# Online Shopping Access and Retail Pricing Behavior

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August 2024

**Abstract**

The rapid expansion of online shopping has reshaped traditional retail markets over the past decade. At the same time, recent studies suggest that prices in physical stores are becoming more flexible. This paper provides new empirical evidence using scanner data to show how consumers' access to online markets affects the pricing behavior of brick-and-mortar stores. By exploiting within-product variation across geographic markets, I demonstrate that a higher share of online spending is associated with increased price flexibility, smaller price adjustments, and reduced price dispersion within narrow categories of goods. I hypothesize that online shopping reduces consumers' marginal search costs, increasing retailer-level demand elasticity and driving changes in the pricing behavior of traditional stores. I find supporting evidence for this hypothesis: the effects of online shopping access are particularly strong in markets with a larger share of bargain hunters – buyers who shop online and are more likely to purchase a given product from different retail chains. A sticky-price model with sequential consumer search suggests that lower marginal search costs due to online shopping intensify competition among traditional retailers, leading to more frequent but smaller price changes and lower overall price dispersion. The calibrated model suggests that online shopping access has long-term effects on inflation dynamics by altering pricing behavior beyond a one-time reduction in markups.

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[†]Researcher(s) own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

# 1 Introduction

E-commerce share of retail is expanding rapidly: according to the U.S. Census Bureau,[1] it went from 3.6 percent in 2008 to 9.6 percent in 2018, and it is expected to reach 13.7 percent in 2021.[2] Moreover, the growth of online retail and its implications for monetary policy has increasingly become an area of concern for central bankers (Fed's Jackson Hole meeting, 2018). Much of the attention has focused on whether the competition between online and traditional retailers is reducing retail markups and putting downward pressure on prices.

Nevertheless, recent evidence by Cavallo (2018) suggests that online competition is affecting the way in which pricing decisions are made. In particular, the frequency of price adjustment in multi-channel retailers (i.e., those that sell online and offline) has been increasing for the past 10 years: as Table 3 shows, implied duration for regular prices has fallen from 6.7 months in 2008–2010 to approximately 3.65 months in 2014-2017. The impact is particularly strong in sectors where online retailers tend to have high market shares, such as electronics and household goods. Furthermore, as the frequency of price changes increases, their size is getting small.[3]

These findings about online pricing of multi-channel retailers are consistent with results in the literature studying online-only retailers. Gorodnichenko and Talavera (2017) and Gorodnichenko et al. (2018) find that prices in online marketplaces such as Google Shopping are far more flexible than prices found in CPI data, but the size of changes is roughly the same. Overall, evidence suggests that online competition might have a much more persistent effect on inflation dynamics than a one-time reduction in markups.

In this paper, I study the effects of online competition on the pricing behavior of traditional retailers. I start by providing empirical evidence that access of consumers to online markets affects the pricing behavior of brick-and-mortar stores. By exploiting within-product variation across geographic markets and conducting an instrumental variable (IV) strategy, I show that a higher online spending share is associated with higher price flexibility, lower size of price changes, less prevalent sales, and lower price

[1] Retrieved from `https://fred.stlouisfed.org/series/ECOMPCTSA`

[2] Published by eMarketer, retrieved from `https://www.statista.com/statistics/379112/e-commerce-share-of-retail-sales-in-us/`

[3] Cavallo (2018) also presents more direct evidence on the effects of online competition: Walmart-online prices of goods that can be easily found on Amazon tend to have implied durations that are 20 percent shorter than the rest.

dispersion within narrow categories of goods. In particular, I find that an increase of 0.01 points between 2006 and 2016 in the online spending share increased the frequency (fraction of changes per month) of regular price adjustment from 0.14 to 0.16, decreased the size of regular price adjustment from 0.21 to 0.19, and decreased price dispersion (measured as the standard deviation of log prices) from 0.13 to 0.12.

I argue that the mechanism behind these effects is that, as online shopping makes it easier for consumers to compare goods and their prices across sellers, their marginal search cost decreases. Moreover, a higher search intensity induces changes in the pricing behavior of traditional stores by impacting their demand elasticity. I find supporting evidence for this hypothesis: the effects of online shopping access are particularly strong in markets with a higher share of bargain hunters, who are more likely to purchase a given good from different retail chains and shop online.

To understand the effects of online shopping access on the price-setting behavior of traditional stores, I develop a sticky-price model with consumer search where I interpret online shopping access as a structural change in the shopping technology.[4] In the model, the shopping technology is a key determinant of the demand elasticity that retailers face.

I assume there is a measure-one continuum of shoppers who purchase a homogeneous good and supply labor. A measure-one continuum of retailers produces and sells the good using labor. Retailers set nominal prices and face a menu cost; they adjust because real prices erode at the deterministic inflation rate and idiosyncratic shocks hit their productivity. The non-degenerate and time-invariant cross-sectional distribution of real prices results from both inflation and idiosyncratic shocks.

Every period, a continuum of shoppers enter, search, purchase, and leave the product market. They take the real-price distribution as given and search sequentially for the lowest price. For each additional price draw, shoppers pay a heterogeneous search cost. Their strategy is to search until finding an offer lower than their reservation price. Each buyer ends up purchasing the good from one of many nearly identical retailers. Therefore, shopping behavior determines the equilibrium demand curve and the retailer-level demand elasticity.

Next, I evaluate whether the model can replicate the observed changes in the price-setting behavior between 2006 and 2016 only by adjusting the shopping technology.

[4]Traditional retailers might adjust to online competition through entry and exit (affecting concentration) and by changing the mix of products they sell (specialization). Since my empirical evidence controls for these factors, I exclude them from the model.

I jointly calibrate the parameters of the model to match an average markup of 30%, the absolute size and frequency of regular price changes in 2006 and 2016, and price dispersion in 2006 and 2016. To match differences in the pricing statistics between both years, I only let the parameters related to the shopping technology adjust.

According to the calibrated model, online shopping access increases the density of shoppers with low marginal search costs and the maximum number of price draws that shoppers can make. Both changes induce shoppers to search more, and a higher search intensity increases the average resource cost of search. Nevertheless, with more search, competition to attract searchers increases: the demand at all prices becomes more elastic, markups decrease, and consumer surplus increases. Moreover, price dispersion decreases since all retailers charge lower prices. For retailers, deviations from the optimal price are more costly, so they adjust prices more often and by smaller amounts, increasing resources spent on menu costs. Overall, the calibrated model suggests that aggregate welfare increased 11.45% in consumption equivalent units.

Although welfare increases for each consumer, high-search-cost shoppers are the ones who benefit the most from online shopping access. The benefits that high-search-cost shoppers perceive are not associated to changes in their own shopping behavior, but to the increased search intensity of low-search-cost shoppers: by increasing competition among retailers, a higher search intensity shifts the real price distribution to the left.

# 2 Data

I use Nielsen's Consumer Panel (HMS) and Retail Scanner data (RMS), available for the 2006-2016 period. The former is reported by households, while the latter is reported by retailers. Both datasets have non-durable items at barcode level (Universal Product Code — UPC), sold mostly by grocery, drugstore, and mass-merchandise chains. These products can be categorized at the module level (i.e., highly substitutable products that differ only in their brand), then at the group level (i.e., modules serving similar purposes), and finally at the department level. An example of a module would be "Electric Knife", in the product group "Housewares-Appliances" from the department "General Merchandise". There are 10 departments, 125 groups, and 1,075 modules, approximately.

The HMS data contains the items (UPC level) that households purchase on each shopping trip, the quantities bought, and the prices paid. While information about

the store is limited, every transaction can be linked to a retail chain. The product categories are the same as in the Retail database, but the HMS covers a broader set of retailers what allows me to construct measures of online shopping access, as I explain in the next section.

Households are sampled from 54 geographically dispersed Scantrack markets (each roughly corresponding to an MSA), and detailed demographic information about them is available. Nielsen provides projection factors to make the sample demographically representative of the Scantrack market population.

The RMS data is reported weekly for each UPC and store pair, and it includes units sold and the corresponding unit price (revenues over units sold), description, brand, multi-pack, size, and additional characteristics in some cases (e.g., flavor). Each store is associated to a retail chain. I use the RMS dataset to compute pricing behavior statistics for brick-and-mortar stores. I exclude private-label products since Nielsen alters the barcode so a particular store cannot be identified: for generics, the UPC does not represent a unique good.

## 2.1 Online shopping access

In the HMS data, each purchase is associated to a retail chain, which in turn are classified into 66 mutually exclusive retail channels. One of them is "Online Shopping", corresponding to 0.7 percent of the transactions and 1.8 percent of spending in the sample (2016, aggregate). I use this classification to estimate, for each product module ($p$) $\times$ market ($m$) $\times$ year ($t$) triplet, measures that reflect e-commerce penetration. Concretely, for each $(p, m, t)$, I compute the online share of spending, the online share of transactions, and the fraction of households with at least one online purchase.[5] In order to minimize measurement error, I only keep product $\times$ market pairs with at least 100 transactions each year, or with a number of transactions above the mean across markets, for each product and year. By adding this last condition, I avoid dropping products that are purchased infrequently. The final sample contains 28,470 product $\times$ market pairs that are available for both 2006 and 2016, and that can also be found in the RMS data.

As Table 4 shows, the access of households to online shopping seems limited for this sample of products: on average, 1.5 percent of 2016 spending and 1 percent of 2016

[5]To aggregate across households, I use the projection factors provided by Nielsen to make the sample demographically representative of the Scantrack market population.

transactions were done online in a given product × market pair, while only 2.14 percent of the households report at least one online purchase. Nonetheless, online shopping has been increasing in the last decade. Particularly, the online share of both spending and transactions has almost tripled, while the fraction of households with at least one online purchase has doubled for the average product × market pair. Figure 5 shows the trends in online spending by department. Both the trends and the rankings are in line with the findings in Hortaçsu and Syverson (2015): "General Merchandise" (e.g., electronics, appliances, books, apparel) dominates, followed by "Health and Beauty", with grocery categories at the bottom.

It is important to mention that these measures underestimate the relevance of e-commerce for two reasons. First, it is likely that the online stores of multi-channel retailers (such as Walmart.com) are not classified under the "Online Shopping" channel by Nielsen, but under the same channel as the parent company (e.g., "Discount Store"). In this case, the measures I construct would capture purchases from online retailers only. Second, the goods that are usually purchased online might be underrepresented in Nielsen's sample. As Kaplan and Schulhofer-Wohl (2017) document for 2012, roughly 61 percent of spending in the sample is on food and beverages, while the CPI weight of this category is only 15 percent. Moreover, this is the sector with the lowest share of online sales in the U.S. economy (see Hortaçsu and Syverson, 2015). For conciseness, I use the online share of spending as my benchmark measure of online shopping access in what follows.

## 2.2 Price stickiness

The main measures of price stickiness I analyze are the frequency and size of sales, posted, and regular price changes. In order to construct these measures, I start by defining a price spell as an uninterrupted sequence of weekly prices for a given UPC × store pair.[6] Following Coibion et al. (2015), I classify the difference between two consecutive prices within a spell as price change when it is larger than one cent or one percent in absolute value (or more than 0.5 percent for prices larger than $5). The purpose of this restriction is to remove small price changes that could arise from rounding errors, given that the weekly price is constructed as revenues over units sold.

Temporary price reductions are not flagged in the RMS data. To identify sales, I use the weekly version of Nakamura and Steinsson's filter, as in Coibion et al. (2015).

[6]This is, I do not impute missing values using the preceding or subsequent price.

In particular, I classify a price as a sale when the price decreases (for up to three weeks) and then returns to its previous level. At the same time, I classify a price change as regular when neither period has a sale episode.

I compute the monthly frequency of sales, posted, and regular price changes as the fraction of weeks in a month when a UPC in a given market exhibits a sale, a posted, or a regular price change, respectively. To compute the size of the changes for each UPC $\times$ market $\times$ month, I take the unweighted average across spells. The size of the sale is the log difference between the sales price and the price preceding the sale. The size of a posted (regular) price change is the log difference between the price in the period identified as having a posted (regular) price change and the price in the preceding period.

Another relevant measure of price stickiness is the synchronization of price changes across stores. As in Lach and Tsiddon (1996), I define synchronization in a given week ($w$) for a given UPC ($j$) $\times$ market ($m$) pair as the share of stores ($s$) adjusting their prices given that another store adjusts:

$$\frac{\left(\sum_{s \in S_{jmw(h)}} \mathbb{I}\left\{\Delta p_{jsmw(h)} \neq 0\right\} - 1\right)}{\left(\#S_{jmw(h)} - 1\right)}$$

where $S_{jmw(h)}$ is the set of stores selling UPC $j$ in market $m$ and week $w$ of month $h$, and the indicator function takes value of one when store $s$ changes its price. Finally, I take the monthly average across weeks. I only compute this measure if there are at least two stores selling the UPC, and if at least one price change is observed. Thus, this statistic indicates the share of competitors with whom a store changes its price simultaneously. Correlation in the timing of price changes might indicate a response to factors common to all stores, or strategic behavior.

To aggregate across UPCs within a product module $\times$ market $\times$ year, I average the UPC $\times$ market $\times$ month statistics using total sales as weights. Table 5 shows descriptive statistics for price stickiness measures at the product module $\times$ market level. As documented by Cavallo (2018), both posted and regular prices have become more flexible between 2006 and 2016, and the size of the price changes has been decreasing in absolute value. On average, the frequency of sales has not changed by much, but their size has decreased. Price changes have become more synchronized.

### 2.3 Price dispersion

In order to make price distributions comparable across products, markets, and time, I follow Kaplan and Menzio (2015) and normalize prices using the market-average level. Specifically, for a given UPC ($j$) $\times$ market ($m$) $\times$ month ($h$) combination, I compute the units-weighted average price as

$$\overline{P}_{jmh} \equiv \frac{\sum_{s,w \in h} P_{jsmw} q_{jsmw}}{\sum_{s,w \in h} q_{jsmw}},$$

where $w\,(h)$ are weeks $w$ in month $h$, and study the normalized price, defined as

$$p_{jsmw} \equiv \frac{P_{jsmw}}{\overline{P}_{jmh}}.$$

I characterize price dispersion using the standard deviation, the log 90-10 and log 95-5 percentile ratios of the normalized prices. I calculate these measures at the UPC $\times$ market $\times$ month level, and then aggregate across all UPCs within a category in a given market and year using expenditure weights.[7] Table 6 shows that average price dispersion has been constant over time, although it has changed across goods within a category and market.

## 3 Empirical strategy

Let $y_{mpt}$ and $x_{mpt}$ be the pricing behavior measures and online spending share, respectively, for each market ($m$), product module ($p$), and year ($t$). The pricing behavior measures include both price stickiness and price dispersion statistics. How does online access by consumers affect the pricing behavior of retailers? To tackle this question, I estimate the following set of linear regressions:

$$\Delta y_{mp} = \beta \Delta x_{mp} + \gamma \Delta w_{mp} + \lambda_p + \epsilon_{mp} \tag{1}$$

where $\Delta$ denotes the 10-year difference (2006-2016) of each variable. I include product category fixed effects ($\lambda_p$) thus I identify the parameter of interest, $\beta$, using within-category variation across markets. I add a set of controls, $w_{mp}$, to take into account

[7] Following Kaplan and Menzio (2015), I drop all transactions with a price equal to zero, and all the goods in a given $(j, m, h)$ where the coefficient of variation greater than one.

other factors that might be changing within the market × category over time. These variables include the number of retail chains, revenues, the number of UPCs, and the market concentration measured as the retail-chain level Herfindahl index ($HI$). I also control for consumer characteristics that might be changing over time, such as the average household size, and the share of shoppers: (i) with a household head younger than 35, (ii) with a college-educated household head, (iii) with internet connection at home, and (iv) in different household income bins.[8] I estimate both unweighted and expenditure-weighted regressions, and compute standard errors clustering observations at the product category level.[9]

As I mentioned earlier, it is likely that the online spending variable I compute using Nielsen's data has measurement error. In this case, estimates of $\beta$ from equation (1) will be affected by attenuation bias. To address this issue, I implement an instrumental variables strategy using the fraction of credit card spending in a given category × market as instrument. Data on the means of payment of transactions are available only since 2013, so I use the 2013-2016 average for each market and category. Online retailers typically require credit or debit cards as means of payment, with credit cards being the most common. In fact, survey evidence from TSYS (2017) indicates that credit cards were the most preferred payment type for 43 percent of the respondents in 2015, and 48 percent in 2017. I argue that the credit card share of spending is not only relevant for online spending, but also exogenous to retailers' pricing behavior: even though brick-and-mortar stores in the U.S. are allowed to offer cash/debit discounts, Stavins and Wu (2017) find that their occurrence is less than 1 percent for the categories I study. Thus, conditional on the product category, the means of payment should not affect retailers' pricing behavior directly.

The first and second stages of the IV regression are given by

$$\begin{aligned} \Delta x_{mp} &= \tilde{\beta} z_{mp} + \tilde{\gamma} \Delta w_{mp} + \tilde{\lambda}_p + \tilde{\epsilon}_{mp} \\ \Delta y_{mp} &= \beta \widehat{\Delta x}_{mp} + \gamma \Delta w_{mp} + \lambda_p + \epsilon_{mp} \end{aligned} \tag{2}$$

respectively, where $z_{mp}$ is the credit card spending share in a given market and category.

[8] Household income bins correspond to: less than \$25,000, between \$25,000-\$50,000, between \$50,000-\$100,000, and \$100,000 or more.

[9] The weights correspond to the 2006/2016 average expenditure share of a given category × market in total spending across all markets and product categories, from the HMS dataset. I compute the expenditure shares by taking into account the sample weights provided by Nielsen to project the data to the Scantrack market level.

Figure 6 shows the relationship between the 2006-2016 change in online spending share and credit card spending share in the data. Figure 7 also shows the relationship between both variables but after removing variation explained by the category fixed effects and the set of controls. Even though the relationship seems weaker after controlling for other variables, the F statistics higher than 90 (see Table 7) suggest that weak identification is not a problem.[10]

# 4 Empirical evidence

In this section, I present three types of evidence about the effects of online access to shopping on the pricing behavior of brick-and-mortar stores. The first type of evidence is about the direct effects and their magnitudes, and the second and third types are about the mechanism behind these effects.

## 4.1 Online shopping access and pricing behavior

Table 7 shows the estimates of $\beta$ for various price-stickiness statistics. OLS regressions suggest that higher online spending share is associated with posted prices adjusting less frequently and by smaller amounts. Nevertheless, when analyzing regular price changes and sales separately, I find that the lower frequency of adjustment is mainly driven by a lower frequency of sales, with regular price changes going in the opposite direction. Note that I measure the size of sales in negative values, so the drop in the size of posted price adjustments is explained by both regular price changes and sales. IV estimates go in the same direction as OLS ones, but the magnitudes are significantly larger. The difference between the estimates is consistent with measurement error in the online spending share biasing $\beta$ towards zero.

Overall, evidence points towards regular prices changing more frequently and by smaller amounts, and being more synchronized across stores, when the online spending share is higher. Results for regular prices are explained by both increases and decreases, with the former being more relevant for the frequency and the latter for the size (see Table 13). At the same time, temporary price cuts are less frequent and smaller in markets where online shopping is more prevalent.

[10] I report the Kleibergen-Paap rk Wald F statistic, which is corrected for clustering. The F statistic should be at least 10 for weak identification not to be considered a problem.

In order to put the magnitudes of the estimates in perspective, notice that the online share of spending increased by 0.01 points on average between 2006 and 2016. According to Column (8) of Table 7, this increment corresponds to an increase of 0.017 points in the frequency of regular price changes (22 percent of the 2006-2016 average increase) and a reduction of 0.013 points in their size (36 percent of the 2006-2016 average reduction). For sales, the 0.01 increase in the online share of spending translates into a reduction of 0.01 points in both their frequency (twice as large as the 2006-2016 average increase) and their size (24 percent of the 2006-2016 average decrease).

Regarding price dispersion, Table 8 provides strong evidence in favor of online shopping access being associated with the prices of a given good being more similar. As it is the case with price stickiness statistics, OLS estimates are significantly smaller in absolute value than IV estimates, supporting the presence of measurement error in the online spending share. While the average price dispersion did not change much between 2006 and 2016, I find that it decreased for products in markets where the online spending share increased. In particular, Column (8) shows that a 0.01 increase is related to a 0.01 reduction in the standard deviation (equivalent to 8 percent of the 2006 mean value), a 2 percent reduction in the 90-10 ratio, and a 1.6 percent reduction in the 95-5 ratio.

## 4.2 Heterogeneous effects by shopping behavior

In the previous section, I documented a strong relationship between changes in the online spending share and changes in retailers' pricing behavior. What might be the mechanism behind these effects? Suppose that online shopping access makes it easier for consumers to compare prices, find substitutes, and postpone purchases. Then, their demand elasticity should increase, inducing changes in the pricing behavior of retailers. In this section, I provide supporting evidence for this mechanism.

Denote $S_{irpt}$ as the total spending of household $i$ in product category $p$ and year $t$ from a retail chain $r$ (i.e., from any store that belongs to that retail chain). I compute the household retailer concentration as the Herfindahl index of the household $\times$ product category $\times$ retailer market shares:

$$H_{ipt} = \sum_r \left( \frac{S_{irpt}}{\sum_r S_{irpt}} \right)^2 .$$

This index shows how concentrated are household purchases in a given category, across retailers. For instance, if a household purchases dental floss (of any brand) only from Walmart (any store), the index is equal to one, meaning that the household concentrates all of its dental floss purchases in one retailer. The lower $H_{ipt}$, the more diversified are household purchases in a given narrow category across retailers.

The inverse of $H_{ipt}$, $H_{ipt}^{-1}$, could be interpreted as the effective number of retailers ($ER_{ipt}$) from which the household buys goods within a category. If the household spends the same amount in $n$ retailers, $ER_{ipt}$ is equal to $n$. Then, an $ER_{ipt}$ of 1.4 (as the average in the data) has a Herfindahl index between that of a household purchasing from one retailer only, and that of a household spending the same amount in two retailers. According to this interpretation, households with an $ER_{ipt}$ of one can be thought of as being loyal to a certain retail chain, while households with higher values can be thought of as bargain hunters.

If online access to shopping increases demand elasticity of consumers, one would expect stronger effects on pricing behavior in markets with more bargain hunters as this type of consumers are more willing to substitute across retailers. To test this hypothesis, I estimate the following specification by OLS:[11]

$$\Delta y_{mp} = \beta \Delta x_{mp} + \alpha lER_{mp} + \delta \Delta x_{mp} \times lER_{mp} + \gamma \Delta w_{mp} + \lambda_p + \epsilon_{mp} \tag{3}$$

where $lER_{mp}$ is the log of the average inverse household retailer concentration across households in a given category $\times$ market for 2006. This variable is bounded between 0 and 1.22 (with a mean of .37), so $\beta$ corresponds to the effect of online shopping access on pricing behavior in markets with loyal customers only.

In order to control for the possibility that households might be purchasing from only one retailer because there are no more options available, I also add interactions with the log of the inverse retail-chain level Herfindahl index, $lIH_{mp} = \log HI_{mp2006}^{-1}$.[12] This variable can be interpreted as the effective number of retail chains in a given market by following the same logic as for $ER_{mp}$. Then, $\delta$ gives heterogeneous effects of online access by consumer type, taking into account differential effects by market concentration.

As reported by Tables 9 and 10, the effects of online shopping access on pricing

[11] IV is unfeasible for the moment, since there are three endogenous regressors and I have one instrument only.

[12] I use $lER_{mp}$ and $lIH_{mp}$ in the initial period to minimize endogeneity concerns. Using $lER_{mp}$ in 2004 or 2005 yields, quantitatively, almost the same results. $lIH_{mp}$ is not available before 2006.

behavior I documented in the previous subsection are particularly strong in markets where consumers behave more like bargain hunters than loyal customers. In fact, in markets with loyal consumers only, these effects are not statistically significant and even have the contrary sign in some cases. Note that differential effects by market concentration cannot explain these results: when statistically significant, the effect of the interaction between online shopping access and the effective number of retailers in the market goes in the opposite direction.

## 4.3 Shopping behavior and online shopping access

Is access to online shopping related to a higher prevalence of bargain-hunting behavior? In this section, I provide evidence supporting the hypothesis that online shopping access increases demand elasticity of households as they can compare their options and purchase from different retailers more easily. In particular, I estimate the following specification at the household ($i$) and product group ($g$) level:

$$ER_{igt} = \alpha + \beta \mathbb{I}\{online\ spending_{igt} > 0\} + \delta_g + \gamma X_{igt} + \varepsilon_{igt} \tag{4}$$

where $ER_{igt}$ the is average inverse household retailer concentration across product modules in a given product group, and $\mathbb{I}\{online\ spending_{igt} > 0\}$ is an indicator function taking a value of one if the household shops online in a given product group and year. I add product group fixed effects ($\delta_g$), so the parameter of interest, $\beta$, is identified from cross-household variation over time. I control for other variables ($X_{igt}$) that might be relevant to explain households' shopping behavior: the log spending, the log number of retailers, and the retail-chain level Herfindahl index in a given product group, and dummy variables for household size, household income bin, household head age and education, Scantrack market, and race.

Table 11 shows that households that shop online in a given category tend to purchase from more retailers than those that do not. Specifically, shopping online is associated to purchasing from 19% more retailers than the mean across households, product groups, and time (1.58). This effect is robust to various controls, statistically and economically large.

# 5 Model

In order to theoretically understand the mechanisms behind changes in retailers' pricing behavior when consumers gain online access for shopping, I develop a sticky-price model with consumer search where I interpret online shopping access as a structural change in the shopping technology.

Time is continuous and no aggregate uncertainty exists. A measure-one continuum of shoppers purchase a homogeneous good and supply labor. The good is sold by a measure-one continuum of monopolistically competitive retailers. Retailers are infinitely lived, set nominal prices, and have a production technology linear in labor. A fixed cost is incurred when changing nominal prices, and retailers would like to adjust them for two reasons: (i) they face idiosyncratic transitory shocks to their productivity, and (ii) the nominal wage is increasing at a deterministic rate. Retailers' price-setting decisions, which they make taking into account the shopping behavior of buyers, produce a non-degenerate and stationary cross-sectional distribution of real prices.

Each instant of time, a continuum of shoppers enter, search, purchase, and leave the product market. Shoppers take the real-price distribution as given and search for the lowest price, paying a cost for each new price draw. The search cost is heterogeneous across buyers. As in a McCall (1970) type of search, buyers follow a reservation-price strategy: they accept offers up to a real reservation price at which they are indifferent between buying and searching again. Each buyer ends up purchasing the good from one of many nearly identical retailers.

Monopolistic competition is an outcome of the model. Because search is costly, each retailer sells the good to a positive share of buyers. In equilibrium, the magnitude of this share depends inversely on the retailer's price. The aggregation of consumer search rules generates a downward-slopping demand curve for the retailer, which depends directly on the shopping technology.

## 5.1 Retailers

A measure-one continuum of monopolistically competitive retailers is indexed by $i$. These retailers are infinitely lived, with discount rate $\rho$. Money is used as the unit of account, so retailers set their prices $P_{i,t}$ in nominal terms. The production technology of each retailer is linear in labor $l_{i,t}$, and the retailer-specific labor productivity is given

by $v_{i,t}$. We assume the retailer's productivity follows the mean-reverting process:

$$d \log v_{i,t} = -\rho_v \log v_{i,t} dt + \sigma_v dZ_{i,t}, \quad \rho_v > 0,$$

where $Z_{i,t}$ is a standard brownian motion with zero drift and unit variance, distributed independently across retailers.

The labor market is competitive and retailers hire labor at a nominal wage $W_t$. We assume all the aggregate prices, particularly the nominal wage, are growing at a constant rate $\pi$. Because real prices are defined with respect to the nominal wage, that is, $p_{i,t} \equiv P_{i,t}/W_t$, a fixed nominal price implies a real price eroding at a rate $\pi$. Each nominal price adjustment costs the retailer $\kappa > 0$ labor units.

A central aspect of the model is that the demand curve that a single retailer faces is endogenously determined by the optimal behavior of shoppers and other retailers. Denote this downward-sloping demand as a function of the real price by $D(p)$. The instantaneous nominal profit function for a retailer charging a nominal price $P_{i,t}$, given the nominal wage $W_t$ and the stochastically determined labor productivity $v_{i,t}$, is

$$\Pi_t (P_{i,t}, v_{i,t}) = \left( P_{i,t} - \frac{W_t}{v_{i,t}} \right) \times D \left( \frac{P_{i,t}}{W_t} \right).$$

At any date $t$, retailers are characterized by a pair $(P_{i,t}, v_{i,t})$. Because nominal aggregates grow at a constant rate and the productivity follows a stationary process, real aggregates are expected to be time invariant. Therefore, we can express the problem in terms of prices relative to the wage, $p$, and conjecture an equilibrium in which the current joint distribution of real prices and productivity, $\phi_t(p, v)$, is time invariant. The equilibrium static real profit function is

$$\Pi (p_{i,t}, v_{i,t}) = \left( p_{i,t} - \frac{1}{v_{i,t}} \right) \times D (p_{i,t}).$$

Let $\psi (p_{i,0}, v_{i,0})$ denote the present value of a retailer that begins at $t = 0$ with the real price $p_{i,0}$ and productivity $v_{i,0}$. Given the strategies of shoppers and other retailers, this retailer chooses a time $T_i \geq 0$ to adjust and a reset price $p_i'$ so as to solve

$$\psi (p_{i,0}, v_{i,0}) = \max_{T_i} \mathbb{E} \left\{ \int_0^{T_i} e^{-\rho t} \Pi (p_{i,t}, v_{i,t}) \, dt + e^{-\rho T_i} \max_{p_i'} \left[ \psi (p_i', v_{i,T_i}) - \kappa \right] \right\}.$$

This time-invariant Bellman equation is standard in the literature, and its solution is

well known. The optimal policy of a retailer with productivity level $v_{i,t}$ is to leave its nominal price unchanged if $p_{i,t}$ is between $p_L(v_{i,t})$ and $p_U(v_{i,t})$. If the real price hits any of these bounds, the retailer pays the menu cost $\kappa$ and adjusts to $\hat{p}(v_{i,t})$.

Before stating the problem of shoppers, defining the stationary posted-price distribution $F$ as the marginal of $\phi(p, v)$ over $v$ is useful:

$$F(p) = \int_{\underline{p}}^{p} \int_{v} \phi(x, v)\, dv dx, \quad p \in \left[\underline{p}, \bar{p}\right],$$

where the bounds $\left\{\underline{p}, \bar{p}\right\}$ are determined in equilibrium by the retailers' optimal pricing behavior.

## 5.2 Shoppers

A measure-one continuum of shoppers buy a homogeneous good and supply labor. Each instant $t$, the shoppers enter, search, purchase, and leave the product market. The shoppers are replaced by a new continuum an instant later. Because the problem of shoppers is static, I drop the time subscripts in what follows.[13] [14]

Shoppers have incomplete information about the prices: they know the posted-price distribution $F$, but not the price that each seller charges. Because the good is homogeneous and price dispersion exists, buyers have incentives to search for the lowest price. Shoppers $j$ search sequentially for a retailer $i$. They receive a first price quote for free but need to pay $\gamma_j$ labor units for each subsequent draw. There is a maximum of $\overline{S}$ draws and recall of previous offers is allowed. We assume the search cost is heterogeneous, randomly distributed across shoppers according to $G$. The shopper searches $S$ times to find a retailer $i$ from whom he buys $q_j$ units of the good at the nominal price $P$.

Given the search outcomes $P$ and $S$, the shopper $j$ chooses labor supply $L_j$ and

[13] Under this assumption, we rule out complex issues such as learning and intertemporal arbitrage. Then, we can focus on the main links between search and price-setting behavior.

[14] The assumption of instantaneous consumers also implies search happens quickly compared with real-price erosion. This implication is reasonable for the U.S. retail between 2006 and 2016, when average inflation was low and sellers took at least 4 months to change the prices of goods that households purchase every week.

quantities of the consumption good to solve

$$\begin{aligned} \max_{q_j, L_j} \quad & \mathbb{E}_j \left[ \frac{q_j{}^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} - L_j \right] \\ s.t. \quad & Pq_j + W\gamma_j (S-1) = WL_j + \mathcal{D} \qquad \forall P, S \end{aligned}$$

where $\mathcal{D}$ are the dividends the shopper gets from the retailers. We assume $\eta > 1$. The solution to this problem implies the indirect utility of the shopper is

$$\begin{aligned} \mathcal{W}_j &= \mathbb{E}_j \left[ V(p) - \gamma_j (S-1) \right] + \frac{\mathcal{D}}{W}; \\ V(p) &= \frac{p^{1-\eta}}{\eta - 1}, \end{aligned} \tag{5}$$

where $V(p)$ is the surplus that each shopper derives from buying $q(p) = -V'(p)$ units of the good at price $p$.

Shoppers take as given the retailers' pricing strategies $F$ and their surplus as a function of the real price, $V(p)$. The optimal strategy of the shoppers is to search for a retailer until they find an offer below their reservation price. To compute the optimal stopping rule, we first define the value that an offer $p$ has for a shopper $j$ after $S$ draws, $B_S(p, \gamma_j)$. For any $S \in \left\{2, \ldots, \overline{S}\right\}$, this value is the maximum between accepting such an offer and continuing to search after paying the search cost $\gamma_j$:

$$B_S(p, \gamma_j) = \max \left\{ V(p), -\gamma_j + \int_{\underline{p}}^{p} B_{S+1}(p', \gamma_j) \, dF(p') + B_{S+1}(p, \gamma_j) \left[ 1 - F(p) \right] \right\},$$

with terminal condition $B_{\overline{S}+1}(p, \gamma_j) = V(p)$. We define the reservation price as the real price that makes shopper $j$ indifferent between buying and searching again. As Lippman and McCall (1976) show, when the marginal search cost is constant and recall is allowed, the reservation price is constant among draws. The reservation price $r_j$ equates the expected benefit and the cost of the marginal search:

$$\Gamma(r_j) \equiv \int_{\underline{p}}^{r_j} \left[ V(p) - V(r_j) \right] dF(p) = \gamma_j. \tag{6}$$

If this equation has a solution, the optimal policy for the shopper is to accept any offer $p$ if $p \leq r_j$, and to continue searching otherwise. On the other hand, a buyer

with $\gamma_j < \tilde{\gamma} \equiv \lim_{r\to\infty} \Gamma(r)$ would rather search than accept a zero-surplus offer: the expected benefit of rejecting the first free offer and searching is greater than the marginal search cost. Because the marginal return to search $\Gamma(r)$ is increasing and continuously differentiable on $\left[\underline{p}, \infty\right)$, the reservation price is well defined and given by $r_j = R(\gamma_j) \equiv \Gamma^{-1}(\gamma_j)$, with $\underline{p} \leq r_j < \infty$.[15] Buyers with $\gamma_j > \tilde{\gamma}$ accept the first free offer as long as it does not exceed their maximum willingness to pay, so we let $R(\gamma_j) \to \infty$.

The reservation price $R(\gamma_j)$ is an increasing function of the search cost. This finding implies all the buyer types $\gamma_j$ for which $p \leq R(\gamma_j)$ accept a given offer $p$. An equivalent and convenient statement is that buyers whose search cost is larger than the marginal return to search at offer $p$, that is, $\gamma_j \geq \Gamma(p)$, are the ones that accept such an offer.

## 5.3 Demand function

Assume $\gamma \in \left[\underline{\gamma}, \bar{\gamma}\right]$ and that the distribution $G$ is continuous and differentiable, with an associated probability density function $g$. Consider a retailer charging real price $p$ for the good. Since the first draw is free, $g(\gamma)$ shoppers type $\gamma$ search at least once and draw $p$. Their probability of success is $F(R(\gamma))$; those with type $\gamma \geq \Gamma(p)$ accept $p$ and those with $\gamma < \Gamma(p)$ continue searching. Therefore, $[1 - F(R(\gamma))]\, g(\gamma)$ shoppers obtain $p$ on their second draw, and their probability of success is $F(R(\gamma))$; those with $\gamma \geq \Gamma(p)$ accept it while those with $\gamma < \Gamma(p)$ continue searching. On their third draw, $[1 - F(R(\gamma))]^2 g(\gamma)$ shoppers get $p$; etc. On their final draw, $[1 - F(R_j(\gamma))]^{\bar{S}-1} g(\gamma)$ shoppers get the offer $p$ and accept it if it is the minimum among all draws $\left\{1, \ldots, \bar{S}\right\}$. Summing up over those who accept the offer, the extensive margin of demand for a retailer charging $p$ is given by:

$$N(p) = \int_{\Gamma(p)}^{\bar{\gamma}} \frac{1 - [1 - F(R(\gamma))]^{\overline{S}-1}}{F(R(\gamma))} g(\gamma)\, d\gamma + \int_{\underline{\gamma}}^{\tilde{\gamma}} [1 - F(R(\gamma))]^{\overline{S}-1} g(\gamma)\, d\gamma.$$

Because the quantity each buyer purchases is independent of its type $\gamma$, we can express the endogenous demand curve as the product of two components:

$$D(p) = q(p) \times N(p).$$

[15] By noting $V(p) = \int_p^\infty q(u)\, du$ and integrating by parts, it is possible to show that $\Gamma(r_j) = \int_{\underline{p}}^{r_j} q(p)\, F(p)\, dp$. Therefore, $\Gamma'(r_j) = q(r_j)\, F(r_j) \geq 0$.

The first term on the right represents the *intensive margin* of demand, or the units that each buyer purchases at price $p$, $q(p) = p^{-\eta}$. The second and novel component for menu-cost models corresponds to the *extensive margin* of demand, $N(p)$. This function indicates the number of shoppers that a seller serves by setting a price $p$.

Using that $\Gamma'(p) = q(p) F(p)$, we can show the extensive margin is decreasing in the price:

$$N'(p) = -\left\{1 - [1 - F(p)]^{\overline{S}-1}\right\} g(\Gamma(p)) q(p) \leq 0.$$

Intuitively, shoppers can take advantage of price dispersion and flee from higher prices. Nonetheless, in an equilibrium where $\gamma > \tilde{\gamma}$, a fraction of the shoppers will accept the first free draw, independently of the price. In this case, the number of transactions at each price is

$$\begin{aligned} N(p) &= 1 - G(\tilde{\gamma}) + \int_{\Gamma(p)}^{\tilde{\gamma}} \left\{ \frac{1 - [1 - F(R(\gamma))]^{\bar{S}-1}}{F(R(\gamma))} \right\} g(\gamma) d\gamma \\ &\quad + \int_{\underline{\gamma}}^{\tilde{\gamma}} [1 - F(R(\gamma))]^{\bar{S}-1} g(\gamma) d\gamma, \end{aligned}$$

where $1 - G(\tilde{\gamma})$ is the fraction of captive shoppers.

On the other hand, the number of shoppers that a retailer can attract by lowering its price is limited. Denote by $\underline{r}$ the minimum reservation price in the market, $R(\underline{\gamma})$. A seller who sets $p \leq \underline{r}$ serves all shoppers and reaches the maximum number of transactions, $N(\underline{r})$.

The extensive margin, which depends on the shopping technology $\{G, \overline{S}\}$, plays a crucial role in determining the price elasticity of demand that a retailer faces. For $p > \underline{r}$, the extensive margin tends to increase the overall elasticity of the demand curve:

$$\epsilon_D(p) = \begin{cases} \eta & p \leq \underline{r} \\ \eta + \epsilon_N(p) & p > \underline{r} \end{cases} \tag{7}$$

$$\epsilon_N(p) = \frac{p}{N(p)} \times \left\{1 - [1 - F(p)]^{\overline{S}-1}\right\} g(\Gamma(p)) q(p) \geq 0. \tag{8}$$

## 5.4 Equilibrium

In a stationary equilibrium:

1. Shoppers $\gamma \in [\underline{\gamma}, \overline{\gamma}]$ choose $R(\gamma)$ given $V(\cdot)$ and the time-invariant posted-price

distribution $F(p)$;

2. Market demand $D(p)$ results from aggregating individual demand from shoppers and is consistent with $R(\gamma)$ and $F(p)$;

3. Retailers choose optimal pricing strategies $\Psi(v) = \{p_L(v), p_U(v), \hat{p}(v)\}$ given $D(p)$;

4. Joint distribution of real prices and productivity $\phi(p, v)$ and posted-price distribution $F(p)$ are consistent with $R(\gamma)$ and $\Psi(v)$.

The equilibrium is solved as a fixed-point problem. Given a guess for the posted-price distribution $F_0(p)$, we compute the optimal search strategies of each buyer $\gamma$, $R_0(\gamma; F_0)$. Then, we aggregate search rules into the retailer-level demand function, $D_0(p; R_0, F_0)$, to obtain the endogenous profit function, $\Pi_0(p; R_0, F_0)$. We solve the retailers' problem to get the policy functions, $\Psi_0(v; R_0, F_0)$, and the associated invariant distribution, $\phi_1(p, v; R_0, F_0)$. Finally, we update the posted-price distribution by taking the marginal of $\phi$ over $v$:

$$F_1(p) = \int_{\underline{p}_1}^{p} \int_{v} \phi_1(x, v; R_0, F_0)\, dv dx, \quad p \in \left[\underline{p}_1, \bar{p}_1\right].$$

We repeat this process until $F_1(p) = F_0(p)$ for every $p$ and find an equilibrium where the total number of transactions equals the total number of buyers:

$$\int_{\underline{p}}^{\bar{p}} N(p; R, F)\, dF(p; R) = 1.$$

The posted-price distribution weighted by the number of transactions, $NdF$, can be interpreted as the distribution of *transaction* prices.

# 6 The effects of online shopping access

In the previous section, I developed a model in which shopping behavior directly impacts the pricing decisions of retailers through changes in the extensive margin of demand and its elasticity. In this section, I evaluate whether the model can replicate the observed changes in the price-setting behavior between 2006 and 2016 only by changing the shopping technology. I jointly calibrate the parameters of the model to match an average markup of 30%, the absolute size and frequency of regular price

Table 1: Additional moments, model fit

| Moment | Year | Model | Data | Targeted |
|---|---|---|---|---|
| Monthly frequency of reg. price adjustment | 2006 | 0.139 | 0.140 | Yes |
| | 2016 | 0.163 | 0.160 | Yes |
| Average abs. size of reg. price changes | 2006 | 0.224 | 0.210 | Yes |
| | 2016 | 0.204 | 0.190 | Yes |
| Standard deviation of log prices | 2006 | 0.129 | 0.130 | Yes |
| | 2016 | 0.126 | 0.120 | Yes |
| Average markup | 2006 | 1.298 | 1.300 | Yes |
| | 2016 | 1.252 | - | No |

changes in 2006 and 2016, and price dispersion in 2006 and 2016. To match differences in the pricing statistics between both years, I only let the parameters related to the shopping technology adjust.

Table 2: Calibrated parameters

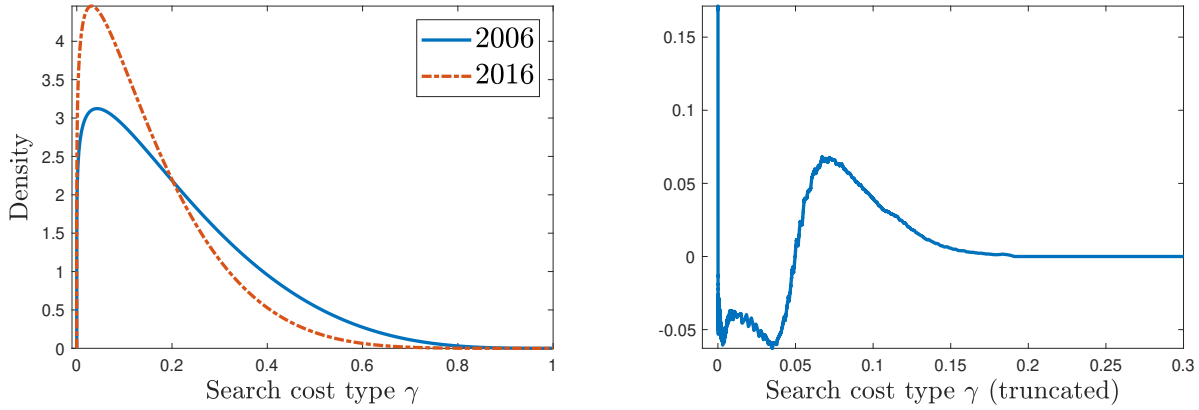
| Parameter | Description | Value |
|---|---|---|
| $\kappa$ | Menu cost | 0.075 |
| $\rho_v$ | Mean-reversion rate of shocks | 0.723 |
| $\sigma_v$ | Volatility of shocks | 0.124 |
| $\alpha_{2006}$ | Shape of search cost distribution | 1.144 |
| $\alpha_{2016}$ | | 1.176 |
| $\beta_{2006}$ | Shape of search cost distribution | 4.221 |
| $\beta_{2016}$ | | 6.371 |
| $\overline{S}_{2006}$ | Maximum number of price draws | 65 |
| $\overline{S}_{2016}$ | | 77 |
| $\eta$ | Intensive margin elasticity of demand | 2.960 |

## 6.1 Parametrization and calibration

We choose a flexible search cost distribution: $\gamma \sim Beta(\alpha, \beta)$, where $\alpha > 1$, $\beta > 1$, and $\gamma \in [0, 1]$. Let $Y \in \{2006, 2016\}$ denote data years. We jointly calibrate the size of menu cost $\kappa$, the persistence $\rho_v$, and volatility $\sigma_v$ of idiosyncratic shocks, the shape parameters $\alpha_Y$ and $\beta_Y$ of search-cost distribution, the maximum number of draws $\overline{S}_Y$,

Figure 1: Changes in the shopping technology, 2006-2016

(a) Search cost distribution $G$ (b) Log expected searches $\breve{S}(\gamma)$, difference




and the price elasticity of demand $\eta$ of shoppers to match the following: (i) the average standard deviation of log prices in 2006 and 2016; (ii) the frequency of regular price changes and the average size of regular price changes in 2006 and 2016; and (iii) an average markup of 30%. Following the literature, we set the monthly discount rate to $\rho = 0.96^{1/12}$. Finally, we set $\pi = 2\%$.

Table 1 shows the model does a relatively good job matching the empirical evidence. The calibrated parameters are in Table 2. Through the lens of the model, higher frequency and lower size of adjustment, and lower price dispersion are associated to a higher density of shoppers with a relatively low marginal search cost: the average marginal search cost decreases, as well as its variance (see Figure 1a). At the same time, the model requires an increase in the maximum number of price draws to match the differences in the moments between 2006 and 2016. As Figure 1b shows, a higher $\overline{S}$ is only binding for the shoppers at the bottom of the marginal search cost distribution.

## 6.2 Aggregate effects

Welfare of each shopper per instant of time $dt$ is given by Equation (5). Expressing its components in terms of the posted-price and the search-cost distributions is useful. The gross surplus from consumption among all shoppers, $\bar{V}$, is the transaction-weighted

average of the shopper's surplus in terms of real prices:

$$\bar{V} = \int_{\underline{p}}^{\bar{p}} V(p) N(p) dF(p).$$

To derive the total expected cost of search, note a shopper type $\gamma$ accepts an offer $p \leq R(\gamma)$ with probability $F(R(\gamma))$ and continues searching with probability $1-F(R(\gamma))$. Therefore, the probability of receiving a successful offer after $s$ searches is

$$\Pr[K(\gamma) = s] = F(R(\gamma)) \times [1 - F(R(\gamma))]^{s-1}.$$

Because the number of searches they can conduct is limited, a shopper with cost $\gamma$ searches, on average, $\breve{S}(\gamma)$ times, where

$$\breve{S}(\gamma) \equiv \sum_{s=1}^{\overline{S}-1} s \times \Pr[K(\gamma) = s] + \bar{S} \times [1 - F(R(\gamma))]^{\bar{S}-1} = \frac{1 - [1 - F(R(\gamma))]^{\bar{S}}}{F(R(\gamma))}.$$

Taking into account that the first price draw is free, the total resources spent on the search for better prices are

$$\bar{C} \equiv \int_0^1 \gamma_j \left(\breve{S}(\gamma_j) - 1\right) dj = \int_{\underline{\gamma}}^{\bar{\gamma}} \gamma \left[\breve{S}(\gamma) - 1\right] dG(\gamma).$$

The expected price paid by a shopper is given by

$$\begin{aligned} \breve{p}(\gamma) \equiv \mathbb{E}[p|\gamma] &= \int_{\underline{p}}^{R(\gamma)} p dF(p) \times \left\{ \frac{1 - [1 - F(R(\gamma))]^{\overline{S}-1}}{F(R(\gamma))} \right\} \\ &\quad + \int_{\underline{p}}^{\overline{p}} p d\left\{1 - [1 - F(p)]^{\overline{S}}\right\} \times [1 - F(R(\gamma))]^{\overline{S}-1}. \end{aligned}$$

On the other hand, each $dt$, real dividends are aggregate real profits net of aggregate adjustment costs. Gross aggregate real profits are

$$\bar{\Pi} = \int_0^1 \Pi(p_{i,t}, v_{i,t}) di = \int_{\underline{p}}^{\bar{p}} \int_v \Pi(p, v) \phi(p, v) dv dp.$$

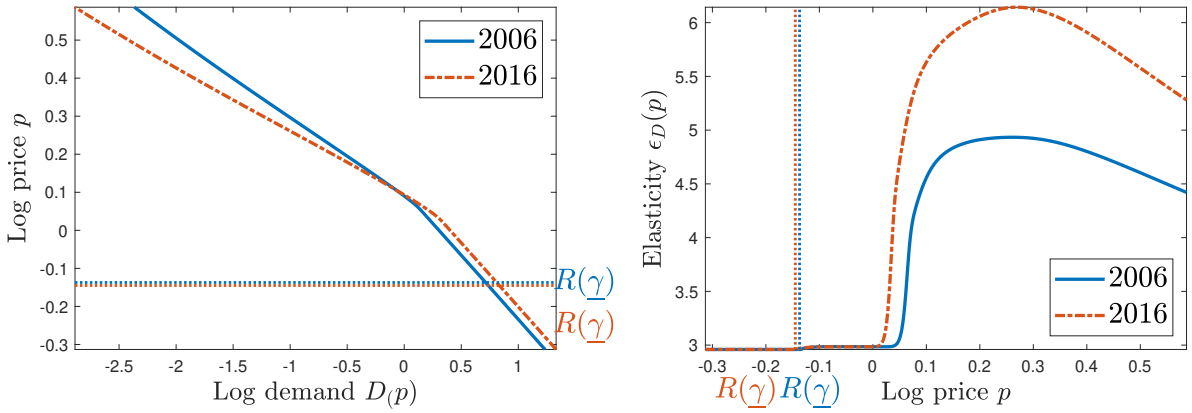
If $\Lambda$ is the number of retailers that reprice each $dt$, total adjustment costs are $\kappa\Lambda$.

Then, social welfare is aggregate consumer surplus net of search costs plus total

Figure 2: Changes in demand function, 2006-2016

(a) Equilibrium demand function

(b) Elasticity of demand



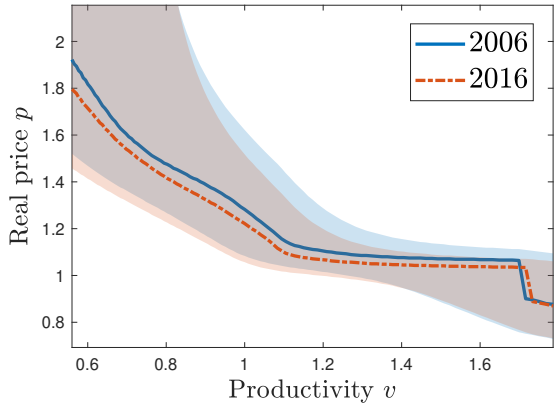

real profits net of adjustment costs. Each one of these terms depends on the shopping technology:

$$\mathcal{W}\left(G,\overline{S}\right)=\bar{V}\left(G,\overline{S}\right)+\bar{\Pi}\left(G,\overline{S}\right)-\bar{C}\left(G,\overline{S}\right)-\kappa\Lambda\left(G,\overline{S}\right).$$

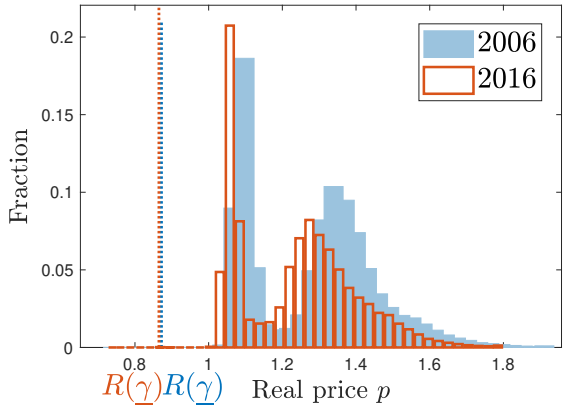
The first two terms on the right correspond to the aggregate gains from trade, and the last two terms to the resources spent on market frictions (i.e., search and price adjustment). According to the calibrated model, online shopping access increases the density of shoppers with low marginal search costs and the maximum number of price draws that shoppers can make. Both changes induce shoppers to search more, and a higher search intensity increases the average resource cost of search. Nevertheless, with more search, competition to attract searchers increases: demand at all prices becomes more elastic (Figure 2), markups decrease, and consumer surplus increases. As Figure 3b shows, price dispersion decreases since all retailers charge lower prices. For retailers, deviations from the optimal price are more costly, so they adjust prices more often and by smaller amounts, increasing resources spent on menu costs (adjustment bands become narrower – see Figure 3a). Overall, the calibrated model suggests that aggregate welfare increased 11.45% in consumption equivalent units.

Figure 3: Changes in pricing behavior, 2006-2016

(a) Adjustment bands




(b) Real price distribution $F$




## 6.3 Differential effects

Although welfare increases for each consumer, high-search-cost shoppers are the ones who benefit the most from online shopping access (Figure 4a). As Figures 1b and 4d show, their shopping behavior is unaffected by online shopping access: they continue to accept the first free offer. The benefits that high search-cost shoppers perceive result from the increased search intensity of low-search-cost shoppers, which increases competition among retailers, shifting the real price distribution to the left.

# 7 Conclusion

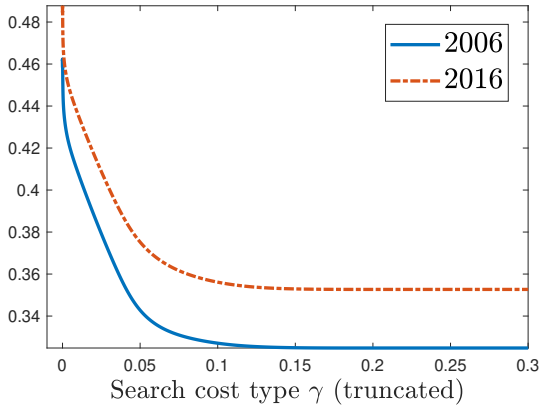
In this paper, I provide evidence on how online shopping access is associated with changes in the pricing behavior of brick-and-mortar retailers. In particular, I find that in markets with a higher online share of spending, prices are more flexible and similar, and change by smaller amounts. I argue that these effects are consistent with online shopping access resulting in a higher elasticity of demand faced by retailers. To understand and quantify the effects of online shopping access on pricing behavior of traditional retailers, I develop a sticky-price model with consumer search where the demand elasticity is a function of the shopping technology.

In the model, online shopping access corresponds to a structural change in the shopping technology. Such a change decreases the marginal search cost of shoppers and the maximum number of draws available, increasing search intensity. As search

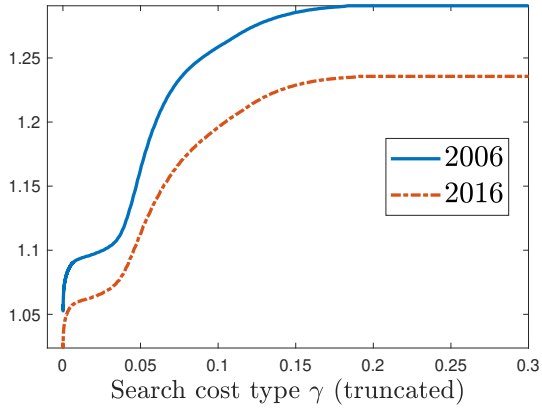
activity increases, competition among retailers intensifies, increasing the elasticity of demand that they face. In the aggregate, resources spent on searching for low prices increase, but higher competition decreases markups, increasing consumer welfare.

Figure 4: Changes in welfare by type $\gamma$, 2006-2016

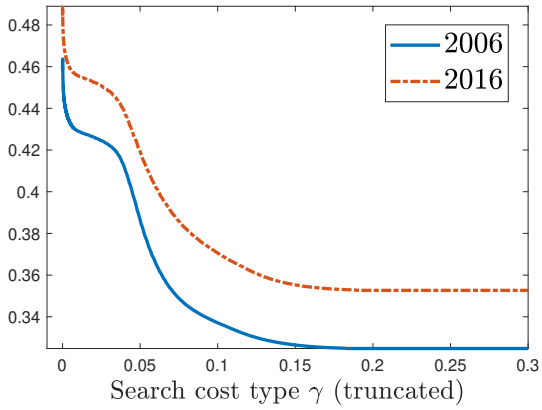
(a) Expected welfare $\mathcal{W}_j$



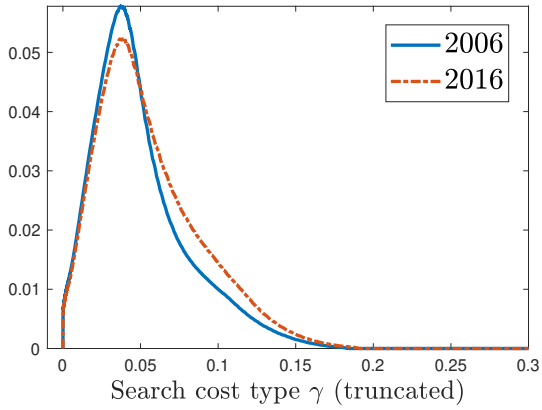

(b) Expected price paid $\breve{p}(\gamma)$




(c) Expected consumer surplus $\mathbb{E}_j[V(p)]$




(d) Expected search cost $\gamma\left[\breve{S}(\gamma)-1\right]$



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# Data tables and figures

Table 3: Facts about online prices (large multi-channel stores)

| | Period Averages | | |
|---|---|---|---|
| | 2008-2010 | 2011-2013 | 2014-2017 |
| *Posted prices* | | | |
| Frequency of price changes (monthly) | 21.28 | 28.02 | 31.72 |
| Implied duration (months) | 4.70 | 3.57 | 3.15 |
| Absolute size of price changes (%) | 18.65 | 17.84 | 15.52 |
| *Regular prices* | | | |
| Frequency of price changes (monthly) | 15.43 | 22.39 | 27.39 |
| Implied duration (months) | 6.48 | 4.47 | 3.65 |
| Absolute size of price changes (%) | 17.45 | 16.24 | 15.02 |
| Goods on sale each month (%) | 4.02 | 3.98 | 3.29 |

*Notes:* Reproduced from Cavallo (2018). Regular prices exclude sale events and are computed using the one-month, v-shaped "Filter A" sale algorithm from Nakamura and Steinsson (2008).

Table 4: Online shopping access, descriptive statistics

| | | | | Percentile | | |
|---|---|---|---|---|---|---|
| | | Mean | Std.Dev. | 25th | 50th | 75th |
| Online share of spending | 2006 | 0.54% | 1.21% | 0.03% | 0.21% | 0.57% |
| | 2016 | 1.47% | 2.37% | 0.21% | 0.65% | 1.80% |
| | Diff. | 0.97% | 2.38% | 0.00% | 0.34% | 1.35% |
| Online share of transactions | 2006 | 0.38% | 0.75% | 0.02% | 0.16% | 0.42% |
| | 2016 | 0.94% | 1.51% | 0.17% | 0.46% | 1.14% |
| | Diff. | 0.60% | 1.50% | 0.00% | 0.24% | 0.81% |
| Fraction of households with | 2006 | 0.95% | 1.12% | 0.08% | 0.65% | 1.41% |
| at least one online purchase | 2016 | 2.14% | 2.19% | 0.67% | 1.54% | 2.88% |
| | Diff. | 1.22% | 2.10% | 0.00% | 0.76% | 1.94% |

*Notes:* Statistics computed for $(p, m, t)$ triples that appear in both 2006 and 2016. Expenditure weights used to aggregate over product modules and markets.

Table 5: Price stickiness, descriptive statistics

| | | 2006 | 2016 | Difference |
|---|---|---|---|---|
| *Frequency* | | | | |
| Posted price changes | Mean | 0.250 | 0.344 | 0.095 |
| | Std. Dev. | 0.102 | 0.105 | 0.088 |
| Regular price changes | Mean | 0.147 | 0.223 | 0.077 |
| | Std. Dev. | 0.071 | 0.086 | 0.072 |
| Sales | Mean | 0.068 | 0.073 | 0.004 |
| | Std. Dev. | 0.041 | 0.033 | 0.030 |
| *Size* | | | | |
| Posted price changes | Mean | 0.209 | 0.174 | -0.036 |
| | Std. Dev. | 0.072 | 0.057 | 0.058 |
| Regular price changes | Mean | 0.206 | 0.170 | -0.036 |
| | Std. Dev. | 0.069 | 0.053 | 0.055 |
| Sales | Mean | -0.204 | -0.164 | 0.041 |
| | Std. Dev. | 0.080 | 0.065 | 0.069 |
| *Synchronization* | | | | |
| Posted price changes | Mean | 0.267 | 0.360 | 0.093 |
| | Std. Dev. | 0.098 | 0.100 | 0.088 |
| Regular price changes | Mean | 0.160 | 0.235 | 0.075 |
| | Std. Dev. | 0.069 | 0.082 | 0.072 |

*Notes:* Statistics computed for $(p, m, t)$ triples that appear in both 2006 and 2016. Size of price changes measured in absolute values, and size of sales in negative values. Statistics computed at the monthly frequency and averaged across product modules and markets for each year. Expenditure weights used.

Table 6: Price dispersion, descriptive statistics

| | | 2006 | 2016 | Difference |
|---|---|---|---|---|
| Standard deviation | Mean | 0.131 | 0.130 | 0.000 |
| | Std. Dev. | 0.048 | 0.043 | 0.035 |
| Log 90-10 ratio | Mean | 0.314 | 0.307 | -0.005 |
| | Std. Dev. | 0.120 | 0.108 | 0.089 |
| Log 95-5 ratio | Mean | 0.384 | 0.384 | 0.003 |
| | Std. Dev. | 0.139 | 0.128 | 0.103 |

*Notes:* Statistics computed for $(p, m, t)$ triplets that appear in both 2006 and 2016. Statistics computed at the monthly frequency and averaged across product modules and markets for each year. Expenditure weights used.

Table 7: Price stickiness and online shopping access

| Dependent variable | Unweighted | | | | Weighted | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS | IV | IV | OLS | OLS | IV | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Frequency* | | | | | | | | |
| Δfreq. posted *dp* | -0.035** | -0.037** | -0.298 | 0.056 | -0.149*** | -0.117*** | -1.042*** | -0.604** |
| | (-0.016) | (-0.016) | (-0.210) | (-0.227) | (-0.032) | (-0.029) | (-0.234) | (-0.275) |
| Δfreq. regular *dp* | 0.020 | 0.011 | 1.513*** | 1.592*** | 0.025 | -0.004 | 1.243*** | 1.743*** |
| | (-0.012) | (-0.012) | (-0.207) | (-0.235) | (-0.025) | (-0.024) | (-0.205) | (-0.320) |
| Δfreq. sales | -0.021*** | -0.020*** | -0.811*** | -0.535*** | -0.050*** | -0.036*** | -1.018*** | -0.925*** |
| | (-0.005) | (-0.005) | (-0.106) | (-0.096) | (-0.009) | (-0.008) | (-0.129) | (-0.163) |
| *Size* | | | | | | | | |
| Δabs. size posted *dp* | -0.101*** | -0.091*** | -0.217 | -0.098 | -0.275*** | -0.200*** | -1.946*** | -1.525*** |
| | (-0.013) | (-0.012) | (-0.187) | (-0.195) | (-0.033) | (-0.028) | (-0.241) | (-0.276) |
| Δabs. size regular *dp* | -0.086*** | -0.079*** | -0.140 | -0.071 | -0.220*** | -0.166*** | -1.497*** | -1.251*** |
| | (-0.012) | (-0.012) | (-0.174) | (-0.185) | (-0.029) | (-0.024) | (-0.203) | (-0.240) |
| Δsize sales | 0.138*** | 0.122*** | 0.259 | 0.131 | 0.318*** | 0.234*** | 1.764*** | 1.140*** |
| | (-0.016) | (-0.016) | (-0.226) | (-0.240) | (-0.038) | (-0.032) | (-0.241) | (-0.279) |
| *Synchronization* | | | | | | | | |
| Δsync. posted *dp* | 0.011 | -0.001 | 0.923*** | 1.333*** | -0.055* | -0.066** | -0.107 | 0.498* |
| | (-0.016) | (-0.016) | (-0.231) | (-0.274) | (-0.031) | (-0.029) | (-0.212) | (-0.285) |
| Δsync. regular *dp* | 0.071*** | 0.051*** | 2.638*** | 2.726*** | 0.139*** | 0.063*** | 2.169*** | 2.715*** |
| | (-0.013) | (-0.013) | (-0.281) | (-0.323) | (-0.025) | (-0.023) | (-0.242) | (-0.405) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| F statistic | - | - | 124.1 | 101.9 | - | - | 196.4 | 96.5 |

*Notes:* Table shows estimates of $\beta$ in equations (1) and (2) for various pricing behavior statistics. *dp* stands for price change. The number of observations is 28,470 category × market pairs. Regression weights in Columns (5)-(8) correspond to the 2006/2016 average expenditure share of a given category × market in total spending across all markets and product categories. The controls include the 2006-2016 log change of revenues, number of retail chains, number of UPCs, Herfindahl index (retail-chain level), and household size, as well as the 2006-2016 change in the share of shoppers in different income, age, and education categories, and in the share with internet at home. The size of sales is measured in negative values. The F statistic (Kleibergen-Paap rk Wald F statistic) is corrected for clustering. Standard errors in parentheses, clustered by product module. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table 8: Price dispersion and online shopping access

| | Unweighted | | | | Weighted | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variable | OLS | OLS | IV | IV | OLS | OLS | IV | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Δstd. dev. | -0.033*** | -0.024*** | -0.700*** | -0.678*** | -0.088*** | -0.059*** | -0.964*** | -0.934*** |
| | (-0.008) | (-0.007) | (-0.118) | (-0.126) | (-0.012) | (-0.010) | (-0.126) | (-0.165) |
| Δ90-10 ratio | -0.096*** | -0.069*** | -1.553*** | -1.293*** | -0.274*** | -0.182*** | -2.436*** | -1.982*** |
| | (-0.023) | (-0.023) | (-0.330) | (-0.347) | (-0.042) | (-0.038) | (-0.344) | (-0.413) |
| Δ95-5 ratio | -0.083*** | -0.058*** | -0.966*** | -0.724*** | -0.198*** | -0.126*** | -1.973*** | -1.568*** |
| | (-0.019) | (-0.019) | (-0.274) | (-0.289) | (-0.031) | (-0.027) | (-0.293) | (-0.345) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| F statistic | - | - | 124.1 | 101.9 | - | - | 196.4 | 96.5 |

*Notes:* Table shows estimates of $\beta$ in equations (1) and (2) for various pricing behavior statistics. The number of observations is 28,470 category × market pairs. Regression weights in Columns (5)-(8) correspond to the 2006/2016 average expenditure share of a given category × market in total spending across all markets and product categories. The controls include the 2006-2016 log change of revenues, number of retail chains, number of UPCs, Herfindahl index (retail-chain level), and household size, as well as the 2006-2016 change in the share of shoppers in different income, age, and education categories, and in the share with internet at home. The F statistic (Kleibergen-Paap rk Wald F statistic) is corrected for clustering. Standard errors in parentheses, clustered by product module. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table 9: Heterogeneous effects, price stickiness

| Dependent variable | Without controls | | | With controls | | |
|---|---|---|---|---|---|---|
| | $\Delta x_{mp}$ | $\Delta x_{mp} \times lER_{mp}$ | $\Delta x_{mp} \times lIH_{mp}$ | $\Delta x_{mp}$ | $\Delta x_{mp} \times lER_{mp}$ | $\Delta x_{mp} \times lIH_{mp}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Frequency* | | | | | | |
| Δfreq. posted *dp* | -0.092 | -0.397** | 0.079 | -0.073 | -0.344** | 0.055 |
| | (-0.094) | (-0.193) | (-0.070) | (-0.090) | (-0.174) | (-0.066) |
| Δfreq. regular *dp* | -0.144** | 0.303** | 0.082 | -0.120 | 0.234* | 0.052 |
| | (-0.075) | (-0.155) | (-0.055) | (-0.075) | (-0.142) | (-0.054) |
| Δfreq. sales | -0.015 | -0.197*** | 0.035* | 0.014 | -0.190*** | 0.007 |
| | (-0.025) | (-0.053) | (-0.021) | (-0.024) | (-0.051) | (-0.020) |
| *Size* | | | | | | |
| Δabs. size posted *dp* | 0.038 | -0.929*** | -0.023 | 0.018 | -0.830*** | 0.010 |
| | (-0.066) | (-0.170) | (-0.049) | (-0.068) | (-0.160) | (-0.049) |
| Δabs. size regular *dp* | 0.060 | -0.733*** | -0.050 | 0.047 | -0.654*** | -0.027 |
| | (-0.065) | (-0.146) | (-0.048) | (-0.066) | (-0.137) | (-0.047) |
| Δsize sales | 0.049 | 1.028*** | -0.039 | 0.082 | 0.924*** | -0.087 |
| | (-0.088) | (-0.190) | (-0.065) | (-0.086) | (-0.184) | (-0.062) |
| *Synchronization* | | | | | | |
| Δsync. posted *dp* | -0.088 | -0.300* | 0.114* | -0.048 | -0.336** | 0.072 |
| | (-0.097) | (-0.182) | (-0.068) | (-0.095) | (-0.160) | (-0.067) |
| Δsync. regular *dp* | -0.126 | 0.472*** | 0.106** | -0.079 | 0.305** | 0.054 |
| | (-0.079) | (-0.173) | (-0.054) | (-0.079) | (-0.150) | (-0.054) |

*Notes:* Table shows estimation of equation (3) for various pricing behavior statistics. *dp* stands for price change. The number of observations is 28,470 category × market pairs. $\Delta x_{mp}$ is the 2006-2016 change in the online spending share, $lER_{mp}$ is the log effective number of retailers from which a household purchases, and $lIH_{mp}$ is the log of the inverse retail-chain level Herfindahl index. Observations are weighted using the 2006/2016 average expenditure share of a given category × market in total spending across all markets and product categories. The controls include the 2006-2016 log change of revenues, number of retail chains, number of UPCs, Herfindahl index (retail-chain level), and household size, as well as the 2006-2016 change in the share of shoppers in different income, age, and education categories, and in the share with internet at home. The size of sales is measured in negative values. Standard errors in parentheses, clustered by product module. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table 10: Heterogeneous effects, price dispersion

| Dependent variable | Without controls | | | With controls | | |
|---|---|---|---|---|---|---|
| | $\Delta x_{mp}$ | $\Delta x_{mp} \times lER_{mp}$ | $\Delta x_{mp} \times lIH_{mp}$ | $\Delta x_{mp}$ | $\Delta x_{mp} \times lER_{mp}$ | $\Delta x_{mp} \times lIH_{mp}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta$std. dev. | -0.012 | -0.340*** | 0.031 | -0.018 | -0.324*** | 0.043* |
| | (-0.030) | (-0.076) | (-0.024) | (-0.029) | (-0.074) | (-0.024) |
| $\Delta$90-10 ratio | -0.149 | -0.975*** | 0.183*** | -0.156 | -0.944*** | 0.207*** |
| | (-0.116) | (-0.218) | (-0.077) | (-0.115) | (-0.216) | (-0.076) |
| $\Delta$95-5 ratio | -0.054 | -0.802*** | 0.116* | -0.054 | -0.798*** | 0.133** |
| | (-0.083) | (-0.189) | (-0.069) | (-0.082) | (-0.187) | (-0.067) |

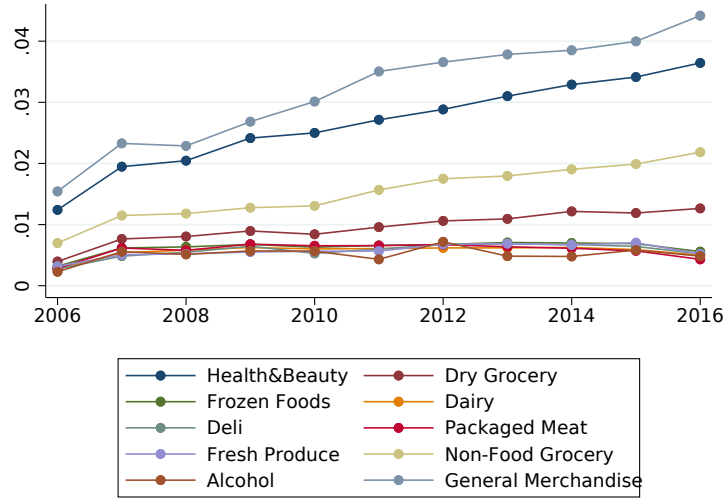
*Notes:* Table shows estimation of equation (3) for various pricing behavior statistics. The number of observations is 28,470 category × market pairs. $\Delta x_{mp}$ is the 2006-2016 change in the online spending share, $lER_{mp}$ is the log effective number of retailers from which a household purchases, and $lIH_{mp}$ is the log of the inverse retail-chain level Herfindahl index. Observations are weighted using the 2006/2016 average expenditure share of a given category × market in total spending across all markets and product categories. The controls include the 2006-2016 log change of revenues, number of retail chains, number of UPCs, Herfindahl index (retail-chain level), and household size, as well as the 2006-2016 change in the share of shoppers in different income, age, and education categories, and in the share with internet at home. Standard errors in parentheses, clustered by product module. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Table 11: Household retailer concentration and online shopping

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *online spending* $> 0$ | 0.325*** | 0.314*** | 0.318*** | 0.275*** | 0.274*** |
| | (0.023) | (0.022) | (0.022) | (0.020) | (0.020) |
| Market concentration | | -0.653*** | -0.657*** | -0.720*** | -0.694*** |
| | | (0.070) | (0.070) | (0.067) | (0.073) |
| log *#retailers* | | 0.105*** | 0.105*** | 0.092*** | 0.235*** |
| | | (0.013) | (0.013) | (0.012) | (0.025) |
| log *spending* | | | | 0.098*** | 0.099*** |
| | | | | (0.009) | (0.008) |
| Household size | No | No | Yes | Yes | Yes |
| Household income | No | No | Yes | Yes | Yes |
| Household head age | No | No | Yes | Yes | Yes |
| Household head educ. | No | No | No | No | Yes |
| Scantrack market | No | No | No | No | Yes |
| Race | No | No | No | No | Yes |

*Notes:* Table shows estimation of equation (4) including different controls, and 11 years between 2006 and 2016. The number of observations is 40,183,958 household × product group × year combinations. All the regressions have product group fixed effects, and observations are weighted using Nielsen sampling weights times household × product group × year spending. Standard errors in parentheses, two-way clustered by household and product group. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

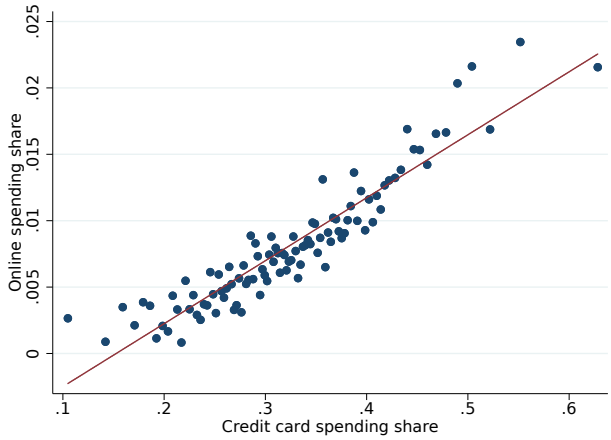
Figure 5: Trends in online spending share by department



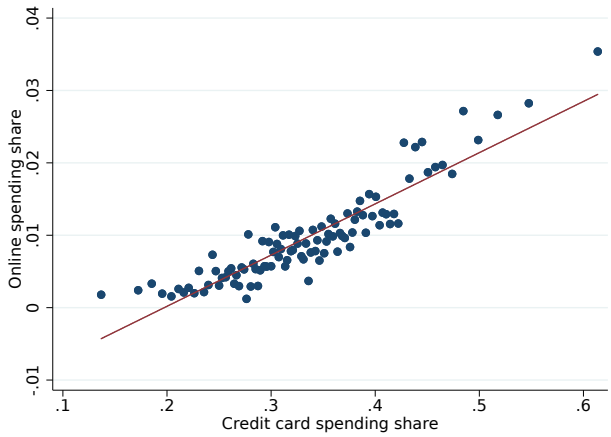

*Note:* The figure shows the online spending share by product department for each year between 2006 and 2016.

Figure 6: First stage, no additional controls

(a) Unweighted



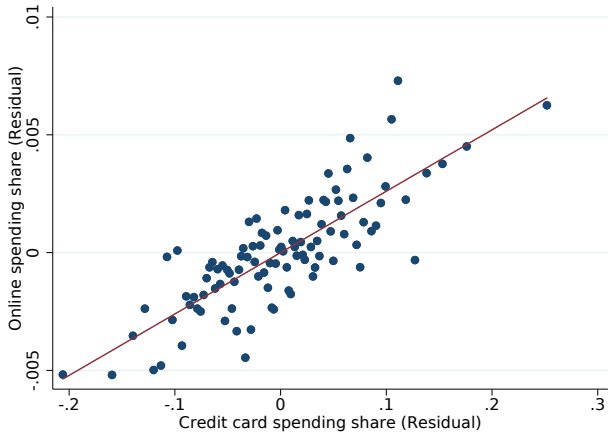

(b) Weighted



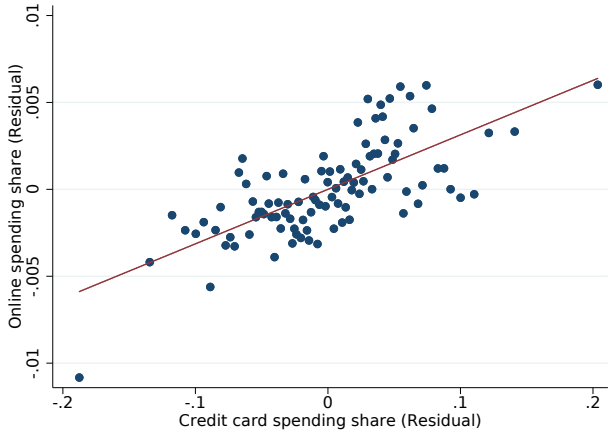

*Notes:* The figures show the relationship between the 2006-2016 change in online spending share and credit card spending share in the data. The scatter plots consider 100 equal-sized bins defined by the credit card spending share, for which the mean of the 2006-2016 change in online spending share is taken. The weights for the second figure correspond to the 2006/2016 average expenditure share of a given category $\times$ market in total spending across all markets and product categories.

Figure 7: First stage, residual variation

(a) Unweighted




(b) Weighted




*Notes:* The figures show the relationship between the 2006-2016 change in online spending share and credit card spending share in the data, after taking into account category fixed effects and the set of controls described in the text. The scatter plots consider 100 equal-sized bins defined by the residual credit card spending share, for which the mean of the residual 2006-2016 change in online spending share is taken. The weights correspond to the 2006/2016 average expenditure share of a given category $\times$ market in total spending across all markets and product categories. The F statistics, corrected for clustering, are 101.9 and 96.5 for the unweighted and weighted regressions, respectively.

# A Additional tables

Table 12: Regular prices, additional descriptive statistics

| | | 2006 | 2016 | Difference |
|---|---|---|---|---|
| *Frequency* | | | | |
| Regular price increases | Mean | 0.073 | 0.110 | 0.037 |
| | Std. Dev. | 0.035 | 0.041 | 0.036 |
| Regular price decreases | Mean | 0.074 | 0.114 | 0.040 |
| | Std. Dev. | 0.037 | 0.045 | 0.036 |
| *Size* | | | | |
| Regular price increases | Mean | 0.194 | 0.160 | -0.035 |
| | Std. Dev. | 0.067 | 0.051 | 0.054 |
| Regular price decreases | Mean | -0.209 | -0.170 | 0.039 |
| | Std. Dev. | 0.073 | 0.054 | 0.058 |

*Notes:* Statistics computed for $(p, m, t)$ triplets that appear in both 2006 and 2016. The size of regular price decreases is measured in negative values. Statistics computed at the monthly frequency and averaged across product modules and markets for each year. Expenditure weights used.

Table 13: Regular price stickiness and online shopping access, continued

| Dependent variable | Unweighted | | | | Weighted | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS | IV | IV | OLS | OLS | IV | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Frequency* | | | | | | | | |
| Δfreq. regular $dp^+$ | 0.009 | 0.006 | 0.798*** | 0.855*** | 0.010 | -0.002 | 0.660*** | 0.949*** |
| | (-0.006) | (-0.006) | (-0.107) | (-0.122) | (-0.013) | (-0.013) | (-0.104) | (-0.163) |
| Δfreq. regular $dp^-$ | 0.011* | 0.006 | 0.714*** | 0.737*** | 0.015 | -0.002 | 0.583*** | 0.794*** |
| | (-0.006) | (-0.006) | (-0.104) | (-0.117) | (-0.012) | (-0.011) | (-0.104) | (-0.159) |
| *Size* | | | | | | | | |
| Δsize regular $dp^+$ | -0.098*** | -0.091*** | -0.138 | -0.050 | -0.223*** | -0.170*** | -1.418*** | -1.188*** |
| | (-0.012) | (-0.012) | (-0.175) | (-0.189) | (-0.029) | (-0.024) | (-0.195) | (-0.230) |
| Δsize regular $dp^-$ | 0.091*** | 0.084*** | 0.135 | 0.101 | 0.234*** | 0.172*** | 1.541*** | 1.251*** |
| | (-0.014) | (-0.013) | (-0.187) | (-0.200) | (-0.031) | (-0.027) | (-0.208) | (-0.245) |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| F statistic | - | - | 124.1 | 101.9 | - | - | 196.4 | 96.5 |

*Notes:* Table shows estimates of $\beta$ in equations (1) and (2) for various pricing behavior statistics, for regular prices. $dp^+$ and $dp^-$ stand for price increase and decrease, respectively. The number of observations is 28,470 category × market pairs. Regression weights in Columns (5)-(8) correspond to the 2006/2016 average expenditure share of a given category × market in total spending across all markets and product categories. The controls include the 2006-2016 log change of revenues, number of retail chains, number of UPCs, Herfindahl index (retail-chain level), and household size, as well as the 2006-2016 change in the share of shoppers in different income, age, and education categories, and in the share with internet at home. The size of price decreases is measured in negative values. The F statistic (Kleibergen-Paap rk Wald F statistic) is corrected for clustering. Standard errors in parentheses, clustered by product module. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).