effect of changes in the layout and display of a store have typically used aggregate store-level data to conduct causal analysis." In this paper, we provide one scalable novel way to assess the effects of layout on conversion, which can be used for layout optimization.

For this purpose, we first build a theoretical model where conversion is affected by the physical effort invested by the visitor to locate products in her shopping list. We then work with a large home improvement retailer for which we observe, during seven months, all offline and online activities. For 16 stores, we observe full transaction records, i.e., composition of individual receipts, and category details and precise location within each store. For the online channel, we observe full clickstreams, i.e., all the clicks with timestamps by distinct geolocated origins of internet traffic. For each store and category, we are thus able to count how many different potential customers might be interested in the category. This is a proxy for the number of store visitors genuinely interested in purchasing the category, and we show that it is indeed a strong predictor of category sales. We are then in a position to study how conversion is moderated by location in the store. After controlling for other shopping funnel factors including store, week and category fixed effects, we find that the distance from the store entrance is a critical determinant of conversion, and items easier to reach – closer to the store entrance – exhibit significantly higher conversion. In contrast, we find that spillovers from adjacent categories are not significant (recall that these are home improvement categories for which there is little impulse shopping), which suggests that using store visits to create cross-selling revenue may not always be possible or desirable, as also suggested by Gao and Su (2017a).

The empirical findings pave the way for optimizing store layout. We formulate this question as an assignment optimization problem, and show that revenues can be increased by about 2% when online information is used to decide category locations, in comparison to a model were only offline information about sales is used. This involves a one-time layout change.

Our work thus contributes to the growing literature on retail analytics, specifically by showing that having access to product preference lists – available in online interactions – as opposed to simply shopping baskets – typical in store transaction records – is very valuable. Our approach is thus a simpler alternative to in-store customer tracking (Hui et al. 2009a), and more importantly gives access to information about which categories attracted visitors to the store (see Chen et al. 1999 for a similar idea applied to advertising). Besides establishing the connection between store layout and sales, we provide an integrative perspective where customer behavior is combined with layout design decisions, which goes beyond minimization of average travel distance (De Koster et al. 2007) or consideration of category adjacencies (Ozgormus and Smith 2020). Finally, note that our prescriptive results are applicable in retail settings where impulse purchases and cross-selling are small. In other contexts, reducing in-store paths may have unintended consequences because it may reduce unplanned spending (Hui et al. 2013).

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 formulates the model of a shopping visit and formulates the layout optimization problem. We estimate the impact of layout on sales in Section 4. Section 5 includes a counterfactual analysis of alternative store layouts. Section 6 concludes the paper.

2. Literature Review

Our work is mainly related to three streams of literature. First, we build on the operations and marketing literature that has studied the shopping funnel. Second, we are connected to the works about offline-online channel interactions. Third, we contribute to the literature on prescriptive models for retail execution.

2.1 From shopping funnels to omnichannel

The concept of funnel is a natural approach to study the effects of different marketing strategies on the customer. The funnel applies to both physical channels, where store visits are transformed into units sold, and online channels, where leads become visits which in turn generate orders. Wiesel et al. (2011) provides a framework to integrate both channels. Lemon and Verhoef (2016) provide an excellent perspective on the customer journey that a potential shopper goes through, and highlight pre-purchase stages – webrooming in our case, defined as "search online, buy in store" – as determinant of later purchasing decisions. They also review the rich marketing literature on these interactions. In terms of modelling, hierarchical models are a convenient way to capture that only a fraction of those showing an initial interest in shopping end up making a purchase (Arora et al. 1998, Martínez-de Albéniz et al. 2020). Detailed decision processes have been developed, such as the use of consideration sets (Wang and Sahin 2018) or product evaluation heuristics (Aouad et al. 2021). It is worth noting that one paper has theorized about the importance of order within the basket. Chen et al. (1999) highlights that some categories are more important than others as they are the reason behind a store visit. They develop the concept *marketing profits* to reflect that profit should be attributed to the category that brought the customer to the store.

When pre-purchase and in-purchase stages take place in different channels, the term "omnichannel" has frequently been employed. The phenomenon has been extensively studied in the last decade. Brynjolfsson et al. (2013) provides an early discussion of the potential of omnichannel for retailers. Gao and Su (2017a,b) develop analytical models for channel choice under omnichannel capabilities. As conceptualized in Bell et al. (2014), the benefits of omnichannel come from better category information, and from better fulfillment possibilities. In other words, there are advantages in showrooming, and in webrooming.

Showroom physical interactions in the store allows to engage with customers more effectively. Bell et al. (2015, 2017, 2020) show how the convenience and the store experience can help pure online players sell more. Kumar et al. (2019) identify the possibility of making in-store returns as another driver of sales increases.

Webrooming can also be valuable. Gallino and Moreno (2014) study the effect of Buy Online Pickup in Store (BOPS) on online and offline sales, and find that store traffic increases due to better information about in-store category availability. Interestingly, the quality of the online experience has an impact on offline sales and customers' overall perception (Bar-Gill and Reichman 2020, Flavián et al. 2020).

Our study reveals a different value driver of omnichannel. It can be used to anticipate demand at the store level, and hence, study the impact of the store layout on the conversion process.

2.2 Path studies

An interesting variation of the study of shopping funnels is possible when interactions between customer and firm occur multiple times, requiring us to consider the sequence in which they occur. Sequential decisions have been considered in the marketing and economics literature across visits (Chintagunta et al. 2012) or within a single visit (Larson et al. 2005, Hui et al. 2009a,b, 2013, Ruiz et al. 2020). Hui et al. (2009a) provides a review of marketing research that considers paths of consumers in store settings. Ruiz et al. (2020) include memory effects as well as one-step forward considerations. This literature suggests that consumers rarely shop the entire store, and quite possibly come with a plan in mind on how to traverse the store.

Closer to our context is Hui et al. (2009b), who model the path between supermarket categories, using a conditional model where transitions from category to category are driven by destination characteristics and path history, which they validate with path data in one store. The data is obtained from individuals moving through the store, tracked by RFID tags, and the model is calibrated using the actual transitions that took place. Interestingly, store layout is included in the decision process through the distance between store regions. We use a similar approach, with some differences. First, we do not have individual path data, but have access to category-level aggregates. Second, we focus on conversion from needs to purchases, so our consideration of cross-category interactions is operationalized in conversion spill-overs, between needs for one category and sales for another, which is moderated by the location of categories in the store. Third, we see variation of category locations across different stores, which allows us to control for category characteristics and separately measure the impact of category location.

Also very close to our approach is Hui et al. (2013), who document that in-store path length strongly increases unplanned purchases, in a grocery retail setting. In this case, RFID tracking was complemented by an entry survey that elicited the customer's shopping list, which allowed the authors to instrument the endogenous in-store path length. In addition to this study, a field experiment using in-store promotions was conducted to validate that longer paths increased unplanned spending. In comparison, we do not find evidence of any strong cross-category spill-over effects, which may be due that our context is home improvement in which impulse shopping is less salient. This suggests that our prescriptions, which seek to reduce in-store distance to increase conversion, may need to be revisited in other retail contexts in which impulse shopping is important.

2.3 Optimization for retail execution

Our work is also connected to works that develop models to improve retail execution. Interventions have focused on different dimensions, which we briefly review. Perdikaki et al. (2012), and Mani et al. (2015) measure the impact of staffing levels on sales, which Chuang et al. (2016) use to develop a labor planning methodology. Caro and Gallien (2010) study inventory distribution across stores and combine demand forecasting and inventory allocation optimization to improve sales at Zara; Gallien et al. (2015) apply a similar approach to new product distribution. Inventory inaccuracy is another cause of suboptimal retail performance. DeHoratius et al. (2008) measure the extent of inaccuracies and DeHoratius and Raman (2008) use inventory replenishment and audits to mitigate their effects. Montoya and Gonzalez (2019) develop a hidden Markov chain model to predict phantom stock-outs based on sales time-series. The effect of store congestion has also been explored: Lu et al. (2013) measure how queues reduce sales conversion.

We discuss here an understudied aspect of retail execution. Indeed, we are not aware of existing work that studies the role of store layout in generating sales. In particular, Larson et al. (2005), Hui et al. (2009b), and Hui et al. (2013) do not investigate store design because they only have data on one store and hence cannot disentangle the effect of category location from the category itself. In contrast, we study layout decisions. The design of a store layout resembles that of designing a warehouse. There exists a broad literature on warehouse layout optimization, see De Koster et al. (2007) for an excellent review. Usually, the design problem is formulated as a large integer program that is solved with heuristic techniques. The methods have also been applied to store layout design, e.g., Mowrey et al. (2018). In these models, customer behavior is integrated through simplified customer behavior assumptions such as considering penalties for categories that are not adjacent (Ozgormus and Smith 2020). In contrast, we use the moderating effect of location on conversion to propose improved layouts.

3. Model

3.1 The Shopping Process

In the same vein as the shopping funnel discussed in Section 2, we make the following assumptions for the shoppers in our model:

1. Store choice: consumers prefer buying at a store that is closest to where they live. Hence, each store has a "natural catchment area" that consists of all the households within a certain radius.

2. Shopping lists: a significant fraction of consumers start their purchasing process with a prioritized list of items in mind that they would like to buy or are considering buying. A list can have multiple categories – e.g., paint, indoor lamps, and curtains – or just a single one, e.g., exhaust fans. Categories that are more important to the consumer are held higher in the list.

3. Webrooming: a significant fraction of consumers does category research online on the retailer's website, and then follow through by visiting the store to purchase (some of) the items they researched online. A consumer's (mental) shopping list dictates the order in which they search the items on the retailer's website. The first item on the shopping list can be understood as the "lead category" for that given consumer (Chen et al. 1999).

4. Store sales moderated by effort: once at the store, consumers try to purchase all the items on their shopping list but might give up on some if they run out of time or if they are not willing to exert the necessary effort to find and fetch the item.

This sequential funnel makes some assumptions regarding customer behavior. First, it requires, implicitly, that consumers highly value their time, so they make their store choice based on proximity, and limit their willingness to shop to fill functional needs, thereby disregarding potential impulse purchases that would require extra effort for a small additional utility. This assumption is reasonable in most retail settings, including home improvement, in which all stores are alike and that carry most of the categories offered online.

Second, we ignore competing stores. Note that we are not assuming that consumers are captive to a particular store, but rather that households are representative of the demand faced by the neighboring stores, even if they do not necessarily shop there.

Third, the shopping list assumption can be justified in retail settings where choices are made before entering the store. Hence, there is prior choice set that is mostly unaffected by the layout. This assumption is consistent with choice models where each customer has a preference list. In the literature, these categories are substitutes and the customer ends up buying a single, preferred category out of the available ones. In our context, we extend this view to consider a preference list of complementary categories, so this can be interpreted as a shopping list.

Fourth, the webrooming assumption is based on a common pattern observed in omnichannel retailing. In fact, industry reports show that the percentage of shoppers doing online research prior to visiting the store can range from 69% to 88% (Accenture 2013, Harris 2013, Deloitte 2017).

Finally, the moderation effect that effort has on sales is justified by the value of time premise. This assumption is consistent with behavioral models in which consumers have a time budget for in-store purchases (such as groceries as shown in Hui et al. 2009b), and is more amenable to functional categories such as home improvement, for which the time spent enjoying the store experience is not a major driver of conversion. Note that in our context, basket sizes are actually smaller during week-ends, when time budgets should be more generous, thus consistent with consumers highly valuing their time. This may not be the case in other retail contexts where impulse spending is high, such as fashion retailing. This provides the boundary conditions for our model and empirical findings: we expect them to carry over to retail contexts in which the priority is facilitating the conversion from explicit potential needs into purchases, regardless of the geographical location (our study uses data from Chile but the results should be applicable to the US or any other country). This includes home improvement of course, but also electronics and white goods. On the contrary, it probably does not hold for retailing with a higher impulse content such as fashion or groceries.

3.2 The Empirical Approach

Our empirical approach is based on the assumptions presented in the previous section. Conceptually at a high level, it has the following form:

$$sales_{ist} = \alpha_i + \alpha_s + \alpha_t + f\big(online\_visits_{ist}, effort_{is}\big) + \epsilon_{ist}. \tag{1}$$

The dependent variable $sales_{ist}$ should be considered in log form, so as to justify an additive structure of independent drivers and to better fit the empirical distribution with is Bell-shaped – this is not the case without applying the log-transformation. The terms $\alpha_i, \alpha_s, \alpha_t$ correspond to category (i), store (s) and time (t) fixed effects, which represents the baseline demand. The next term amplifies demand as a function of webrooming moderated by effort, through a generic function $f(\cdot)$ that increases with online visits and decreases with effort. Here, $online\_visits_{ist}$ represents a vector of relevant metrics that characterize online traffic, and $effort_{is}$ should capture the time (disutility) involved in finding category i at store s. Note that the latter excludes the fixed time/cost it takes to arrive to the store, which would be captured by the store fixed effect. Finally, ϵ_{ist} is the usual error term.

A few more remarks are noteworthy. We consider two amplification components in Equation (1). Namely, (i) primary demand: people that came to the store with the intention of buying, and exerted the effort to find the category; and (ii) secondary demand: people that came to the store searching for something else, but got exposed to the category and ended up buying (spillover in path, spillover nearby. spillover within aisle). Both components should be captured by $online\_visits_{ist}$.

We can observe that there are no substitution effects included in Equation (1). This formulation is appropriate when different categories are solutions to non-overlapping functional needs. Our empirical analysis is performed at the category level, with 165 different ones. At this level, substitution effects across categories should be negligible.

The effect of store execution is captured mainly by the store fixed effect. This includes the impact of assortments – which are quite stable over time, staff intervention – which are limited because these are large stores with emphasis on self-service, and display – also stable because there are no changes in layout within a store. In particular, all stores may have different assortment breadths, but service level is extremely high, meaning that there is always at least one product with available stock within each category, i.e., there is large variety every day during the entire period. Moreover, all the results are unchanged when restricting our attention to categories in which the service level is 100%. In other settings, such as apparel or groceries, it may be necessary to include inventory levels in Equation (1) to control for potential demand censoring when there are stockouts (Boada-Collado and Martínez-de-Albéniz 2020), but in our case it is not needed.

Finally, promotional activities may be an important control to include, but these tend to be the same in all stores, and hence, they are controlled by the time fixed effect in our model.

4. Application to Home Improvement Retailing

4.1 Context

We collaborated with a South American chain of home improvement stores, a leader in this industry, which operated 61 stores across Chile and an online channel at the time of the collaboration. We obtained a comprehensive proprietary dataset providing information about stores, categories and customer interactions, which we describe below.

The retailer sells a variety of home improvement categories, such as tools or materials. For the sake of illustration, the items in the assortment belong to categories such as paint, sawn timber, gardening tools, roofing, electric extension cords, or interior car accessories, to name a few. The same assortment is sold in stores and online. In the categories available in the data, we list 380,134 SKUs that are categorized in different hierarchical levels in the following manner: 5 Level-D clusters, 21 Level-0 clusters, 168 Level-1 clusters (our focus), 787 Level-2 clusters, and finally other more fine-grained clusters. We select for our analysis 165 level-1 categories, after removing 3 legacy categories with zero sales.

At this retailer, the weight of the online channel is small, as it is responsible for only 2.63% and 6.20% of total receipts and revenues, respectively. At the same time, in this industry webrooming is known to be an important factor affecting the shopping process; for instance, Home Depot states that it influences about 60% of store purchases even though the online channel only contributes to 6% of sales (Digital Commerce 360 2017). Because categories are functional and product research is typically done in advance, this seems to be the ideal setting to assume that customers build a shopping list before entering the store, and to empirically connect online browsing to purchases.

Three types of data are available to us, which reflect customer behavior in online and offline channels:

- *Transaction data.* It describes the subset of the assortment's categories that are purchased together. Each product bought belongs to a receipt, which is assigned to a physical store and a date. We refer to the purchase data as shopping-cart or shopping-basket data hereafter. From the raw information, we compute how many receipts issued by a certain store in a certain date included categories of each category.

- *Clickstream data.* It describes the online journey that potential customers navigate when visiting the retailer's website. It consists of time-stamped observations of category-level visits, with an IP address identifier (totalling 3,691,442 different identifiers). We refer to the clickstream data as shopping-list data or webrooming data hereafter. To process clickstream data, we first define a session as the web journey that a potential customer (given by an IP identifier) navigates in one day, i.e., at any time within a given date. One session is formed by a list of ranked categories, represented in a ranked vector. IP identifiers are geolocated, so we are able to associate each session with stores nearby. Specifically, the catchment area of a given store is a 5km radius for stores in the Santiago Metropolitan area and 20km elsewhere. There is one special IP identifier that is worth mentioning: it corresponds to a gateway assigned to all wireless connections from mobile networks. Despite this point being geolocated in Santiago, it comprises all the mobile connections that originate in Chile. For this reason, mobile traffic cannot reliably be assigned to a nearby store, so it is left out of our analysis. This traffic represents only 0.158% of all clicks (we replicate the analysis allocating mobile visits to the stores proportionally, and results remain unchanged). Furthermore, we do not consider web visits that are thought to be generated by bots through web-scraping. To remove those visits, we filter the visits by those IP identifiers that either visit one category more than 40 times or visit more than 300 products in a given day (we also replicate the analysis including these visits, and results again remain unchanged).

- *Store layout data.* It describes the layout of the store, i.e., it details each Level-1 category's location in each store. The layouts of 16 brick-and-mortar stores are available in *pdf* files. We process these files automatically and we obtain the locations of the category labels within the layouts. These locations are described in (x, y) coordinates, and measured in pixels, but for each file, the scale conversion is available, through the width of checkout corridors which measures 1.65 meters. Hence, we can compute the distance in meters that a potential customer has to walk in the retailer's store, so as to buy from a category. From this map, we can thus compute the distance between categories and between a category, the store entrance and the checkout lanes. We use Manhattan distances in meters, so as to reflect the true walking distance given the existence of horizontal and vertical aisles in the stores.

Given the information about layouts, we focus our study on 16 of the retailer's brick-and-mortar stores (26.2% of the total), and its online channel. From these stores, nine are located in the Santiago Metropolitan area, while the remaining stores belong to other regions. We use daily data from December 1st, 2018 to June 30th, 2019, with the exception of 19 days that were removed from the analysis due to missing values. The total study period is thus 30 weeks long (we replicate the analysis excluding holiday dates, and again results remain unchanged).

Tables 1 and 2 compare stores and category metrics for these 16 stores compared to the entire network. We observe that stores included in our subsample are slightly larger in scale (number of receipts, size, assortment) but similar to the rest regarding basket composition (price, basket size), hence suggesting that no bias is introduced by focusing on our chosen store subset.

4.2 Descriptive Statistics

In this section we operationalize the variables from our conceptual model (see Section 3). The data is aggregated weekly to avoid within-week fluctuations: each observation corresponds to a week t, a Level-1 category i (which we call category for simplicity), and a store s. Hence, we define the following variables of interest:

- N_{ist}: Number of receipts that include category i issued at store s during week t.
- N_{st}: Total number of receipts issued at store s during week t. Note that $N_{st} \leq \sum_i N_{ist}$ because a receipt may include multiple categories.
- $V_{1,ist}$: Number of online sessions in which category i is viewed as the first item, within the catchment area of store s during week t.
- $V_{2-4,ist}$: Number of online sessions in which category i is viewed as the second, third, or fourth item, within the catchment area of store s during week t.
- $V_{5+,ist}$: Number of online sessions in which category i is viewed as the fifth item or further, within the catchment area of store s during week t.
- V_{ist}: Number of online sessions in which category i is viewed in any order, within the catchment area of store s during week t. It follows that $V_{ist} = V_{1,ist} + V_{2-4,ist} + V_{5+,ist}$.

Table 1: Store descriptive statistics, 30 week sample.

	In-sample stores						*Out-of-sample stores*					
Statistic	N	Mean	St. Dev.	Min	Median	Max	N	Mean	St. Dev.	Min	Median	Max
General												
Total revenue (mn. Chilean Pesos)	16	17,581	6,230	6,133	17,861	31,099	44	12,863	5,405	5,034	11,474	29,020
Total number of receipts	16	437,020	131,293	181,833	456,678	653,842	44	319,913	107,947	101,343	315,076	559,126
Total number of online sessions (mn.)	16	1.115	3.604	0.048	0.235	14.620	44	0.945	3.106	0.009	0.178	14.837
Average basket value (Chilean Pesos)	16	39,977	6,007	26,674	38,988	49,203	44	39,971	7,550	26,058	39,173	62,756
Average basket size	16	3.25	0.34	2.76	3.25	4.14	44	3.18	0.25	2.68	3.21	3.61
Layout												
Store size (square meters)	16	11,825	3,012	7,040	11,796	18,461	44	9,792	2,506	5,000	9,363	15,080
Number of aisles	16	79.6	19.0	50	81.5	123	–	–	–	–	–	–
Number of checkout lanes	16	17.3	4.7	8	17	27	–	–	–	–	–	–
Average distance on avenue (meters)	16	29.75	8.99	15.08	31.65	52.55	–	–	–	–	–	–
Average distance on aisle (meters)	16	18.63	4.57	11.32	19.46	25.65	–	–	–	–	–	–
Inventory												
Number of distinct SKUs carried	16	31,258	4,236	23,892	32,273	36,024	44	25,864	5,012	13,306	24,830	38,093
Number of distinct SKUs sold	16	27,860	4,232	20,437	28,838	33,400	44	22,755	4,676	11,238	21,807	33,640
Number of distinct categories carried	16	163.6	1.0	162	164	165	44	161.5	6.3	122	162.5	165
Number of distinct categories sold	16	161.5	1.3	159	162	165	44	161.8	5.9	125	163	165
Prices												
Average SKU price (Chilean Pesos)	16	4,534	1,180	2,154	4,668	6,765	44	4,653	1,472	2,667	4,619	12,899

Table 2: Category descriptive statistics, 30 week sample.

	In-sample stores						*Out-of-sample stores*					
Statistic	N	Mean	St. Dev.	Min	Median	Max	N	Mean	St. Dev.	Min	Median	Max
General												
Average revenue, per store (Chilean Pesos)	165	953,587	2,119,414	5,110	454,995	24,727,340	165	890,978	2,487,860	8,772	367,424	30,012,816
Average number of receipts, per store	165	5,721	6,889	1.3	3,128	43,929	165	4,163	5,097	3.2	2,206	32,031
Average number of online visits, per store	165	561.24	623.62	0.03	367.66	4,337.30	165	456.91	506.75	0.03	300.63	3,520.34
Inventory												
Average number of distinct SKUs carried, per store	165	187.28	223.92	1.36	107.63	1,295.5	165	155.37	183.52	1.486	93.16	1,078.5
Average number of distinct SKUs sold, per store	165	165.76	209.37	0.25	89.69	1,418.81	165	135.50	171.61	1.00	75.25	1,223.39
Prices												
Average SKU price (Chilean Pesos)	165	17,621	28,389	296	7,783	203,485	165	17,089	26,773	291	7,485	151,007

Note: In some categories, there are SKUs that are sold without presenting a positive stock in the inventory data.

- V_{st}: Total number of online sessions within the catchment area of store s during week t. It follows that $V_{st} = \sum_i V_{1,ist}$. Note that $V_{st} \leq \sum_i V_{ist}$ because a session may include multiple categories.

- V_{it}: Total number of online sessions in which category i is viewed in any order during week t. It follows that $V_{it} = \sum_s V_{ist}$.

- D_{is}: Distance to pick item i in store s measured in meters, i.e., the distance between the store entrance and category i plus the distance between category i and the checkout lanes. Note that there are no changes in layout during the time window of study, so this variable is independent of time.

In our study, we use all variables except distance in log form for ease of interpretation of the coefficients and to remove skewness, i.e., we transform variable X into $x := \log(1+X)$ (we add one to avoid problems with zero values of X). With this notation, the variable n_{ist} is our proxy for $sales_{ist}$, and D_{is} is our for proxy $effort_{is}$. Our proxy for $online\_visits_{ist}$ includes $v_{ist}, v_{1,ist}, v_{2-4,ist}, v_{5+,ist}$, and might also include these same variables for other categories j whose traffic is relevant to the sales of category i.

Table 3 contains the descriptive statistics of the logged variables, and Table 4 their correlations. One can observe that the amount of generic online traffic v_{st} has a small correlation with sales indicators n_{st} or n_{ist}. However, category-specific online traffic $v_{it}, v_{ist}, v_{1,ist}, v_{2-4,ist}$ and $v_{5+,ist}$ has a high positive correlation with category-specific sales n_{ist}. This indicates that indeed online activity can be used as a key input for store demand forecasting, and this insight is a promising starting point to develop a more sophisticated model as discussed in Section 3.

Table 3: Descriptive statistics of the main model variables.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
n_{ist}	78,750	4.13	1.85	0.00	3.18	4.43	5.51	8.71
n_{st}	78,750	9.28	1.55	0.00	9.23	9.52	9.82	10.45
$v_{1,ist}$	78,750	2.96	1.41	0.00	1.95	3.00	3.95	7.77
$v_{2-4,ist}$	78,750	2.76	1.34	0.00	1.79	2.77	3.71	7.59
$v_{5+,ist}$	78,750	1.85	1.25	0.00	0.69	1.79	2.71	6.63
v_{ist}	78,750	3.73	1.41	0.00	2.83	3.78	4.72	8.42
v_{st}	78,750	8.66	0.84	6.74	8.01	8.78	9.31	10.24
v_{it}	78,750	5.88	1.37	0.00	5.17	5.98	6.78	9.79
D_{is}	78,750	119.09	51.80	28.55	77.77	114.13	151.40	377.37

To further illustrate the available data, Figure 1 shows the joint evolution of V_{ist} and N_{ist} for two stores and two categories. We can see that both series tend to move together, although their relative

Table 4: Correlation matrix between the variables of interest.

	n_{ist}	n_{st}	$v_{1,ist}$	$v_{2-4,ist}$	$v_{5+,ist}$	v_{ist}	v_{st}	v_{it}
n_{ist}	1							
n_{st}	0.4018 ***	1						
$v_{1,ist}$	0.3999 ***	−0.0386 ***	1					
$v_{2-4,ist}$	0.3015 ***	−0.0590 ***	0.8798 ***	1				
$v_{5+,ist}$	0.2209 ***	−0.0672 ***	0.7434 ***	0.8793 ***	1			
v_{ist}	0.3534 ***	−0.0527 ***	0.9499 ***	0.9669 ***	0.8700 ***	1		
v_{st}	−0.0074 **	−0.0618 ***	0.5400 ***	0.6277 ***	0.6227 ***	0.6178 ***	1	
v_{it}	0.4902 ***	−0.0234 ***	0.8165 ***	0.7036 ***	0.5616 ***	0.7746 ***	0.0773 ***	1

*p<0.1; **p<0.05; ***p<0.01

values (i.e., their ratio) changes across stores and categories, which is natural given that some categories may require relatively more browsing to achieve a certain level of sales, and the customers around some stores may have higher natural conversion between browsing and purchasing, compared to others. These structural, static differences will be captured by store and category fixed effects in our model.

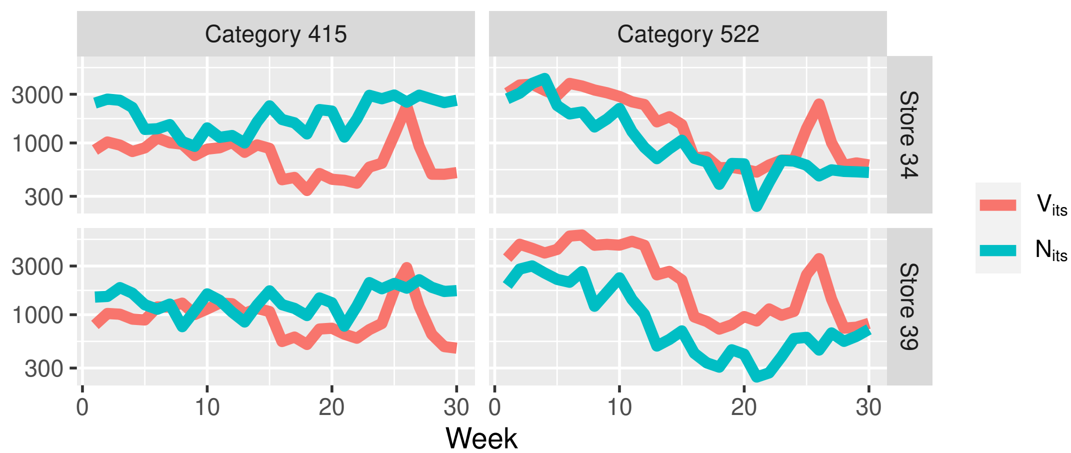

Figure 1: Evolution of clickstream and sales figures, for two categories and two stores.

As shown in Table 4, n_{ist} and v_{ist} are highly correlated. Hence, clickstream activity seems a useful lead indicator of category i's performance. Taking into account this relationship, we can further study the impact of the store layout on conversion. Figure 2 plots conversion for a given store, measured as $n_{ist} - v_{ist} = \log((1 + N_{ist})/(1 + V_{ist})) \approx \log(N_{ist}/V_{ist})$, averaged over 30 weeks. We observe that, while conversion fluctuates, we see a clear trend showing that the conversion of distant categories is lower than those near the entrance or center. This model-free evidence suggests that a category's location in the store strongly affects the conversion from category interest to actual sales.

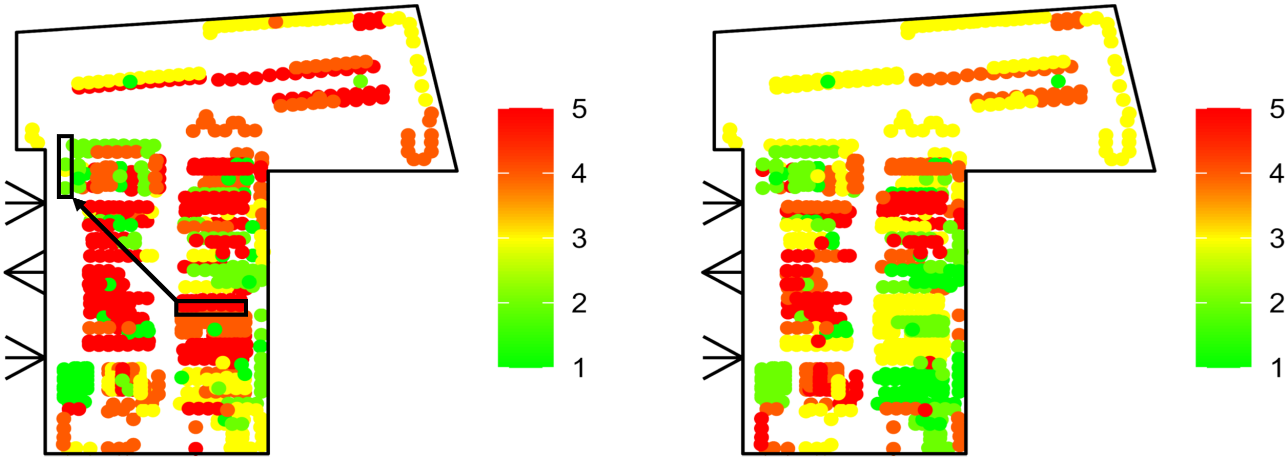

Figure 2: Model-free representation, with sales (left) and conversion (right) in quintiles. The arrows correspond to store entrances and exit. The layout on the left also shows the current and proposed location for the laminated flooring category that is discussed in Section 5.2.

4.3 Model Specification

We can now rewrite Equation (1) into our main model specification:

$$n_{ist} = \alpha_i + \alpha_s + \alpha_t + \beta v_{ist} + \gamma D_{is} + \epsilon_{ist} \tag{2}$$

We also consider variations of this specification, in which we incorporate quality-segregated online visits, via $v_{1,ist}, v_{2-4,ist}, v_{5+,ist}$ instead of v_{ist}.

Furthermore, this equation captures the direct influence where sales are simply the consequence of a true demand need existing prior to a store visit. Beyond this direct influence, the literature has identified other indirect influences, namely spill-over effects between categories. In other words, if there is a flow of shoppers interested in buying a certain category, these visitors will be exposed to other categories on their way to their primary shopping objective. For instance, Hui et al. (2013) documents a significant positive spill-over in a grocery context.

To study these cross-category interactions, we consider three potential drivers of sales arising from spill-over effects. First, for a certain category i, we consider the primary demand associated with categories j that require the shopper to walk by i in their path to j. For this purpose, we define the binary variable $INPATH_{ijs}$, which is equal to one if the shortest path from entrance to j and then to exit coincides with either the shortest path from entrance to i to j to exit, or from entrance to j to i to exit. Otherwise, it equals zero. For the paths to coincide, they must have the same Manhattan distance with up to a 10% deviation.[4] We then define $PATH_{ist}$ as the number of online sessions within 5km of the store that include any category $j \neq i$ such that $INPATH_{ijs} = 1$:

[4]In a large store there are multiple shortest paths with equal Manhattan distance. All of them are considered in the computation of $INPATH_{ijs}$.

$$PATH_{ist} = \sum_{j \neq i} INPATH_{ijs} \times V_{jst}, \tag{3}$$

and let $path_{ist} = \log(1 + PATH_{ist})$. This variable should thus capture spill-overs into items that are in central locations within the store, that see a high amount of traffic for primary items that are further inside the store. It results in the following specification

$$n_{ist} = \alpha_i + \alpha_s + \alpha_t + \beta v_{ist} + \gamma D_{is} + \delta path_{ist} + \epsilon_{ist} \tag{4}$$

One may note that visitor flows in the store might not necessarily coincide with the shortest path, since it is common that visitors prioritize the main ‘avenues' within the store to move faster. Moreover, as visitors move faster, it is possible that they will pay less attention to other products, in contrast to when they move slower in the smaller aisles closer to the product that they are looking for. Hence, we should focus on more localized traffic. For this reason, we consider a second potential spill-over effect, with two specific forms. We consider the primary demand of categories j in the vicinity of i, defined through the binary variable $NEARBY_{ijs}$ which is equal to one if the distance between i and j is less than 20 meters. We then define $NEAR_{ist}$ as the number of online sessions within 5km of the store that include any category $j \neq i$ such that $NEARBY_{ijs} = 1$:

$$NEAR_{ist} = \sum_{j \neq i} NEARBY_{ijs} \times V_{jst}, \tag{5}$$

and let $near_{ist} = \log(1+NEAR_{ist})$. Alternatively, we define the binary variable $SAMEAISLE_{ijs}$ which is equal to one if categories i and j are located in the same aisle in store s. We then let $AISLE_{ist}$ as the number of online sessions within 5km of the store that include any category $j \neq i$ such that $SAMEAISLE_{ijs} = 1$:

$$AISLE_{ist} = \sum_{j \neq i} SAMEAISLE_{ijs} \times V_{jst}, \tag{6}$$

and let $aisle_{ist} = \log(1 + AISLE_{ist})$. Both $near_{ist}$ and $aisle_{ist}$ variables capture spill-overs related to proximity to store hot spots, and lead to model specifications similar to Equation (4) in which the $path_{ist}$ variable is replaced by either $near_{ist}$ or $ailse_{ist}$.

4.4 Estimation

We could estimate Equation (2) using ordinary least squares (OLS), but one may be concerned about the endogeneity of the distance variable D_{is}. Namely, it is possible that the store manager, knowing that category i is popular in the region of store s, decides to place the category in a more accessible store location. If this is the case, then the number of receipts n_{ist} might be negatively associated with D_{is} but this would not be a causal relationship, but a link due to the latent sales expectation. Because of this potential problem, we proceed using a standard two-stage least squares (2SLS) approach. In a first stage, we instrument D_{is} with a Hausman-type variable, i.e., the average $D_{is'}$, with s' being in the set $SIMILAR_s$ made of the two stores that are most similar to s, as measured by the overall correlation between $D_{is'}$ and D_{is}. We then denote $D_{is}^H := \left(\sum_{s' \in SIMILAR_s} D_{is'}\right) / |SIMILAR_s|$. Indeed, layout planning may be coordinated across stores, so certain categories tend to be located at the front or the back of the store, and hence we expect D_{is}^H to be positively correlated with D_{is}. At the same time, stores have different constructive features – such as store size or shape – and they cater to different catchment areas. Hence, the product location in other stores should not influence the number of receipts n_{ist} at the focal store, which means that the instrument D_{is}^H satisfies the exogeneity criterion. We thus regress D_{is} with D_{is}^H as well as all other covariates from (2); since the covariates are time-varying, we actually obtain an estimate $\hat{D}_{ist}$ in the first stage. In the second stage, the distance D_{is} in Equation (2) is replaced by the first-stage predicted value $\hat{D}_{ist}$. We thus obtain an unbiased estimate of the distance coefficient γ with the 2SLS procedure. In our results, we report both the OLS and the 2SLS estimates, and we discuss below their differences. Finally, we have considered variations to our approach, with more or less stores (1 to 4) in $SIMILAR_s$, and using proximity instead of similarity, and our insights are robust in these alternative formulations.

4.5 Results

We first study the use of nearby online interactions as determinants of store sales. For that purpose, we set $\gamma = 0$ in Equation (2). The results are reported in Table 5. Model (1) presents a benchmark model that only incorporates fixed effects for category, week and store. As we can see, fixed effects alone lead to a R^2 of 0.32, which suggests that cross-category and cross-store heterogeneity, as well as seasonality (cross-week variation), are high in our context. Model (2) incorporates the total online traffic for each store and week, in the same way Gallino and Moreno (2014) used online interactions as a driver of store sales. In comparison to them, we find that general online traffic is non-significant and does not help predict category-level sales, suggesting that accounting both for store and time variation through fixed effects is sufficient and store-level online traffic simply contains redundant information. In contrast, when we consider category-level online interactions in Models (3) and (4), prediction improves steeply, to $R^2 = 0.56 - 0.57$. This implies that category-level clicks provide a strong signal about sales. Moreover, the coefficient in Model (3) is equal to 1.0307 and highly significant, which suggests that the relationship between (logged) clicks and sales is approximately proportional, i.e., we can write $N_{ist} \approx kV_{ist}$. In other words, if online clicks increase by 10%, sales also increase by a similar amount. Model (4) breaks down clicks into different 'quality grades', by considering separately clicks in which the focal category was the first one in the session (the sequence of categories viewed by the consumer; the first one should be the most important for the consumer), and the clicks in which the focal category was in positions 2 to 4, or 5+. We can observe that indeed clicks in the first position have the highest coefficient 0.7435, while later clicks had lower coefficients 0.2336 and 0.0666 (all of them are statistically significant). This supports our interpretation that online interactions are a proxy for true consumer interest, and it is revealed especially when it appears early in the online search sequence of the consumer. Namely, a 10% increase in first-position of clicks leads to an increase of about 7% of store sales, while a 10% increase in clicks in the fifth position increases sales by less than 1%.

We next incorporate the three spill-over variables from Section 4.3 in Models (5)-(8). We can see that primary demand v_{ist} remains significant and with a coefficient similar to that in Model (3). In contrast, $near_{ist}$ is insignificant, while $path_{ist}$ and $aisle_{ist}$ are positive and significant but very small in magnitude. The coefficient of $aisle_{ist}$ is in fact the largest among the spill-over variables considered, indicating that an increase in interest (online clicks) for neighboring items within an aisle slightly increases sales. This suggests that spill-over effects are positive but of second-order importance, which is understandable given the functional, non-impulse nature of the categories sold in our home improvement context. Another possible interpretation of this result is that webrooming informs a more focused consumer that will spend less time roaming at the store, and therefore, opportunities for cross-selling are diminished. Other authors have discussed similar effects of webrooming, see for instance Gao and Su (2017a).

The previous models establish that online clicks are a valuable determinant of store sales. We can now study the impact of category location on sales, corresponding to Equation (2) with $\gamma \neq 0$. As described earlier, we operationalize ease of access to the category in the store via the distance from entrance to the category and then to exit. Table 6 shows the result of the estimation. The table first provides the results without instrumenting the distance variable, in a standard OLS estimation, in Models (9) and (10), without and with online clicks respectively.

We first observe, in Models (9) and (10), that distance is significant but only marginally improves the result of Models (1) and (3). The coefficient for v_{ist} in Model (10) compared to Model (3) remains almost the same, which means that the role of distance, driver of conversion, seems orthogonal to that of online interactions, a proxy for true consumer needs.

Similar to the models in Table 5, we observe that adding online visits improves the accuracy of the model significantly, as shown by the R^2 which increases from 0.32 to 0.56. This implies that a model that ignores online visits will confound the attribution of sales potential to categories, measured exclusively by their fixed effect α_i in Model (9). Specifically, Models (9) and (10) differ in how they attribute sales potential to categories after accounting for the effect of distance. Namely, Model (9) without online visits cannot distinguish between actual product potential and being at a good location: higher online visits might be explaining a higher performance, which leads to a confounded estimate of sales potential. Similarly, some categories with a high level of online visits but low conversion will be attributed a sales potential that is lower than their real potential,

Table 5: Models using online interactions.

	Dependent variable: n_{ist}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
v_{st}		−0.0762						
		(0.0728)						
v_{ist}			1.0307***		1.0309***	1.0307***	1.0019***	1.0010***
			(0.0061)		(0.0061)	(0.0061)	(0.0061)	(0.0061)
$v_{1,ist}$				0.7435***				
				(0.0079)				
$v_{2-4,ist}$				0.2336***				
				(0.0109)				
$v_{5+,ist}$				0.0666***				
				(0.0089)				
$path_{ist}$					0.0003***			0.0004***
					(0.00004)			(0.00004)
$near_{ist}$						−0.0001		−0.0006***
						(0.0001)		(0.0001)
$aisle_{ist}$							0.0578***	0.0596***
							(0.0021)	(0.0021)
Fixed effects	Week	Week	Week	Week	Week	Week	Week	Week
	Category	Category	Category	Category	Category	Category	Category	Category
	Store	Store	Store	Store	Store	Store	Store	Store
Observations	78,750	78,750	78,750	78,750	78,750	78,750	78,750	78,750
R^2	0.3196	0.3197	0.5582	0.5691	0.5585	0.5582	0.5629	0.5635
Adjusted R^2	0.3191	0.3191	0.5578	0.5688	0.5581	0.5578	0.5625	0.5632
Residual Std. Error	1.5299	1.5299	1.2330	1.2176	1.2325	1.2330	1.2263	1.2254
	(df=78685)	(df=78684)	(df=78684)	(df=78682)	(df=78683)	(df=78683)	(df=78683)	(df=78681)
F Statistic	577.6***	568.7***	1,529.1***	1,551.2***	1,508.1***	1,506.0***	1,535.3***	1,494.0***
	(df=64; 78685)	(df=65; 78684)	(df=65; 78684)	(df=67; 78682)	(df=66; 78683)	(df=66; 78683)	(df=66; 78683)	(df=68; 78681)

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

which can represent a missed opportunity. In other words, the more refined Model (10) 'cleans up' errors in attribution of sales potential to categories. As a result, optimizing the store layout without a proxy for product interest (or demand) will likely identify the wrong product-location assignments, as we show later in Section 5.2 where we discuss the case of the laminated flooring category highlighted in Figure 2.

Table 6 then reports the results of the 2SLS procedure, which controls for potential endogeneity of in-store distance, see Section 4.4. First, we observe that the first stage in Models (11) and (12) is working correctly: in-store distance is indeed significantly correlated with the instrument (relevance criterion). Second, the results show a strong effect of distance, with a coefficient of -0.0054 in Model (12). The coefficient is about five times higher than that coming out of OLS in Models (9) and (10), suggesting that there is some endogeneity of D_{is}. Surprisingly, the retailer is not necessarily placing higher selling items in locations with easier access. In fact, the opposite is happening, e.g., highest selling categories are placed at the back of the store. For example in the right image of Figure 2, we see that some high-conversion categories (in orange) are placed in locations far from the entrance. This was perhaps done with the hope of generating cross-selling – despite our analysis not uncovering strong cross-selling patterns. As a result, OLS underestimates the effect of distance, and it becomes necessary to pursue a 2SLS analysis. Moreover, the coefficient γ has a relatively high value: distance within the store roughly varies between 50 and 250 meters, which implies that the difference in sales between the closest and furthest categories is about $-0.0054 \times (250-50) = -1.08$, a 66% decrease (since $e^{-1.08} = 0.34$).

4.6 Robustness

While our main models in Tables 5 and 6 are kept simple to focus on the direct impact of online visits and effort, we run several robustness checks to discard possible confounders and to identify possible interactions between model variables. We discuss below the findings and include details in the Appendix.

First, there could be store-specific factors that influence category success and seasonality, which may be related to online visit patterns and thus bias our estimation. To discard this possible confounder, we replicate the estimation of our main Models (11) and (12) with alternative fixed effect configurations, which incorporate possible interactions between week, category and store. The results are shown in Models (13) to (18) in Table 7. We confirm that our main findings are preserved. In fact, the estimate of the distance coefficient γ doubles in magnitude when category-store fixed effects are considered, which strengthens the relevance of D_{is}. We also tested a model without the distance covariate, which allowed replicating the analysis with the full store sample – 60 stores instead of 16, see Table 1 for comparison – and we obtained that the coefficient for v_{ist} remains highly significant though slightly smaller in magnitude compared to the 16-store subsample.

Table 6: Models using online interactions and category location.

	Dependent variable:			
	n_{ist}			
	OLS		*2SLS*	
	(9)	(10)	(11)	(12)
v_{ist}		1.0311^{***}		1.0324^{***}
		(0.0061)		(0.0061)
D_{is}	-0.0010^{***}	-0.0012^{***}	-0.0050^{***}	-0.0054^{***}
	(0.0001)	(0.0001)	(0.0004)	(0.0003)
First stage, $IV(D_{ist})$			0.5120^{***}	0.5120^{***}
$R^2 = 0.515$			(0.0084)	(0.084)
Fixed effects	Week	Week	Week	Week
	Category	Category	Category	Category
	Store	Store	Store	Store
Observations	78,750	78,750	78,750	78,750
R^2	0.3201	0.5587	0.3134	0.5511
Adjusted R^2	0.3195	0.5584	0.3128	0.5507
Residual Std. Error	1.5295	1.2322	1.5370	1.2428
	(df = 78684)	(df = 78683)	(df = 78684)	(df = 78683)
F Statistic	569.8^{***}	$1{,}509.4^{***}$		
	(df = 65; 78684)	(df = 66; 78683)		
Wald test			565.3^{***}	$1{,}485.4^{***}$
			(df = 65; 78684)	(df = 66; 78683)

Note: Robust standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Fixed effects for Models (11) and (12) are reported in Table 10 in the Appendix.

Second, even though we do have cross-store layout variation, one may think that, if stores are far apart, then customers may be intrinsically different so in reality separate estimations should be conducted for each of the stores. To remedy this, we focus on the nine stores located in the Santiago Metropolitan area, which serve a common pool of customers living in the same city who arguably have more homogeneous tastes than across cities. We replicate the estimation Models (9) through (12) with the data from these nine stores, see Table 8. Again, we observe that the main findings are preserved.

Finally, we may be concerned about possible lags between webrooming and store visits. We thus expand our main model by including $v_{is,t-1}$, i.e., the amount of online visits in the week before. Since v_{ist} and $v_{is,t-1}$ are highly correlated, we may introduce colinearity in this new model, thereby introducing noise in the coefficients of these variables. We find that indeed the coefficient of v_{ist} drops from 1.03 in Model (12) down to 0.53 in this alternative specification, Model (25) in Table 9, while $v_{is,t-1}$ has a coefficient of 0.55. Most importantly, the coefficient of distance remains at -0.0055, hence nearly identical to that of Model (12).

5. Store Layout Optimization

5.1 A Category-Position Assignment Problem

Our model assumes and empirically demonstrates that a category's location within the store has a significant impact on the conversion it generates. In this section, we are interested in prescribing improved layouts that increase total sales, taking consumer true needs as fixed captured via their online interactions.

Product location optimization is a relatively well-studied area of research, mainly in warehouse settings, see De Koster et al. (2007) for a review. In these contexts, one usually minimizes picking costs, which results in placing high-rotation items in easily accessible locations, while slow-movers are sent to more remote locations. In a store, the costs to bring items to the shelf are relatively small and insensitive to location within the store. As a consequence, we focus on the main driver of profits coming from the impact of category location on sales conversion.

We can formulate the layout design problem as the following assignment problem. Let x_{isp} be a binary variable that equals one when category $i \in \mathcal{I}$ is located in position $p \in \mathcal{P}$, in store s. (Note that it is straightforward to extend this formulation to time-dependent assignments; in our case, adding time-dependency improved profits minimally, by less than 0.5% compared to that of a one-time change.) One category can go into one position, and one position can only take one category.

Let d_p be the distance a consumer must travel from the entrance when a category is located in position p (at a given store s, subindex removed for simplicity). Then, the location-dependent demand of category i at time t can be written as $r_{istp} = r_i d_{istp}$, where r_i is the average revenue from the category per receipt in which the category is present, and $d_{istp} = \exp\Big(\alpha_i + \alpha_s + \alpha_t + \beta v_{ist} + \gamma d_p\Big)$, as predicted by Model (12). We then let $r_{isp} = \sum_t r_{istp}$, and formulate the layout design problem:

$$J_s := \max_x \sum_{i \in \mathcal{I}} \sum_{p \in \mathcal{P}} r_{isp} x_{isp} \tag{7}$$

$$s.t. \sum_{i \in \mathcal{I}} x_{isp} \leq 1 \quad \forall p \in \mathcal{P} \tag{8}$$

$$\sum_{p \in \mathcal{P}} x_{isp} \leq 1 \quad \forall i \in \mathcal{I} \tag{9}$$

$$x_{isp} \in \{0, 1\}. \tag{10}$$

The formulation J_s only includes constraints pertaining to the impossibility of placing two categories in the same location, or one category being sent to two locations. It is easy to incorporate additional linear constraints reflecting business conditions for the category in the store. For example, if a category can only be located in a particular part of the store, then we can set $x_{isp} = 0$ for infeasible locations. If categories i and j must be adjacent, then we can set $x_{isp} \leq \sum_{p'} A_{pp'} x_{jsp'}$ with $A_{pp'} = 1$ if p and p' are adjacent and zero otherwise; in other words, if $x_{isp} = 1$, then one adjacent p' (with $A_{pp'} = 1$) is such that $x_{jsp'} = 1$. In the absence of additional constraints, Equations (8)-(9) make a Totally-Unimodular Matrix (TUM), and hence constraint $x_{isp} \in \{0, 1\}$ can be replaced with $0 \leq x_{isp} \leq 1$ without changing the optimal solution of (7). In other words, J_s can be obtained by solving a linear program. Otherwise, we solve an integer program.

Note that we can write $r_{isp} = \bar{r}_{is} g_p$, with $g_p = \exp(\gamma d_p)$ and $\bar{r}_{is} = \exp(\alpha_i + \alpha_s) \sum_t \exp(\alpha_t + \beta v_{ist})$, which will allow us to find the optimal assignment in closed form. Indeed, we can write the objective as $\sum_{i \in \mathcal{I}} \sum_{p \in \mathcal{P}} \bar{r}_{is} g_p x_{isp}$. This is maximized by assigning the location p with the largest g_p to the category i with the largest $\bar{r}_{is}$: assign the best in-store position (highest g_p) to the best-selling category (highest $\bar{r}_{is}$).

Finally, observe that the objective function in problem (7) has a separable structure. In other words, the sales of category i are independent of the location of other categories. This formulation is thus applicable to settings in which cross-selling is small. It requires a more complex, non-linear objective function when there are cross-category interactions, such as unplanned spending effects (Hui et al. 2013).

5.2 Improving on Existing Layouts

We can now apply the method of Section 5.1 to reengineer the actual layouts observed in our data. We first provide an in-depth analysis for one store and then provide results for the complete set of stores.

We define positions p in the same way as categories, i.e., we let $\mathcal{P} = \mathcal{I}$ and $p \in \mathcal{P}$ denotes the (current) location of category p. We compute r_i to be equal to the average spending per receipt that contains category i over the season of 30 weeks. To limit the number of changes, we formulate the following decision problem:

$$J_s(z) := \max_x \sum_{i \in \mathcal{I}} \sum_{p \in \mathcal{P}} r_{isp} x_{isp} \tag{11}$$

$$s.t. \sum_{i \in \mathcal{I}} x_{isp} \leq 1 \quad \forall p \in \mathcal{P} \tag{12}$$

$$\sum_{p \in \mathcal{P}} x_{isp} \leq 1 \quad \forall i \in \mathcal{I} \tag{13}$$

$$\sum_{p \in \mathcal{P}} x_{psp} \geq |\mathcal{P}| - z \tag{14}$$

$$x_{isp} \in \{0, 1\} \tag{15}$$

In contrast to J_s, the problem formulation $J_s(z)$ includes the additional parametric constraint (14), where z is an integer variable. This constraint limits the number of actual category assignment changes to be z at the most. For example, if $z = 0$, the only feasible solution is to set $x_{psp} = 1$ for all $p \in \mathcal{P}$. If $z = |\mathcal{P}|$, then the constraint is innocuous. When z takes intermediate values, it provides us with interventions with varying degrees of complexity. Note, however, that constraint (14) breaks the TUM structure of the constraint matrix, and thus requires us to solve a set of integer programs. In addition, we consider two versions of the decision set $\mathcal{P}$: one that includes all categories, and another one that excludes construction categories that are typically bulkier and located at the side of the store, and hence, are difficult to place in any other store position. Our formulation ignores all other business constraints, e.g., adjacencies, space limitations, etc. but still our results are useful to understand the potential of layout optimization as suggested by our empirical findings.

Consider store 51, depicted in Figure 2. In this store, we have 165 different categories assigned to 165 positions shown in the map. As z increases, $J_s(z)$ increases from $J_s(0)$ (current layout) to about $1.4 \times J_s(0)$ when there are no limitations on the layout, or to about $1.15 \times J_s(0)$ when we exclude construction items. Of course, this improvement is due to the ability to optimize product locations compared to the status quo. This can be achieved with our Model (12) or with simpler models that also identify distance as a driver of sales, such as Model (11). To capture the value of our empirical findings, it is thus more appropriate to compare the incremental gain of using online information and a more sophisticated and accurate model, vs. that of the simpler model without such online information.

As discussed in Section 4.5, Models (11) and (12) differ in how they attribute sales potential to categories. Given this difference in demand estimation, the optimization program $J_s(z)$ may propose different product swaps in the layout to maximize impact. The difference is driven by $\bar{r}_{is}$, since the estimates of γ (and hence g_p) are almost identical for Models (11) and (12). If the ranking of $\bar{r}_{is}$ is the same for Models (11) and (12), then the recommended layout will be the same. In contrast, if the estimates $\bar{r}_{is}$ vary, the recommended swaps might be different and the more sophisticated model will lead to higher performance. We thus solve $J_s(z)$ with r_{isp} determined by Models (11) and (12) separately, and then evaluate the performance obtained by the recommended layout using Model (12), which is taken as the ground truth because of its better accuracy. Let $REV_s^{full\_info}(z) = J_s(z)$ be the performance achieved with r_{isp} from Model (12), and let $REV_s^{no\_online\_info}(z)$ be the objective value of the optimal layout under Model (11), but evaluated with r_{isp} coming from Model (12) – so $REV_s^{no\_online\_info}(z) \leq J_s(z)$.

Figure 3 shows the incremental value of using Model (12) vs. (11) in store 51, measured by $100 \times REV_s^{full\_info}(z)/REV_s^{no\_online\_info}(z)$ and as a function of the number of changes allowed z. Interestingly, when the number of changes is very small, the recommended swap is made of the top performer in a bad location against the worst performer in a good location. As a result, the revenue lift is very small. In other words, low hanging fruit is the same for both models. As we budget for more changes, e.g., after about 10 changes allowed – or five swaps, we see that the model with full information, is able to generate about 2-3% higher revenues compared to the recommendations that do not have access to online visits. At the other extreme, when the number of changes is unlimited ($z = 165$), the lift in revenue comes from errors in attribution leading to changes in the ranking, which is about 2% both when we allow all the products to be moved, or when we exclude construction items from the layout optimization program. Note that a lift of 2% is very significant for a home improvement retailer, where margins are thin and increasing the top line typically has a very strong effect on net margins.

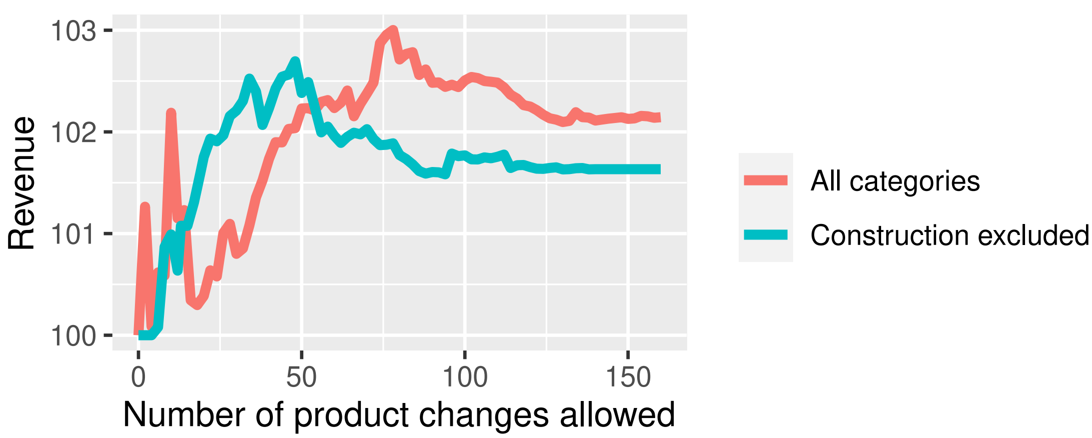

Figure 3: Improvement in store 51 due to the layout optimization using our model with online clicks, compared to the layout optimized using the model without online information, assuming that the true model is given by the former. Optimizing with full information suggests swaps that have a higher impact and results in about a 2% revenue lift when the number of changes is unlimited.

When examining in more detail the type of changes recommended in this scenario, we see that top-selling categories located towards the back of the store are moved to the front, and some minor ones in front positions are relegated to the back of the store. As a more concrete example, consider the laminated flooring category highlighted in Figure 2. This category is a high seller (as shown in the left image of Figure 2), but exhibits moderate conversion with respect to its online visits (as seen in the right image). Its current location p has a distance $d_p = 104.4$ meters, which is just slightly above the average distance in the store (98.7 meters). We solve $J_s(z)$ allowing for 10 changes (or 5 swaps), which is a realistic number of changes that could be implemented at a store, and excluding the construction categories (so there are 150 categories in total).

We first use Model (12) to estimate the sales potentials $\bar{r}_{is}$. Under this model, the laminated flooring category ranks 6th in terms of sales potential, but the top two categories – paint and ceramic tiles – are already located in positions with a short distance, so they do not need to be moved. Hence, the laminated flooring category becomes a candidate to be relocated. The optimized layout suggests putting it in the location currently used by the smart-house connectivity category, which has a sales potential that ranks 138th out of 150, and a distance of 46.2 meters (see the left image in Figure 2). This changes means a 37% sales uplift for the laminated flooring category, since $e^{-0.0054\times(46.4-104.4)} = 1.37$. The optimized layout using Model (11) also identifies the smart-house connectivity category as a prime location that could be better used. However, Model (11) misses the opportunity of the laminated flooring category because it is unaware of its high level of online visits and moderate conversion. Indeed, under Model (11), the sales potential of the laminated flooring category ranks 21st. Instead, under Model (11) the smart-house connectivity location is used to place the locks category, which is not the best choice because the locks category already sells quite well relative to its online visits (i.e., it has high conversion). In fact, the sales potential of the the locks category under Model (12) ranks 15th, so it would only be relocated if at least 30 changes (or 15 swaps) were allowed at store 51.

Finally, we can extend the optimization to our subsample of 16 stores for which we can reengineer the layout. Figure 4 shows the distribution of the revenue improvements achieved with an unconstrained layout change and one limited excluding construction categories, again comparing the performance of the optimized layout using Model (12) vs. Model (11). As we can see, the revenue lift of using the more sophisticated Model (12) can be significant, with some stores achieving improvements of more than 4%.

6. Conclusion

In this paper, we have provided a new perspective on how omnichannel, via webrooming customer interactions, can help retailers manage better their physical stores. Specifically, we have posited that, when sales are preceded by a need that crystallizes into a shopping list and pre-purchase

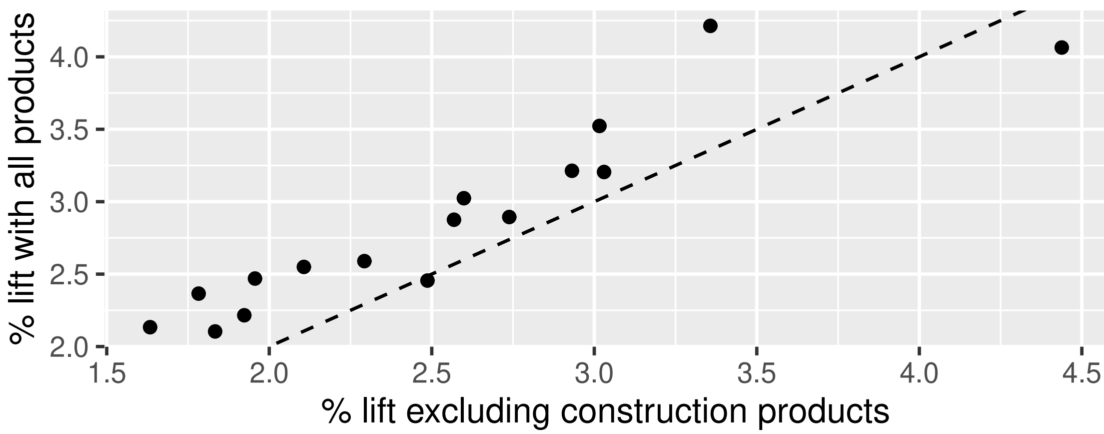

Figure 4: Distribution of $100 \times (REV_s^{full\_info}(\infty)/REV_s^{no\_online\_info}(\infty) - 1)$ across 16 stores. Each point corresponds to a store.

category search, then store sales are driven by both the amount of nearby online visits and the effort that it takes to fetch the category in the store. We validate our conceptual model with data from a home improvement chain, over multiple categories, weeks and locations. The data provides variation of category interest and in-store location, and allow us to identify the effect of online visits and effort on sales. We find that sales grow proportionally with online visits, and that easy-to-reach store positions lead to significantly higher conversion. In addition, we show that there is a small, second-order cross-selling effect in this context, although this is not the focus of our research.

Our results have important implications for the management of physical stores. First, they suggest that layout reengineering using the information provided by online visits can provide a tempting lift in revenues, of around 2-3% compared to that obtained when online information is ignored. Second, they imply that the efforts to generate store visits, in the hope that they will generate unplanned purchases, may not be fruitful. In other words, it may be better that stores do not accept new roles as delivery points (Faithfull 2018, Jones 2019), if the categories on sale are related to a functional need that requires previous research. Third, our results identify the effort to find categories in the store as a hindrance to conversion. In other words, actions to make in-store category search simpler may lead to increased sales. One such action could be to provide category 'addresses' to consumers when they prepare their shopping lists, as Target does, see Figure 5. Finally, our results have been demonstrated for home improvement retailing. When impulse purchases are important, it may be advisable to pursue a different strategy with longer in-store paths, to sustain unplanned spending (Hui et al. 2013).

This study highlights the importance of better understanding the role of store design on customer experiences. This is a promising direction for future research. Indeed, the adoption of Internet Of Things technologies in stores provides new data sources for a more granular understanding of the trajectories of customers over time (the funnel view) and space (transitions between home, work and shopping destinations). This requires the full digitalization of the store conditions, and precise category locations, a piece of information that to date is rarely available, with the exception of supermarket planograms, common in grocery retailing, or RFID sources, installed by Walmart or Zara among others. It can potentially reveal the causal impact of different interventions such as category viewing, category information provision – to differentiate the effect of reducing cognitive load from search vs. that of physical movement to reach an item, staff advice or fitting (Musalem et al. 2021), as well as environmental stimuli such as music or temperature (Martínez-de Albéniz and Belkaid 2021). Furthermore, if both online and offline activities could be connected at the customer level, one may be able to separate primary demand – from those that searched online before visiting the store – vs. secondary demand made of spill-overs from entering an aisle. Indeed, combining on-premise data with online interactions is particularly interesting, so that conceptual frameworks such as Bell et al. (2014) can be operationalized and translated into prescriptive advice for retailers.

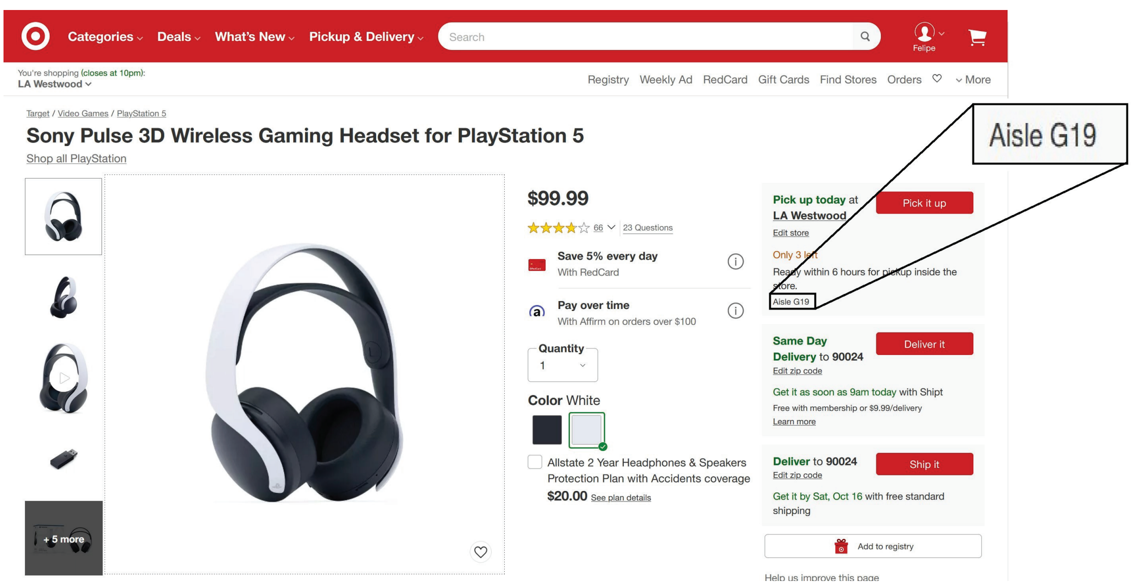

Figure 5: Standard category page on target.com, where the address of the category in the store of your choice is indicated.

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Appendix: Supporting Tables for Robustness

Table 7: Alternative fixed effects for Models (11) and (12).

	Dependent variable:					
	n_{ist}					
	(13)	(14)	(15)	(16)	(17)	(18)
v_{ist}		1.0377^{***}		1.0443^{***}		1.0501^{***}
		(0.0062)		(0.0063)		(0.0063)
D_{is}	-0.0094^{***}	-0.0104^{***}	-0.0050^{***}	-0.0054^{***}	-0.0094^{***}	-0.0104^{***}
	(0.0008)	(0.0007)	(0.0004)	(0.0004)	(0.0008)	(0.0007)
Fixed effects	Week	Week	Category-Week	Category-Week	Category-Week	Category-Week
	Category-Store	Category-Store	Store	Store	Category-Store	Category-Store
Observations	78,750	78,750	78,750	78,750	78,750	78,750
R^2	0.3251	0.5628	0.3305	0.5606	0.3423	0.5723
Adjusted R^2	0.3220	0.5607	0.3250	0.5570	0.3343	0.5671
Residual Std. Error	1.5267	1.2288	1.5233	1.2341	1.5128	1.2198
	(df = 78385)	(df = 78384)	(df = 78104)	(df = 78103)	(df = 77805)	(df = 77804)
Wald test	105.6^{***}	279.9^{***}	61.1^{***}	156.5^{***}	43.6^{***}	111.5^{***}
	(df=364; 78385)	(df=365; 78384)	(df=645; 78104)	(df=646; 78103)	(dt=944;77805)	(df=945;77804)

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 8: Models (9) through (12) estimated with the subset of stores within the Santiago Metropolitan area, taking the two stores with the highest correlated distances for the IV.

	Dependent variable:			
	n_{ist}			
	OLS		*2SLS*	
	(19)	(20)	(21)	(22)
v_{ist}		1.0227^{***}		1.0253^{***}
		(0.0085)		(0.0086)
D_{is}	-0.0011^{***}	-0.0013^{***}	-0.0067^{***}	-0.0073^{***}
	(0.0002)	(0.0002)	(0.0006)	(0.0005)
Fixed effects	Week	Week	Week	Week
	Category	Category	Category	Category
	Store	Store	Store	Store
Observations	44,100	44,100	44,100	44,100
R^2	0.3433	0.5533	0.3300	0.5383
Adjusted R^2	0.3424	0.5527	0.3292	0.5377
Residual Std. Error	1.5693	1.2943	1.5851	1.3159
	(df = 44041)	(df = 44040)	(df = 44041)	(df = 44040)
F Statistic	397.0^{***}	924.7^{***}		
	(df = 58; 44041)	(df = 59; 44040)		
Wald test			390.8^{***}	897.2^{***}
			(df = 58; 44041)	(df = 59; 44040)

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 9: Models (2), (11) and (12) including one-week lagged online visits.

	Dependent variable:		
	n_{ist}		
	OLS		*2SLS*
	(23)	(24)	(25)
v_{ist}	0.5322***	0.5326***	0.5337***
	(0.0134)	(0.0134)	(0.0136)
$v_{is,t-1}$	0.5482***	0.5483***	0.5485***
	(0.0136)	(0.0136)	(0.0137)
D_{is}		−0.0012***	−0.0055***
		(0.0001)	(0.0004)
Fixed effects	Week	Week	Week
	Category	Category	Category
	Store	Store	Store
Observations	76,125	76,125	76,125
R^2	0.5693	0.5699	0.5621
Adjusted R^2	0.5690	0.5696	0.5617
Residual Std. Error	1.2127	1.2119	1.2228
	(df = 76059)	(df = 76058)	(df = 76058)
F Statistic	1,547.0***	1,527.1***	
	(df = 65; 76059)	(df = 66; 76058)	
Wald test			1,501.6
			(df = 66; 76058)

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 10: Fixed effects and robust standard errors (in parenthesis) for Models (11) and (12)

	(11)		(12)	
Week 2	0.0348	(0.0455)	-0.1216^{***}	(0.0368)
Week 3	0.0479	(0.0455)	-0.0221	(0.0369)
Week 4	-0.1012^{**}	(0.0448)	-0.0130	(0.0368)
Week 5	-0.4622^{***}	(0.0436)	-0.4173^{***}	(0.0360)
Week 6	-0.4333^{***}	(0.0433)	-0.6975^{***}	(0.0356)
Week 7	-0.3746^{***}	(0.0436)	-0.6502^{***}	(0.0359)
Week 8	-0.7191^{***}	(0.0427)	-1.0222^{***}	(0.0352)
Week 9	-0.6364^{***}	(0.0430)	-0.7757^{***}	(0.0354)
Week 10	-0.2885^{***}	(0.0439)	-0.4255^{***}	(0.0359)
Week 11	-0.4923^{***}	(0.0432)	-0.6381^{***}	(0.0354)
Week 12	-0.6152^{***}	(0.0430)	-0.7955^{***}	(0.0351)
Week 13	-0.6849^{***}	(0.0418)	-0.6276^{***}	(0.0331)
Week 14	-0.2713^{***}	(0.0434)	-0.4109^{***}	(0.0343)
Week 15	0.0612	(0.0440)	0.0917^{***}	(0.0350)
Week 16	-0.2268^{***}	(0.0436)	0.5682^{***}	(0.0351)
Week 17	-0.3531^{***}	(0.0436)	0.3994^{***}	(0.0354)
Week 18	-0.5365^{***}	(0.0431)	0.4316^{***}	(0.0351)
Week 19	-0.0949^{**}	(0.0441)	0.7097^{***}	(0.0358)
Week 20	-0.1588^{***}	(0.0440)	0.6465^{***}	(0.0357)
Week 21	-0.6580^{***}	(0.0429)	0.1158^{***}	(0.0348)
Week 22	-0.3470^{***}	(0.0435)	0.5549^{***}	(0.0356)
Week 23	0.1007^{**}	(0.0446)	0.8271^{***}	(0.0355)
Week 24	0.0407	(0.0444)	0.6056^{***}	(0.0356)
Week 25	0.1539^{***}	(0.0447)	-0.1685^{***}	(0.0361)
Week 26	-0.0990^{**}	(0.0442)	-0.5437^{***}	(0.0374)
Week 27	0.0700^{*}	(0.0448)	0.1515^{***}	(0.0360)
Week 28	-0.0058	(0.0446)	0.7361^{***}	(0.0363)
Week 29	-0.0595	(0.0447)	0.8233^{***}	(0.0359)
Week 30	-0.0813^{*}	(0.0449)	0.7918^{***}	(0.0365)
Category (lvl. 0) 100	2.1369^{***}	(0.0444)	1.4798^{***}	(0.0361)
Category (lvl. 0) 206	1.5931^{***}	(0.0377)	1.7378^{***}	(0.0301)
Category (lvl. 0) 207	1.7477^{***}	(0.0398)	2.0916^{***}	(0.0321)
Category (lvl. 0) 208	0.8327^{***}	(0.0415)	0.9922^{***}	(0.0337)
Category (lvl. 0) 209	0.9768^{***}	(0.0434)	0.3139^{***}	(0.0330)
Category (lvl. 0) 210	2.7543^{***}	(0.0347)	2.0720^{***}	(0.0276)
Category (lvl. 0) 211	-0.5760^{***}	(0.0460)	-0.1188^{***}	(0.0404)
Category (lvl. 0) 312	2.1534^{***}	(0.0743)	2.0336^{***}	(0.0475)
Category (lvl. 0) 313	0.3671^{***}	(0.0361)	-0.0122	(0.0286)
Category (lvl. 0) 314	0.5926^{***}	(0.0379)	0.4690^{***}	(0.0315)
Category (lvl. 0) 316	0.5546^{***}	(0.0490)	-0.7868^{***}	(0.0372)
Category (lvl. 0) 415	1.4585^{***}	(0.0538)	0.9234^{***}	(0.0391)
Category (lvl. 0) 417	1.2888^{***}	(0.0336)	-1.1888^{***}	(0.0314)
Category (lvl. 0) 418	1.7098^{***}	(0.0375)	1.8567^{***}	(0.0302)
Category (lvl. 0) 419	1.6981^{***}	(0.0505)	0.5318^{***}	(0.0372)
Category (lvl. 0) 420	2.3532^{***}	(0.0353)	2.3396^{***}	(0.0309)
Category (lvl. 0) 421	-2.2493^{***}	(0.0713)	0.1022^{**}	(0.0576)
Category (lvl. 0) 427	0.7838^{***}	(0.0409)	0.3613^{***}	(0.0301)
Category (lvl. 0) 522	0.9180^{***}	(0.0452)	-0.1320^{***}	(0.0358)
Category (lvl. 0) 523	2.2451^{***}	(0.0345)	1.6048^{***}	(0.0300)
Store 23	-0.0054	(0.0299)	0.0243	(0.0234)
Store 33	-2.1488^{***}	(0.0384)	-3.5299^{***}	(0.0359)
Store 34	0.1203^{***}	(0.0309)	-1.3630^{***}	(0.0260)
Store 39	0.1407^{***}	(0.0304)	-1.7527^{***}	(0.0261)
Store 43	-0.1400^{***}	(0.0296)	-1.5229^{***}	(0.0245)
Store 44	0.2231^{***}	(0.0306)	-1.7318^{***}	(0.0268)
Store 51	-0.3965^{***}	(0.0312)	-1.5462^{***}	(0.0256)
Store 54	0.1530^{***}	(0.0315)	-1.3143^{***}	(0.0265)
Store 55	-0.9389^{***}	(0.0320)	-0.7525^{***}	(0.0260)
Store 57	-0.6808^{***}	(0.0300)	-1.5884^{***}	(0.0245)
Store 63	0.2170^{***}	(0.0314)	0.4597^{***}	(0.0251)
Store 70	-0.0963^{***}	(0.0334)	-2.3467^{***}	(0.0299)
Store 75	0.2481^{***}	(0.0302)	-0.3678^{***}	(0.0236)
Store 83	-0.1477^{***}	(0.0300)	-1.8340^{***}	(0.0252)
Store 88	0.2776^{***}	(0.0299)	-0.4399^{***}	(0.0234)
Constant	3.9548^{***}	(0.0753)	1.2771^{***}	(0.0633)

*p<0.1; **p<0.05; ***p<0.01