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WP 14-17

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Abstract

We study a tractable model of firm price setting with customer markets and empirically evaluate its predictions. Our framework captures the dynamics of customers in response to a change in the price, describes the behavior of optimal prices in the presence of customer acquisition and retention concerns, and delivers a general equilibrium model of price and customer dynamics. We exploit novel micro data on purchases from a panel of households from a large U.S. retailer to quantify the model and compare it to the counterfactual benchmark of the standard monopolistic competition setting. We show that a model with customer markets has markedly different implications in terms of the equilibrium price distribution, which better fit the available empirical evidence on retail prices. Moreover, the dynamic of the response of demand to shocks that affects price dispersion is also distinctive. Our results suggest that inertia in customer reallocation across firms increases the persistence in the response of demand to these shocks.

JEL classification: E30, E12, L16

Keywords: customer markets, price setting, product market frictions

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1 Introduction

The customer base of a firm, that is, the set of customers buying from it at a given point in time, is an important determinant of firm performance and survival.[1] Its effects are long lasting, as customer-supplier relationships are subject to a certain degree of stickiness (Hall (2008)).[2] Therefore, firms actively seek to maintain and grow their customer base and this effort impacts their pricing, as the price is an obvious instrument to attract and retain customers (Phelps and Winter (1970)). Despite the centrality of price and demand dynamics in informing several domains of public policy (e.g. monetary policy), our understanding of how customer base concerns affect firms' pricing is still scant.

In this paper we develop a model of firm price-setting with customer markets. We contrast its predictions with those of the standard monopolistic competition framework and quantitatively evaluate them exploiting novel data. In the model, firms set prices responding to idiosyncratic productivity shocks taking into account the effects of a price change on the dynamics of their customer base. Customers respond to price changes but face search frictions that reduce their ability to reallocate across firms. This model is of interest in itself because, while being tractable, it provides a rich laboratory to study how the relationship between customer and price dynamics is shaped, in equilibrium, by idiosyncratic production and search costs. Moreover, whereas the lack of appropriated data has so far limited the possibility to measure the importance of customer markets, we exploit novel micro data to estimate and quantify our model.

We combine the model and data to highlight two important implications of customer markets. First, competition for customers creates a strong incentive for firms to cluster prices. This results in a shape of the price distribution matching the one found in our data and consistent with the findings of a recent literature documenting the pricing of homogeneous goods (Kaplan and Menzio (forthcoming)). Second, with a counterfactual exercise, we show that search frictions in customer reallocation shape in a sizeable and persistent fashion the dynamic response of demand to shocks that affect price dispersion (e.g. exchange rate shocks, changes in sales taxes, etc.). Inertia in customer reallocation tends to dampen short-term effects and to magnify long-run ones.

The model features two types of agents, firms and customers. Firms produce a homogeneous good with a linear production function in a single variable input. Customers derive utility from the consumption of the homogenous good. Customers perfectly observe the variables characterizing the relevant state of the firm they buy from: its idiosyncratic productivity, which follows an exogenous Markov process with stationary normal distribution;

[1]See Foster et al. (2013) for recent evidence.

[2]See also Blinder et al. (1998) and Fabiani et al. (2007) for survey evidence.

and its customer base, the mass of customers who bought from it in the previous period. Customers start each period matched to the same firm from which they bought in the previous period. Once firms have drawn the new productivity level and posted a price for the period, customers have faculty to search for a new supplier. To search, customers must pay an idiosyncratic search cost, drawn every period from an i.i.d. distribution. After the search cost is paid, the customer gets randomly assigned another firm, she observes the state of the new firm, compares it to that of her old supplier, and decides where to buy (*extensive* margin of demand). After customers have made their search and matching decisions, each customer decides her purchased quantity of the good (*intensive* margin of demand). In this framework, firms face a trade-off between charging a higher price and extracting more surplus from high search costs customers, versus posting a lower price to extract a lower surplus but from a larger mass of customers. Since the customer base is sticky, changes in the customer base have persistent effects on demand, making the price-setting problem of the firm a dynamic one. The equilibrium of our model features both price dispersion and customer dynamics. In particular, the equilibrium prices are decreasing in productivity whereas the growth in the customer base is increasing in productivity, with more productive firms gaining customers at the expenses of less productive ones.

We complement our modeling effort with an empirical analysis that relies on novel micro data documenting pricing and customer base evolution for a large retail firm. We take advantage of scanner data from a major U.S. retailer recording purchases for a large sample of households between 2004 and 2006. Household-level scanner data are particularly well suited to study customer base dynamics. First, we observe a wealth of details on all the shopping trips each household makes to the chain (list of goods purchased, prices, quantities, etc.). More importantly, we can infer when customers leave the retailer by looking at prolonged spells without purchases at the chain. These data allow us to study the relation between a customer's decision to abandon the firm and the price of the good-or rather, in this case, bundle of goods-she consumes there. We show that customer dynamics are indeed affected by variation in the price: A 1% change in the price of the customer's typical basket of grocery goods would raise the firm yearly customer turnover from 14% to 21%.

We use the estimated price elasticity of the customer base, jointly with moments from the distribution of prices posted by the chain, to identify the key objects of the model: the distribution of search costs and the properties of the productivity process. We assess the relevance of customer markets for price dynamics by comparing our model to a counterfactual economy where only the intensive margin is present. This is an interesting benchmark, as the pricing problem of the firm in such economy is similar to the one of standard macro models where competition comes only from the downward-sloping demand of each customer, and the customer base is constant. We design the experiment so that the counterfactual economy is observationally equivalent with respect to average demand elasticity, price persistence, and dispersion. The most obvious difference between our model and those that do not feature an extensive margin of demand is that the former predicts equilibrium customer dynamics whereas the latter imply no customer reallocation. Quantitatively, our model delivers a yearly average turnover of 6%, nearly half of what we measure in the data (14%). This implies that customer dynamics triggered by variation in prices due to idiosyncratic cost shocks can explain a large fraction of the overall turnover.

We find that customer markets also have implications for firms' pricing and document that they are nontrivial in magnitude. First, we look at the implications for the shape of the price distribution. The strategic complementarity effect leads firms facing high extensive margin elasticity to set similar prices, generating a high mass of prices that cluster around the mean that results in a distribution with high peakedness. A large fraction of prices bunched around the mean also characterizes the price distribution in our data. In fact, the model and data display a similar excess kurtosis even though the shape of the price distribution was not targeted in our estimation procedure, and the underlying invariant distribution of productivity is normal. The model without customer markets instead fails to capture the distinctive characteristics of our pricing data as it delivers a nearly perfectly normal price distribution.

Finally, we use our model to explore the effects of customer markets for the dynamics of the response of demand to shocks. In particular, our model represents an interesting setting to study the response of demand to shocks that, by hitting firms asymmetrically, affect price dispersion. This, in fact, influences the incentives of customers to search, generating persistent dynamics in demand, as it takes time for customers to reallocate across firms. In our model demand responds to variation in prices through two channels. The first one is the intensive margin: Customers can adjust the quantity of the good they purchase from their supplier. This channel is static and its adjustment happens immediately. The second channel is the extensive margin: Customers can decide to leave the firm. This channel is dynamic because of the presence of a search friction. Therefore, the adjustment is delayed, as it takes time for customers to relocate to firms with lower prices, and persistent because once customers have moved, it is costly for them to change firm again. The shape of the response of demand depends on the strength of these two components. This is a quantitative question that we explore by simulating a persistent cost shock that affects a subset of the firms.[3] We

[3]This is far from an abstract setup: It captures the main features of an exchange rate shock (which affects firms' costs differently according to whether or not they buy inputs on the international market) or a change in the state sales tax (which penalizes and benefits competing firms on the basis or where their headquarters are established).

find that the extensive margin dominates: The long-run response of demand is substantially larger than the short-run one. In the counterfactual economy, where the absence of customer markets implies that only the intensive margin is at work, the response of demand on impact of the same shock is much larger and decays monotonically as the effect of the shock on prices vanishes.

Related Literature. Our paper relates to the seminal work by Phelps and Winter (1970) who study the pricing problem of the firm facing customer retention concerns. In their paper, the response of the firm's customer base to a change in the firm's price is modeled with an ad hoc function. We instead endogenize customer dynamics in response to firms' pricing as the outcome of customers' optimal search decisions. Fishman and Rob (2003), Alessandria (2004), and Menzio (2007) also study the firm price-setting problem in models where search costs prevent customers from freely moving to the lowest price supplier. These papers focus on different issues. Fishman and Rob (2003) study the implications of customer markets for firm dynamics. Alessandria (2004) shows that such a model can generate large and persistent deviations from the law of one price, consistent with the empirical evidence on international prices. Menzio (2007) looks at the role of asymmetric information and commitment in the optimal pricing decision of the firm. Differently from our paper, in these papers customers face an homogeneous search cost and, as a result, optimal pricing is such that no endogenous customer dynamics occur in equilibrium.

Unlike the literature cited above, we exploit scanner data to discipline our model and provide a quantitative assessment of the relevance of customer markets for pricing. In documenting the shape of the price distribution, our paper also relates to the recent empirical work by Kaplan and Menzio (forthcoming). While their focus is on customers and the price they pay for the same good (or bundle of goods), we are interested in the point of view of sellers and the price they charge. Our finding on the dynamics of demand relates to studies documenting the short-run and long-run elasticity of demand. In particular, it is consistent with evidence on the short- vs. long-run Armington elasticity in the international economics literature (Ruhl (2008)).

A related set of contributions use customer markets to address questions different from the ones we study here. Gourio and Rudanko (2014) explore the relationship between the firm's effort to capture customers and its performance. They show that customer markets have nontrivial implications for the relationship between investment and Tobin's q. Drozd and Nosal (2012) introduce in a standard international real business cycle model the notion that, when they want to increase sales, producers must exert effort to find new customers. This extension help to rationalize a number of empirical findings on the dynamics of international prices and trade. Dinlersoz and Yorukoglu (2012) focus on the importance of customer markets for industry dynamics in a model where firms use advertising to disseminate information to uninformed customers. Shi (2011) studies a model where firms cannot price discriminate across customers and use sales to attract new customers. Kleshchelski and Vincent (2009) examine the impact of customer markets on the pass-through of idiosyncratic cost shocks to prices in a symmetric equilibrium that does not allow us to study the relationship between customer dynamics and the price distribution. Burdett and Coles (1997) study the role of firm size for pricing when firms use the price to attract new customers. Their work complements ours: Price and customer dynamics in their setting are shaped by the heterogeneity in firm size (age). For us, the driving force is the heterogeneity in productivity.

Finally, a stream of studies analyzes the implications of product market frictions for business cycle fluctuations (Petrosky-Nadeau and Wasmer (2011), Bai et al. (2012) and Kaplan and Menzio (2013)). In these papers, aggregate shocks alter the opportunity cost of searching, influencing markup and demand dynamics over the business cycle. While we abstain from this type of analysis, our quantified model could be extended to allow for the search opportunity-cost to vary with the aggregate state and be used as a laboratory to answer similar questions.

The rest of the paper is organized as follows. In Section 2 we lay out the model, and in Section 3 we characterize the equilibrium. Section 4 presents the data and descriptive evidence of the relationship between customer dynamics and prices. In Section 5 we discuss identification and estimation of the model. In Section 6 we present some quantitative predictions of the model, contrast them with the outcomes from a model without customer markets, and compare them empirical evidence from our data. In Section 7 we introduce an application of the model, which we use to study the implications of customer markets for the dynamics of demand. Section 8 concludes.

2 The model

The economy is populated by a measure one of firms producing an homogeneous good and a measure Γ of customers who consume it.

Customers. We use the index i to denote customers. Let $d(p)$ and $v(p)$ denote, respectively, the static demand and customer surplus as a function of the price p of the good. We assume that: (i) $d(p)$ is continuously differentiable with $d'(p) < 0$, and bounded below with $\lim_{p\to\infty} d(p) = 0$; and (ii) $v(p)$ is continuously differentiable with $v'(p) < 0$, and bounded above with $\lim_{p\to 0^+} v(p) < \infty$. These properties are satisfied in standard models of consumer demand.

Firms. Firms produce a homogenous good and are indexed by j. The only choice firms make is to set the price p of the good they produce each period. We assume a linear production technology $y^j = z^j \ell^j$ where ℓ is the production input, and z^j is the firm-specific productivity. Idiosyncratic productivity is distributed according to a conditional cumulative distribution function $F(z'|z)$ with bounded support $[\underline{z}, \bar{z}]$. We also assume that $F(z'|\, z_h)$ first order stochastically dominates $F(z'|\, z_l)$ for any $z_h > z_l$ to induce persistence in firm productivity. Heterogeneity in firm productivity will be the driver of price dispersion in the type of equilibrium we will focus on.[4] The profit per customer accrued to the firms are $\pi(p, z) \equiv d(p)(p - w/z)$, where the constant $w > 0$ denotes the marginal cost of the input ℓ. We assume that profits per customer are single-peaked in p. Finally, we denote by m^j_{t-1} the *customer base* of firm j, consisting of the mass of customers who bought from firm j in period $t-1$. As we will show later, the state of the firm j in period t is the pair $\{z^j_t, m^j_{t-1}\}$.

Search, matching, and exit from the customer base. Each customer starts period t matched to the firm she bought from in period $t-1$. The customer observes perfectly the state of the firm she is matched to (i.e. z^j_t and m^j_{t-1}), which allows her to assess the probability distribution of the path of prices of that firm. Later we will be more specific about the mapping from the state of the firm to the path of prices. After observing the state of her current match, the customer decides if she is incurring a search cost and draws another firm. In particular, each customer i is characterized by an idiosyncratic random search cost $\psi^i \geq 0$ measured in units of customer surplus, which is drawn each period from the same distribution with density $g(\psi)$, and associated cumulative distribution function denoted by $G(\psi)$. For tractability, we restrict our attention to density functions that are continuous on all the support. Heterogeneity, albeit transitory, in search costs allows us to study firms' pricing decisions that are not necessarily knife-edge in the trade-off between maximizing demand and markups. The customer can search at most once per period. Search is random, with the probability of drawing a particular firm j' being proportional to its customer base, i.e. $m^{j'}_{t-1}/\Gamma$. This assumption captures the idea that consumers search new suppliers not by randomly sampling firms but by randomly sampling other consumers and following their behavior.[5] On the technical side, this assumption implies that firms will gain customers proportionally to their customer base. This simplifies the characterization of the firm problem and implies that firm growth is independent of firm size consistent with

[4]For tractability we will abstract from (possible) equilibria where symmetric firms charge different prices as in Burdett and Judd (1983).

[5]This behavior is known as preferential attachment in the extensive literature on network formation.

Gibrat's law (Steindl (1965)). Conditional on searching, the customer takes then another decision concerning whether to exit the customer base of her initial firm and match to the new firm. In particular, the customer compares the distribution of the path of current and future prices at the two firms and buys from the firm offering higher expected value. Finally, we assume for simplicity no recall in the sense that the customer cannot go back to a firm she was matched with in the past or whose price offer she rejected unless she randomly draws it again when searching.

Timing of events. The timing of events is as follows: (i) productivity shocks are realized for all firms and each firm j posts a price p_t^j; (ii) each customer draws her search cost ψ_t^i and observes the price p_t^j as well as the relevant state of the firm she is matched with (z_t^j and m_{t-1}^j); (iii) each customer decides whether to search for a new firm or remain matched to her current one; (iv) if the customer decides to search, she pays the search cost and draws a new supplier j' with probability $m_{t-1}^{j'}/\Gamma$. The customer perfectly observes not only the price but also the productivity and customer base of the prospective match and decides whether to exit the customer base of the current supplier to join that of the new match or to stay with the current match. Finally, (v) customer surplus $v(p_t^j)$ and firm profits $m_t^j\,\pi(p_t^j, z_t^j)$ realize.

Equilibrium. A firm and its customers play an anonymous sequential game. We look for a stationary Markov Perfect equilibrium where strategies are a function of the current state. There are no aggregate shocks. Although the relevant state for the pricing decision of the firm could include both the stock of customers and the idiosyncratic productivity, we conjecture and later show the existence of an equilibrium where optimal prices only depend on productivity, and we denote by $\mathcal{P}(z)$ the equilibrium pricing strategy of the firm.

The relevant state for the search decision of a customer includes the expectations about the path of current and future prices of the firm she is matched to, as well as the idiosyncratic search cost. Given the Markovian equilibrium we study, the current realization of idiosyncratic productivity is a sufficient statistic for the distribution of future prices. As a result, the search strategy of the customer depends on the current price and productivity of the firm she is matched to, and on her own search cost. We denote the search decision as $s(p, z, \psi) \in \{0, 1\}$, where $s = 1$ means that the customer decides to engage in search. Conditional on searching, the exit decision depends on the continuation value associated to the firm the customer starts matched to (the outside option), which is fully characterized by posted price and productivity, as well as on productivity of the firm she has drawn upon the search, z^{new}, which determines the continuation value associated to the new firm. We denote the exit decision as $e(p, z, z^{new}) \in \{0, 1\}$, where $e = 1$ means that the customer decides to exit the customer base of her original firm.

2.1 The problem of the customer

Let $V(p_t^j, z_t^j, \psi_t^i)$ denote the value function of a customer i who has drawn a search cost ψ_t^i and is matched to firm j, which has current productivity z_t^j and posted price p_t^j. This value function solves the following problem,

$$V(p_t^j, z_t^j, \psi_t^i) = \max\left\{\bar{V}(p_t^j, z_t^j)\,,\, \tilde{V}(p_t^j, z_t^j) - \psi_t^i\right\}\ , \tag{1}$$

where $\bar{V}(p, z)$ is the customer's value if she does not search, and $\tilde{V}(p, z) - \psi$ is the value if she does search. The value in the case of not searching is

$$\bar{V}(p_t^j, z_t^j) = v(p_t^j) + \beta \int_0^\infty \int_{\underline{z}}^{\bar{z}} V(\mathcal{P}(z'), z', \psi')\, dF(z'|z_t^j)\, dG(\psi')\ . \tag{2}$$

We notice that the state of the firm problem depends on the on the productivity z because the pricing function $\mathcal{P}(\cdot)$ mapping future productivity into prices in the Markov equilibrium makes productivity z a perfect statistic for the distribution of future prices at the firm.[6] The value when searching is given by

$$\tilde{V}(p_t^j, z_t^j) = \int_{-\infty}^{+\infty} \max\left\{\bar{V}(p_t^j, z_t^j)\,,\, x\right\} dH(x)\ , \tag{3}$$

where the customer takes expectations over all possible draws of potential new firms, and where $H(\cdot)$ is the equilibrium cumulative distribution of continuation values from which the firm draws a new potential match when searching. For instance, $H(\bar{V}(p_t^j, z_t^j))$ is the probability of drawing a potential match offering a continuation value smaller than or equal to the current match. The following lemma describes the customer's optimal search and exit policy rules.

Lemma 1 *The customer matched to a firm with productivity z_t^j charging price p_t^j: i) searches if she draws a search cost $\psi_t \leq \hat{\psi}(p_t^j, z_t^j)$, where $\hat{\psi}(p, z) \equiv \int_{\bar{V}(p,z)}^{\infty} \left(x - \bar{V}(p, z)\right) dH(x) \geq 0$ is the threshold to search; ii) conditional on searching, exits if she draws a new firm promising a continuation value $\bar{V}^{new}$ larger than the current match, i.e. $\bar{V}^{new} \geq \bar{V}(p_t^j, z_t^j)$.*

[6] We also notice that the state of the firm problem includes the current price p, despite in equilibrium productivity is enough to determine the current price, as this notation is needed to study the game between the firm and its customers where the firm could, in principle, deviate from the equilibrium price.

The proof of the lemma follows immediately from equations (1)-(3). The lemma states that, as search is costly, not all customers currently matched to a given firm exercise the search option, only those with a low search cost do so. Notice that the threshold $\hat{\psi}(p, z)$ depends both on the price of the firm, p, and its productivity, z. The dependence on the price is straightforward, following from its effect on the surplus $v(p)$ that the customer can attain in the current period. The intuition behind the dependence on the firm's productivity is that, as searching is a costly activity, the decision of which firm to patronize is a dynamic one, and involves comparing the value of remaining in the customer base of the current firm with the value of searching. Because of the Markovian structure of prices, the customer's expectation about future prices is completely determined by the firm's current productivity.

The next lemma discusses some properties of the continuation value function $\bar{V}(p, z)$ and, as a consequence, of the threshold $\hat{\psi}(p, z)$.

Lemma 2 *The value function $\bar{V}(p, z)$ (the threshold $\hat{\psi}(p, z)$) is strictly decreasing (increasing) in p. If $\hat{V}(z) \equiv \bar{V}(\mathcal{P}(z), z)$ is increasing in z, the value function $\bar{V}(p, z)$ (the threshold $\hat{\psi}(p, z)$) is increasing (decreasing) in z.*

The proof of Lemma 2 is in Appendix A.1. The lemma states that customers obtain strictly higher value from firms offering a lower current price and, if $\hat{V}(z)$ is increasing in z, also from firms characterized by higher current productivity. Notice that, under persistence in the productivity process, a sufficient condition for the latter is that equilibrium prices are decreasing in productivity. As a result, not only are customers more likely to search and exit from firms charging higher prices, but also they are more likely to do so from firms with lower productivity if $\hat{V}(z)$ is increasing in z.

2.2 The problem of the firm

In this section we describe the pricing problem of the firm. We start by discussing the dynamics of the customer base as a function of price and productivity, given the optimal search and exit strategy of the customers. Then, we move to the characterization of the firm optimal pricing strategy.

The customer base of firm j evolves as follows:

$$m_t^j = m_{t-1}^j - \underbrace{m_{t-1}^j \, G\left(\hat{\psi}(p_t^j, z_t^j)\right)\left(1 - H(\bar{V}(p_t^j, z_t^j))\right)}_{\text{customers outflow}} + \underbrace{\frac{m_{t-1}^j}{\Gamma} \, Q\Big(\bar{V}(p_t^j, z_t^j)\Big)}_{\text{customers inflow}}, \qquad (4)$$

where $G(\hat{\psi}(p_t^j, z_t^j))$ is the fraction of customers searching firm j' customer base, a fraction $1 - H(\bar{V}(p_t^j, z_t^j))$ of which actually finds a better match and exits the customer base of firm j. The ratio m^j_{t-1}/Γ is the probability that searching customers in the whole economy draw firm j as a potential match. The function $Q(\bar{V}(p^j_t, z^j_t))$ denotes the equilibrium mass of searching customers currently matched to a firm with continuation value smaller than $\bar{V}(p^j_t, z^j_t)$. Therefore, the product of the two amounts to the mass of new customers entering the customer base of firm j. We can express the dynamics of the customer base as $m^j_t = m^j_{t-1}\,\Delta(p^j_t, z^j_t)$, where the function $\Delta(\cdot)$ denotes the growth of the customer base and is given by

$$\Delta(p, z) \;\; \equiv 1 - G\left(\hat{\psi}(p, z)\right)\left(1 - \;H(\bar{V}(p, z))\right) + \tfrac{1}{\Gamma}\,Q\Big(\bar{V}(p, z)\Big)\;. \tag{5}$$

Notice that the growth of a firm is independent of its customer base and, therefore, of its size. This result is known as Gibrat's Law and is consistent with existing empirical evidence on the distribution of firms' size (see Luttmer (2010)), and depends on our assumption that customers draw new firms with probability proportional to their share of customers. The next lemma discusses the properties of the customer base growth with respect to prices and productivity.

Lemma 3 *Let $\bar{p}(z)$ solve $\bar{V}(\bar{p}(z), z) = \max_z \{\bar{V}(\mathcal{P}(z), z)\}$; $\Delta(p, z)$ is strictly decreasing in p for all $p > \bar{p}(z)$, and constant for all $p \leq \bar{p}(z)$. If $\hat{V}(z) \equiv \bar{V}(\mathcal{P}(z), z)$ is increasing in z, then $\Delta(p, z)$ is increasing in z.*

The proof of Lemma 3 follows directly from Lemma 2. The growth of the customer base is decreasing in the current price because a higher price reduces the current surplus and therefore the value of staying matched to the firm. When the price is low enough that no firm in the economy offers a higher value to the customer, the customer base is maximized and a further decrease in the price has no impact on the customer growth. If $\hat{V}(z)$ is increasing in z, the growth of the customer base increases with firm productivity, as a larger z is associated to higher continuation value which increases the value of staying matched to the firm.

We next discuss the pricing problem of the firm. The firm pricing problem in recursive form solves

$$\tilde{W}(z^j_t, m^j_{t-1}) \;=\; \max_p \; m^j_t \; \pi(p, z^j_t) \;+\; \beta \int_{\underline{z}}^{\bar{z}} \tilde{W}(z', m^j_t)\; dF(z'|\, z_t)\;,$$

subject to equation (4), where $\tilde{W}(z^j_t, m^j_{t-1})$ denotes the firm value at the optimal price and $\pi(p, z^j_t) = d(p)\,(p - w/z^j_t)$ are profits per customer. We study equilibria where the pricing decision of the firm only depends on productivity. Thus, we conjecture that in this equilibrium the value function of a firm is homogeneous of degree one in m, i.e., $\tilde{W}(z, m) = m\,\tilde{W}(z, 1) \equiv$

$m\, W(z)$. $W(z)$ solves

$$W(z) \;=\; \max_p \;\Delta(p,z)\; \underbrace{\left(\pi(p,z) + \beta \int_{\underline{z}}^{\bar{z}} W(z')dF(z'|\, z)\right)}_{\text{present discounted value of a customer } \equiv \, \Pi(p,z)} \;, \tag{6}$$

and where we used equation (4) and we dropped time and firm indexes to ease the notation. We assume that the discount rate β is low enough so that the maximization operator in equation (6) is a contraction. Therefore; by the contraction mapping theorem we can conclude that our conjecture about homogeneity of $\tilde{W}(z,m)$ is verified.

We can express the objective of the firm maximization problem as the product of two terms. The first term is the growth in the customer base, $\Delta(p,z)$, which according to Lemma 3 is strictly decreasing in the price for all $p > \bar{p}(z)$ and is maximized at any price $p \leq \bar{p}(z)$. The second term is the expected present discounted value of each customer to the firm, which we denote by $\Pi(p,z)$. The function $\Pi(p,z)$ is maximized at the static profit maximizing price,

$$p^*(z) \equiv \frac{\varepsilon_d(p)}{\varepsilon_d(p) - 1}\, \frac{w}{z} \;. \tag{7}$$

It follows that setting a price above the static profit maximizing price is never optimal. Moreover, if $\bar{p}(z) \leq p^*(z)$, the optimal price will not be below $\bar{p}(z)$, because in that region profit per customer increase with the price but the customer base is unaffected. Hence, $\hat{p}(z) \in [\bar{p}(z), p^*(z)]$. If instead $\bar{p}(z) \geq p^*(z)$, then the optimal price is the static profit maximizing price, $\hat{p}(z) = p^*(z)$, as at this price both the customer base and the profits per customer are maximized. The following proposition collects these results.

Proposition 1 *Let $\bar{p}(z)$ solve $\bar{V}(\bar{p}(z), z) = \max_{z \in [\underline{z}, \bar{z}]} \{\bar{V}(\mathcal{P}(z), z)\}$, and let $p^*(z)$ expressed in equation (7) be the price that maximizes static profits. Denote by $\hat{p}(z)$ a price that solves the firm problem in equation (6). We have $\hat{p}(z) \in [\bar{p}(z), p^*(z))$ if $\bar{p}(z) < p^*(z)$, and $\hat{p}(z) = p^*(z)$ otherwise.*

A proof of the proposition can be found in Appendix A.2.

3 Equilibrium

In this section we define an equilibrium, discuss its existence, and characterize its general properties. We start by defining the type of equilibrium we study.

Definition 1 *Let* $\hat{V}(z) \equiv \bar{V}(\mathcal{P}(z), z)$ *and* $p^*(z)$ *be given by equation (7). We study stationary Markovian equilibria where* $\hat{V}(z)$ *is non-decreasing in* z*, and for all* $z \in [\underline{z}, \bar{z}]$ *the firm pricing strategy* $\hat{p}(z)$ *solves the first order condition to the firm problem in equation (6) given by*

$$\frac{\partial \Pi(p,z)}{\partial p} \frac{p}{\Pi(p,z)} = -\frac{p}{\Delta(p,z)} \frac{\partial \Delta(p,z)}{\partial p} \geq 0 \ . \tag{8}$$

A stationary equilibrium is then

(i) a search and an exit strategy that solve the customer problem for given equilibrium pricing strategy $\mathcal{P}(z)$*, as defined in Lemma 1;*

(ii) a firm pricing strategy $\hat{p}(z)$ *that solves equation (8) for each* z*, given customers' strategies and equilibrium pricing policy* $\mathcal{P}(z)$*, and is such that* $\hat{p}(z) = \mathcal{P}(z)$ *for each* z*;*

(iii) two distributions over the continuation values to the customers, $H(x)$ *and* $Q(x)$*, that solve* $H(x) = K(\hat{z}(x))$ *and* $Q(x) = \Gamma \int_{\underline{z}}^{\hat{z}(x)} G(\hat{\psi}(\hat{p}(z), z))\, dK(z)$ *for each* $x \in [\hat{V}(\underline{z}), \hat{V}(\bar{z})]$*, where* $\hat{z}(x) = \max\{z \in [\underline{z}, \bar{z}] : \hat{V}(z) \leq x\}$*, and* $K(z)$ *solves*

$$K(z) = \int_{\underline{z}}^{z} \int_{\underline{z}}^{\bar{z}} \Delta(\hat{p}(x), x)\, dF(s|x)\, dK(x)\, ds \ , \tag{9}$$

for each $z \in [\underline{z}, \bar{z}]$ *with boundary condition* $\int_{\underline{z}}^{\bar{z}} dK(x) = 1$*.*

We study equilibria where the continuation value to customers is non-decreasing in productivity, implying that customers' rank of firms coincides with their productivity. This is a natural outcome as more productive firms are better positioned to offer lower prices and therefore higher values to customers. The first order condition in equation (8) illustrates the trade-off the firm faces when setting the price in a region where customer retention is a concern. When $\bar{p}(z) < p^*(z)$, the optimal price balances the marginal benefit of an increase in price (more profit per customer) with the cost (decrease in the customer base). The requirement that the solution to the firm problem must satisfy the first order condition implies that we study equilibria where the firm objective, and in particular $\Delta(p, z)$, is differentiable in p. The next proposition states conditions under which such an equilibrium exists and characterizes its properties.

Proposition 2 *Let productivity be i.i.d. with* $F(z'|z_1) = F(z'|z_2)$ *continuous and differentiable for any* z' *and any pair* $(z_1, z_2) \in [\underline{z}, \bar{z}]$*, and let* $G(\psi)$ *be differentiable for all* $\psi \in [0, \infty)$*, with* $G(\cdot)$ *differentiable and not degenerate at* $\psi = 0$*. There exists an equilibrium as defined in Definition 1 where* $\hat{p}(z)$ *satisfies equation (8), and* *(i)* $\hat{p}(z)$ *is strictly decreasing in* z*, with* $\hat{p}(\bar{z}) = p^*(\bar{z})$ *and* $\hat{p}(\bar{z}) < \hat{p}(z) < p^*(z)$ *for* $z < \bar{z}$*, implying that* $\hat{V}(z)$ *is strictly increasing. Moreover, the optimal markups are given by*

$$\mu(p, z) \equiv \frac{p}{w/z} = \frac{\varepsilon_d(p)}{\varepsilon_d(p) - 1 + \varepsilon_m(p, z)\,\Pi(p, z)/(d(p)\,p)}\ , \qquad (10)$$

where $\varepsilon_d(p) \equiv \partial \log(d(p))/\partial \log(p)$*,* $\varepsilon_m(p, z) \equiv \partial \log(\Delta(p, z))/\partial \log(p)$*, and* $p = \hat{p}(z)$ *for each* z*.*

(ii) $\hat{\psi}(\hat{p}(z), z)$ *is strictly increasing in* z*, with* $\hat{\psi}(\hat{p}(\bar{z}), \bar{z}) = 0$ *and* $\hat{\psi}(\hat{p}(z), z) > 0$ *for* $z < \bar{z}$*, implying that* $\Delta(\hat{p}(z), z)$ *is strictly increasing, with* $\Delta(\hat{p}(\bar{z}), \bar{z}) > 1$ *and* $\Delta(\hat{p}(\underline{z}), \underline{z}) < 1$*.*

Differentiability of the distribution of productivity F is not needed for the existence of an equilibrium. We assume it to ensure that $H(\cdot)$ and $Q(\cdot)$ are almost everywhere differentiable so that equation (8) is a necessary condition for optimal prices. However, even when F is not differentiable and the first order condition cannot be used to characterize the equilibrium, an equilibrium with the properties of Proposition 2 exists where $\hat{p}(z)$ and $\hat{\psi}(\hat{p}(z), z)$ are monotonic in z but not necessarily strictly monotonic for all z. Monotonicity of optimal prices follows from an application of Topkis' theorem. In order to apply the theorem to the firm problem in equation (6) we need to establish increasing differences of the firm objective $\Delta(p, z)\,\Pi(p, z)$ in $(p, -z)$. Under the standard assumptions we stated on $\pi(p, z)$, it is easy to show that $\Pi(p, z)$ satisfies this property. The customer base growth does not in general verify the increasing difference property. However, under the assumption of i.i.d. productivity, $\Delta(p, z)$ is independent of z, which, together with Lemma 3, is sufficient to obtain the result. Finally, while the results of Proposition 2 refer to the case of i.i.d. productivity shocks, numerical results in Section 6 show the properties of Proposition 2 extend to the case of a persistent productivity process. More details on the proof of the proposition can be found in Appendix A.3.

We now comment on the properties of the equilibrium highlighted in the Proposition. The equilibrium is characterized by price dispersion: More productive firms charge lower prices and, therefore, offer higher continuation value to customers. This is important, as price dispersion is what motivates customers to search for lower prices. As in Reinganum (1979), price dispersion hinges on the fact that there is heterogeneity in productivity. If all the firms had the same productivity, Proposition 2 would imply a unique equilibrium where the price is that which maximizes static profits, $p^*(\tilde{z})$, and as a result the customer base of every firm would be constant.[7] The equilibrium is also characterized by dispersion in customer base

[7] This special case is useful to understand our relation to Diamond (1971), which shows in a simple search model that the resulting equilibrium when search cost is positive exhibits no price dispersion and

growth: More productive firms grow faster, and there is a positive mass of lower productivity firms that have a shrinking customer base and a positive mass of higher productivity firms that are expanding their customer base.

Optimal markups in equation (10) depend on three distinct terms: $\varepsilon_d(p)$, $\varepsilon_m(p, z)$, and $x(p, z) \equiv \Pi(p, z)/(d(p)\, p)$. The terms $\varepsilon_d(p)$ and $\varepsilon_m(p, z)$ represent the price elasticities of quantity purchased (per-customer) and of customer growth, respectively. An increase in price reduces total current demand both because it reduces quantity per customer (*intensive margin effect*) and because it reduces the number of customers (*extensive margin effect*). Moreover, the optimal markup solves a dynamic problem as a loss in customers has persistent consequences for future demand due to the inertia in the customer base. This dynamic effect is captured by the term $x(p, z)$, which measures the firm present discounted value of a customer scaled by the current revenues. It follows that active customer markets are associated with a strictly lower markup than the one that maximizes static profit; the lower, the larger the product $\varepsilon_m(p, z)\, x(p, z)$.

The importance of the dynamic effect on optimal markups can be better understood performing the following thought experiment. Define the overall demand elasticity of an economy as the sum of its quantity elasticity and its customer growth elasticity: $\varepsilon_q(p, z) \equiv \varepsilon_d(p)+\varepsilon_m(p, z)$. Take two firms characterized by the same productivity z and the same overall demand elasticity $\varepsilon_q(\cdot)$, but by different combinations of $\varepsilon_d(\cdot)$ and $\varepsilon_m(\cdot)$. In particular, one firm has lower quantity elasticity but higher customer growth elasticity than the other. Then the optimal markup for the former is strictly lower than that for the latter.[8] Intuitively, a loss in demand associated to a loss in customers is a persistent loss and, therefore, has a larger impact on firm value, inducing it to charge lower markups with respect to a firm that operates in a market where the customer base is less elastic.

Finally, the next remark explores two interesting limiting cases of our model and showcases the effect of the search friction on price dispersion.

Remark 1 *Let search costs be scaled as $n\, \psi$, where $n > 0$. That is, let the value function in equation (1) be*

$$V(p, z, \psi) = \max\left\{\bar{V}(p, z)\, ,\, \tilde{V}(p, z) - n\psi\right\}\ .$$

Two limiting cases of the equilibrium stated in Definition 1:

(1) Let $n \to \infty$. Then, in equilibrium: (i) the optimal price maximizes static profits, i.e. $\hat{p}(z) = p^*(z)$ for all $z \in [\underline{z}, \bar{z}]$, and (ii) there is no search in equilibrium. Furthermore,

firms behaving as monopolists. Our model delivers a different outcome because we allow firms to differ in idiosyncratic productivity but can generate the Diamond (1971) results if heterogeneity in producvtivity is shut down.

[8] More details are available in Appendix A.4.

the equilibrium is unique.

(2) Let $\pi(p^*(\bar{z}), \underline{z}) > 0$ and let the assumptions of Proposition 2 be satisfied. Then, $\hat{p}(\bar{z}) = p^*(\bar{z})$ and $\max\{\hat{p}(z)\} = \hat{p}(\underline{z})$ approaches $p^*(\bar{z})$ as $n \to 0$. As a result, in the limit, there is no price dispersion in equilibrium and customers do not search.

A proof of the remark can be found in Appendix A.5. The first limiting case explores the resulting equilibrium when we let search costs diverge to infinity. The model then reduces to one where customer base concerns are not present. Because the customer base is unresponsive to prices, the firm problem reverts to the standard price-setting problem under monopolistic competition widely explored in the macroeconomics literature: The firm sets the price p, taking into account only its impact on static demand $d(p)$. Not surprisingly, the equilibrium is unique, optimal prices maximize static profits, i.e. $\hat{p}(z) = p^*(z)$ for all $z \in [\underline{z}, \bar{z}]$, there is price dispersion, and there is no search in equilibrium. The second limiting case explores the resulting equilibrium when search costs become arbitrarily small. We restrict attention to the model that satisfies the assumptions of Proposition 2, so that the first order condition presented in equation (8) is necessary for optimality.[9] In this case, as the scale of search costs becomes arbitrarily small, equilibrium prices approach the lowest price in the economy, $p^*(\bar{z})$. As a result, there is no price dispersion and customers do not search.

4 Data and descriptive evidence

We complement the theoretical analysis with an empirical investigation that relies on cashier register data from a large U.S. supermarket chain. The empirical analysis has two purposes. In this section we provide descriptive evidence that the price posted by the firm influences customers' decision to exit the customer base and measure the size of this effect. In Section 5, we will use the data to estimate our model and quantify the importance of customer markets in shaping firm price setting.

4.1 Data sources and variable construction

The supermarket chain shared with us scanner data detailing purchases by a panel of households carrying a loyalty card of the chain.[10] The chain operates over a thousand stores across

[9] The assumption $\pi(p^*(\bar{z}), \underline{z}) > 0$ is purely technical, and it ensures that the first derivative of the profit function is bounded in the relevant range.

[10] The chain is able to associate the loyalty cards belonging to different members of a same family to a single household identifying number, which is the unit of observation in our data. Therefore, in the analysis we use the terms "customer" and "household" interchangeably.

10 states, and the data reflect this geographical dispersion. For every trip made at the chain by customers in the sample between June 2004 and June 2006, we have information on the date of the trip, store visited, and list of goods (identified by their Universal Product Code, UPC) purchased, as well as quantity and price paid.

The population of shoppers visiting a retail store in a given time period can be divided into regular and occasional customers. Regular customers shop routinely, at least for some period of time, at the same store. Occasional customers are instead agents who typically shop elsewhere and visit the chain for convenience, for instance because they happened to be in the vicinity. To obtain an estimate of the extensive margin elasticity, we want to restrict attention to regular customers who are the ones the firm is trying to retain.[11] Luckily, our data are ideal to separate regular and occasional customers as they only include information on households carrying a loyalty card of the chain. The willingness to sign up for the loyalty card signals some form of commitment of these households to the chain, which random shoppers are unlikely to bother with. The customers in our sample make an average of 150 shopping trips at the chain over the two years; if those trips were uniformly distributed, that would imply visiting a store of the chain six times per month. The average expenditure per trip is $69 for the average household. There is a great deal of variation (the 10th percentile is $29; the 90th is $118) explained, among other things, by income and family size of the different households.

In the theoretical model we studied the behavior of customers buying from firms producing a single homogeneous good; our application documents the exit decisions of customers from supermarket stores where they buy bundles of goods.[12] This can be reconciled if we assume that customers' behavior depends on the price of the basket of goods they typically buy at the supermarket.[13] Although the multiproduct nature of the problem may have implications for the pricing decision of the firm, we abstract from the price-setting process and focus only on the resulting price index of the customer basket in order to retrieve the response of the customer base to variation in prices. In particular, to measure the comovement between the customer's decision to exit the customer base and the price of her typical basket of goods posted at the chain, we need to construct two key variables: (i) an indicator signaling when the household is exiting the chain's customer base, and (ii) the price of the household

[11] Occasional customers' behavior does not contribute to the estimation of the extensive margin elasticity and may, in fact, confound it. These customers could instead be useful if we wanted to relax our assumptions on the customer attraction process.

[12] The choice of focusing on the customer base of the store rather than that of one of the branded product it sells is data driven. With data from a single chain we cannot track the evolution of the customer base of a single brand. In fact, if we observed customers not longer buying a particular brand we could only infer that they are not buying it at the chain we analyze, but we could not exclude they are buying it elsewhere.

[13] Note that since customers baskets are in large majority composed of package goods, which are standardized products, the assumption that the basket is a homogenous good is not unwarranted.

basket. Below we briefly describe the procedure followed to obtain them; the details are left to Appendix B.

We consider every customer shopping at the retailer in a given week as belonging to the chain's customer base in that week. We assume that a household has exited the customer base when she has not shopped at the chain for eight or more consecutive weeks, and we assume that the decision to exit occurred the last time the customer visited the chain. The eight-week window is a conservative choice given the shopping frequency of households in our sample.[14] Regular customers are unlikely to experience a eight-week spell without shopping for reasons other than having switched to another chain (e.g. consuming their inventory). In fact, on average, four days elapse between consecutive trips and the 99th percentile of this statistic is 28 days, half the length of the absence we require before inferring that a household is buying its groceries at a competing chain.

We construct the price of the basket of grocery goods usually purchased by the households in the following fashion. We identify the goods belonging to a household's basket using scanner data on items the household purchased over the two years in the sample. In a particular week t, the price paid by customer i, shopping at store j and for its basket, represented by the collection of UPC's in K_i is

$$p_{it} = \sum_{k \in K_i} \omega_{ik} \, p_{kt} \ , \qquad \omega_{ik} = \frac{\sum_t E_{ikt}}{\sum_{k \in K_i} \sum_t E_{ikt}} \ , \tag{11}$$

where p_{kt} is the price of UPC k at the store customer i is matched to in week t and E_{ikt} is the expenditure (in dollars) by customer i in UPC k in week t. Note that the price of the basket is household specific because households differ in their choice of grocery products (K_i) and in the weight such goods have in their budget (ω_{ik}). We face the common problem that household scanner data only contain information on prices and quantities of UPCs when they are actually purchased. Therefore, we complement them with store level data on weekly revenues and quantities sold.[15] This data allows us to back out weekly prices of each UPC in the sample by dividing total revenues by total quantity sold as in Eichenbaum et al. (2011).

[14] We experimented with four weeks and 12 weeks as alternative lengths of the period of absence required to infer the exit from the customer base. In both cases the results are qualitatively similar. However, in the 12-week case the number of exit events becomes so small that we do not have the power to detect significant effects.

[15] The retailer changes the price of the UPCs at most once per week, hence we only need to construct weekly prices to capture the entire time variation.

4.2 Evidence on customer base dynamics

The availability of individual level data allows us to study the determinants of a customer's decision to exit the customer base of the firm she is currently shopping from. We estimate a linear probability model where the dependent variable is an indicator for whether the household has left the customer base of the chain in a particular week. Our aim is to capture the effect of the price posted by the chain for the basket of goods purchased by the customer on her decision to exit. To isolate this magnitude in a way consistent with the mechanism described in the theoretical model, we need to include a series of controls.

We are interested in the effect of price variation induced by cost shifts idiosyncratic to a firm. Aggregate cost shocks do not change the relative price and, therefore, should not trigger exit from the customer base. Furthermore, our retailer is a major player in the markets included in our sample and it is likely that the competition takes its prices into consideration when deciding on their own. This possibly introduces correlation between price variations at the chain and price variations at the alternative outlets the customer may visit. To identify idiosyncratic price variations, we control for the prices posted by the competitors of the chain using the IRI Marketing data set. This source includes weekly UPC's prices for 30 major product categories for a representative sample of chain stores across 64 markets in the United States.[16] Thanks to this data, we can observe the weekly price of a specific UPC at every chainstore sampled by IRI in the Metropolitan Statistical Area of residence of a customer. We can, therefore, construct the price of the basket bought by the customer at each store in the MSA (at least for the part of it falling into product categories sampled by IRI) in the same fashion described for the price of the basket at our chain. We take the average of such prices across all stores, weighted by market share, to compute the average market price of the basket (p^{mkt}). To further control for sources of aggregate variation, we include in the regression year-week fixed effects to account for time-varying drivers of the decision of exiting the customer base common across households (e.g., disappearances due to travel during holiday season).

The coefficient on the retailer price of the basket is identified by *UPC-chain* specific shocks as those triggered, for example, by the expiration of a contract between the chain and a manufacturer of a UPC. Within the chain, the price of a same good moves differently in different stores. This can be due, for instance, to variation in the cost of supplying the store due to logistics (e.g. distance from the warehouse), which will hit differently goods with different intensity in delivery cost (e.g. refrigerated vs. nonrefrigerated goods). Therefore,

[16] A detailed description of the data can be found in Bronnenberg et al. (2008). All estimates and analyses in this paper based on Information Resources Inc. data are by the authors and not by Information Resources Inc.

we can also exploit variation in our data from *UPC-store* specific shocks for identification. It is worth stressing that to trigger an exit from the customer base we do not need to observe shocks that make a supermarket uniformly more expensive than the competition. Rather, it is enough that they change the comparative advantage of a chain with respect to a subset of goods on sale. If a chain becomes more expensive in some goods (even though it may become cheaper for other goods), this is enough to induce the customers who particularly care about those goods to leave. Kaplan and Menzio (forthcoming) use independent scanner data to provide ample evidence for this source of variation. They report that the bulk of price dispersion arises not from the difference from high-price and low-price stores but from dispersion in the price of a particular good (or product category) even among stores with similar overall price level.

Another set of regressors is meant to acknowledge that, unlike posited in the model, customers are heterogenous in more dimensions than their cost to search. We start by controlling for customer heterogeneity, including observable characteristics (age, income, and education) matched from Census 2000. We also consider location as a potential driver of the decision to exit. We control for the size of the set of potential store choices by including the number of supermarket stores in the zip code of residence of the customer and factor her convenience in shopping by calculating the distance in miles between her residence and the closest store of the chain and the closest alternative supermarket. To pick up the heterogeneity in the types of goods different customers include in their basket, we control for the price volatility of the customer-specific basket and for its price in the first week in the sample, as a scaling factor. Finally, we calculate customer tenure, defined as the number of consecutive weeks the customer has spent in the customer base of the chain, and include it in the regression to account for the fact that long-term customers of the chain may be less willing to leave it *ceteris paribus*.

In Table 1, we report results of regressions of the following form,

$$Exit_{it} = b_0 + b_1 \log(p_{it}) + b_2 \log(p_{it}^{mkt}) + b_3 tenure_{it} + X_i' c + \varepsilon_{it} \ . \tag{12}$$

The retailer price in equations (12) would be endogenous if the chain conditioned the price to unobserved (to the econometrician) variables that also influence the customer's decision to leave. Since the prices we include in the regression are customer specific, the firm would need to acquire relevant information on each customer (market-level variables would not suffice) and be willing to tweak the prices of their baskets in response to that.[17] Nevertheless,

[17]Note that if blockbuster goods, i.e. goods that account for a significant share of many consumers' baskets, exist, the chain may face a combinatorial problem and be unable to tune the prices of the individual baskets at will. For instance, the chain may want to have the price of the basket rise for some customers and fall for

the retailer provided, along with the store price data, a measure of replacement cost as in Eichenbaum et al. (2011). This represents a natural instrument so that we can estimate equations (12) through instrumental variables and be protected against potential endogeneity of price. We use the replacement cost measure to construct, for each customer in each week, the cost of their basket, following the same procedure described in equation (11) to obtain the price of the basket. The cost of the basket is then used as an instrument for the price of the basket in all the specifications.

Table 1: Effect of the price of the basket on the probability of exiting the customer base

Exiting: Missing at least 8 consecutive weeks	**(1)**	**(2)**	**(3)**	**(4)**
$\log(p)$	0.14**	-0.01	0.16*	0.15**
	(0.071)	(0.030)	(0.089)	(0.070)
Walmart entry			0.019*	
			(0.011)	
$\log(p^{mkt})$	0.001	0.000		0.001
	(0.001)	(0.001)		(0.001)
Tenure	-0.002***	-0.003***	-0.004***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.000)
Observations	52,670	52,670	66,182	52,101

Notes: An observation is a household-week pair. The results reported are calculated through two-stages least squares where we use the logarithm of the cost of the basket (constructed based on the replacement cost provided for each UPC by the retailer) as instrument for the logarithm of the price of the basket. In column (2), the price of the household basket is substituted with a price index for the store overall. In column (4), the exit of the customer is attributed to the first week of absence in the eight (or more) weeks spell without purchase at the chain instead that to the week of the last shopping trip before the hiatus. We trim from the sample households in the top and bottom 1% in the distribution of the number of trips over the two years. A series of variables are not reported for brevity: demographic controls, that rely on a random subsample of households for which information on the block-group of residence was provided, including ethnicity, family status, age, income, education, and time spent commuting (all matched from Census 2000) as well as distance from the closest outlet of the supermarket chain and distance from the closest competing supermarket (provided by the retailer). The logarithm of the price of the household basket in the first week in the sample and the standard deviation of changes in the log-price of the household basket over the sample period are included as a controls in all specifications. Week-year fixed effects are also always included. Robust standard errors are in parenthesis. ***: Significant at 1% **: Significant at 5% *: Significant at 10%.

The results are reported in Table 1. The main specification in column (1) shows that the basket price posted by the retailer significantly impacts the probability of leaving. The effect is also quantitatively important. The average probability of exiting the customer base (0.3% weekly) implies a yearly turnover of 14%; if the retailer's prices were 1% higher, its

others. However, if it raises the price of a blockbuster good, it may prove hard to undo this with "reasonable" price decreases in other goods and obtain lower basket prices for some customers.

yearly turnover would jump to 21%. The coefficient on the competitors' price, which we would expect to enter with a negative sign, is not significant. This may be due to the fact that the IRI data only allow us to imperfectly capture competitors' behavior. First, the IRI dataset contains price information only on a subset of the goods included in a customer's basket, although it arguably covers all the major product categories. Furthermore, we can only match a customer with the stores in her Metropolitan Statistical Area of residence. The set of stores the customer considers as alternative to the chain are probably located in a much smaller area, which introduces measurement error. The negative coefficient on tenure confirms the intuition that the longer the relationship between a firm and a customer, the less likely they are to be interrupted. Among the several individual characteristics we control for it is worth mentioning that distance from stores of the chain and distance from the closest competing store enter with the expected sign. Customers living in proximity of a store of the chain are less likely to leave it, and those living closer to competitors' stores are more inclined to do so.

In columns (2)-(4) we assess the robustness of these findings. We start by replacing the price of the individual basket with a price index for the store basket, defined as the average of the prices of the UPC's sold by the store where the customer buys, weighted for their sales. This price is, by construction, equal for all the customers shopping in the same store. Column (2) shows that this results in a price coefficient that is negative and not significant. We take this as evidence that the customer-specific basket price used in our main specification is a meaningful object, whose significance stems from being able to capture the set of prices each customer cares about and not just reflecting some aggregate trend in pricing. The fact that the competitor price comes up as not significant may raise suspicion that the variable is too noisy to control for the effect of competition. This is important because we are interested in price movements driven by idiosyncratic firm shocks. To assess whether this is the case, we experiment in column (3) with an alternative way to control for the effect of competition: We exploit episodes of entry by Walmart, a major retailer with which our chain is in direct competition. We use data from Holmes (2011) to identify the date of entry by a Walmart supercenter-i.e. a store selling groceries on top of general discount goods-in a zip code where our retailer also operates a supermarket. The resulting event study allows us to measure the effect of the retailer price on the probability of exit controlling for the most relevant change in the competitive environment. The estimated coefficient falls in the same ballpark as that estimated in the main specification, which reassures on the effectiveness of the IRI price in measuring the competitors' behavior. In column (4), we change the assumption on the imputation of the date of exit. Rather than assuming that the customer left on the occasion of her last trip to the store, we posit that the exit occurred in the first week of her absence.[18] Even in this case, the main result stays unaffected. Finally, we performed a placebo test running 1,000 times the main specification, randomly assigning exits from the customer base but keeping their total number the same as in the actual data. This exercise is meant to assess the likelihood that the significance of our result is only due to a lucky occurrence. We find that only in 2.8% of the cases the simulation yields and price coefficient are positive and significant at 5%.

5 Parametrization and analysis of the model

In this section we discuss the procedure followed to estimate the model. We need to choose the discount factor β as well as four functions: the demand function, $d(p)$, the surplus function $v(p)$, the distribution of search costs $G(\psi)$, and the conditional distribution of productivity $F(z'|z)$. Below we discuss the parametrization of the model in detail.

We assume that a period in the model corresponds to a week to mirror the frequency of our data. We fix the firm discount rate to $\beta = 0.995$. In the set of parameters that we consider, this level of β ensures that the max-operator in equation (6) is a contraction.[19]

We assume that customers have logarithmic utility in consumption. Consumption is defined as a composite of two types of goods $c \equiv \left(d^{\frac{\theta-1}{\theta}} + n^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}$, with $\theta > 1$.[20] The first good (that we label d) is supplied by firms facing product market frictions as described in Section 2.2; the other good (n) acts as a numeraire and it is sold in a frictionless centralized market. The sole purpose of good n is to microfound a downward sloping demand $d(p)$ and, therefore, allowing for an intensive margin of demand. The parameter θ is chosen so that the implied average intensive margin elasticity of demand ($\varepsilon_d(p)$) is 7, a value in the range of those used in the macro literature. The customer budget constraint is given by $p\,d + n = I$, where I is the agent's nominal income, which we normalize to one.[21]

While we fix the parameters listed above using external sources, our data allows us to estimate those characterizing the idiosyncratic productivity process and the search cost distribution using a minimum-distance estimator. These are the key parameters of the model:

[18] This alternative assumption matches more closely our model where the customer leaves after having seen the prices of her current supplier and decided not to buy there.

[19] This level of β reflects that the effective discount rate faced by the firm is the product of the usual time preference discount factor and a rescaling element which takes into account the time horizon of the decision maker, as for instance the average tenure of CEOs in the retail food industry reported in Henderson et al. (2006).

[20] Moving from these assumptions we can derive a demand function ($d(p)$) and a customer surplus function ($v(p)$) consistent with the assumptions made in Section 2.

[21] In Appendix C we show that I can be derived based on a model of the labor markets.

The productivity process influences the variability of prices, which is necessary for customers to obtain any benefit from search. The parameters of the search cost distribution, on the other hand, directly determine how costly it is to search. Below, we pick functional forms for these objects and explain which moments we select in our data helps to identify them.[22]

We assume that the productivity evolves according to a process of the following form:

$$\log(z_t^j) = \begin{cases} \log(z_{t-1}^j) & \text{with probability } \rho, \\ \log(z') \sim N(0,\sigma) & \text{with probability } 1-\rho \end{cases}$$

When solving the model numerically, we approximate the normal distribution on a finite grid, using the procedure described in Tauchen (1986). Finally, we normalize the nominal wage equal to the price of the numeraire good, so that $w = 1$.[23]

The model specifies how the parameters of the productivity process impact on the autocorrelation and volatility of firm prices. We therefore estimate persistence and volatility of productivity by matching the autocorrelation and the volatility of the logarithm of firm prices to those measured in the data using a store-level price index.[24]

We assume that the search cost is drawn from a Gamma distribution with shape parameter ζ, and scale parameter λ. The Gamma is a flexible distribution and fits the assumptions we made over the G function in the specification of the model. In particular, for $\zeta > 1$, we obtain that the distribution of search costs is differentiable at $\psi = 0$.[25]

To identify the parameters of the search cost distribution we exploit the estimates of the relationship between price and probability of exiting the customer base discussed in Section 4. We identify the scale parameter λ by matching the average effect of log-prices on the exit probability predicted by the model in equilibrium to its counterpart in the data measured by the parameter b_1 in equation (12). [26] The parameter ζ measures the inverse of the coefficient

[22]The discussion on identification is provided only for the sake of intuition; given the nonlinearity of the model, all the moments contribute to the identification of all the parameters.

[23] This is equivalent to assume that the numeraire good n is produced by a competitive representative firm with linear production function and unitary labor productivity. See Appendix C for details.

[24]The store price index (p_{jt}) is computed in a fashion analogous to the customer price index. It is the average of the price of all the UPCs sold in store j, weighted for the share of revenues they represent. To estimate persistent and volatility of prices in the data, we exploit the first year of the sample span to obtain the store-level average of the price index and use it to demean the variables so to remove store fixed effects. We then estimate on the second year of data the equation $(\log(p_{jt}) - \overline{\log(p_j)}) = k_0 + k_1(\log(p_{jt-1}) - \overline{\log(p_j)}) + \tau_t + \epsilon_{jt}$ pooling all stores. The time fixed effects are included to purge the data from aggregate effects and isolate the variation in price driven by the idiosyncratic component.

[25]In our estimation procedure we do not impose any constraints on the values the parameter $\zeta > 1$ can take. Our unconstrained point estimate lies in the desired region.

[26]In particular, the equilibrium probability of exiting the customer base of a firm charging p and with productivity z is $E(z) \equiv G(\hat{\psi}(p,z))(1 - H(\bar{V}(p,z)))$ where $p = \hat{p}(z)$ for all z, so that the model counterpart to b_1 is given by $Cov(E(z), \log(\hat{p}(z)))/Var(\log(\hat{p}(z)))$. The exit probability is decreasing in λ *for given equilibrium prices*. This is exactly the case we are considering since we are targeting the persistence and volatility of the empirical price distribution, which is indeed fixed in our analysis.

of variation of the search cost distribution. In the model, higher dispersion of search costs (i.e., lower ζ) implies more mass on the tails of the distribution of search costs. The latter is associated with larger variation in the sensitivity of exit probability to price. In the data, we measure this variation by fitting a spline to equation (12), allowing for the marginal effect of price on the probability of exit to vary for different terciles of price levels. We find that higher prices imply a higher value of b_1 as predicted by the model, and the dispersion in the estimates of b_1 is 0.03. The parameter ζ is estimated by matching this number to an equivalent statistic generated by the model.[27]

Table 2: Parameter estimates

	Value	Target
Persistence of productivity process, ρ	0.60	Log-price autocorrelation: 0.58
Volatility of productivity innovations, σ	0.11	Log-price dispersion: 0.02
Scale parameter of search cost distribution, λ	0.033	Average marginal effect, b_1: 0.14
Shape parameter of search cost distribution, ζ	3.00	Dispersion of b_1: 0.03

We define $\Omega \equiv [\zeta\ \lambda\ \rho\ \sigma]'$ as the vector of parameters to be estimated and estimate it with a minimum-distance estimator. Denote by $v(\Omega)$ the vector of the moments predicted by the model as a function of parameters in Ω, and by v_d the vector of their empirical counterparts. Each iteration n of the estimation procedure unfolds according to the following steps:

1. Pick values for the parameters ρ_n, σ_n, λ_n and ζ_n from a given grid,

2. Solve the model and obtain the vector $v(\Omega_n)$,

3. Evaluate the objective function $(v_d - v(\Omega_n))'\Xi\ (v_d - v(\Omega_n))$. Where Ξ is a weighting matrix that we assume to be the identity matrix.

We select as estimates the parameter values from the proposed grid that minimize the objective function.

[27] In the model the marginal effect of prices on the exit probability is proportional to $G'(\hat{\psi}(p,z))/G(\hat{\psi}(p,z))(1-H(\bar{V}(p,z)))^2$, where $p = \hat{p}(z)$ for all z. We compute the dispersion in this measure across the different firms.

Implementing step 2 requires solving a fixed point problem in equilibrium prices. In particular, given our definition of equilibrium and the results of Proposition 2, we look for equilibria where prices are in the interval $[p^*(\bar{z}), p^*(\underline{z})]$. In principle, our model could have multiple equilibria; however, numerically we always converge to the same equilibrium despite starting from different initial conditions. In Appendix D we provide more details on the numerical solution of the model. The estimation results are summarized in Table 2.

6 Price and customer dynamics

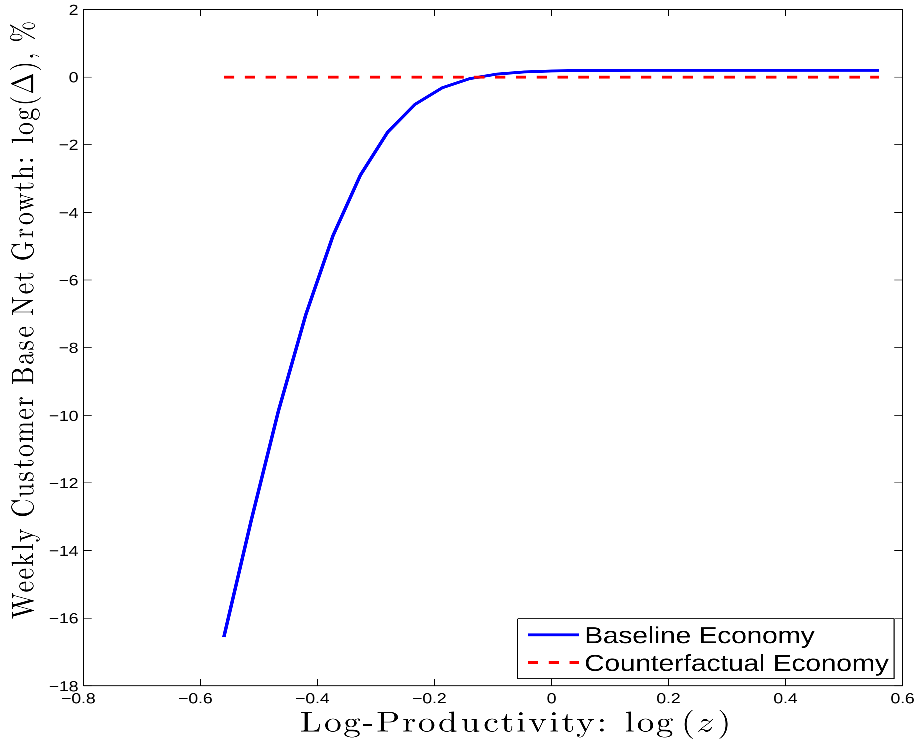
In this section we use the parameter estimates reported in Table 2 to solve for the equilibrium pricing and searching policies predicted by our model (henceforth "baseline economy"). To appreciate the importance of customer markets for equilibrium dynamics we contrast these results with those implied by the limiting case where competition for customers is shut down by raising the scale of search costs (λ) to infinity. We refer to this benchmark as "counterfactual economy." To make the comparison meaningful, we fix θ in this counterfactual economy so that the resulting average total elasticity of demand is the same as in our baseline economy (i.e. $\varepsilon_q = \varepsilon_d$) and choose σ and ρ targeting the same volatility and autocorrelation of prices as in the baseline estimates. Hence the two economies are observationally equivalent with respect to the (average) price elasticity of demand and the equilibrium price process.

This exercise allows us to compare qualitatively the baseline and the counterfactual economy and also to quantitatively assess the properties of the model. We start by analyzing customer dynamics, plotted in Figure 1. In fact, a first order difference between our model and the counterfactual economy is the presence of customer dynamics in equilibrium. In particular, firms with high productivity experience positive net growth of their customers base, whereas lower productivity firms are net losers of customers. Quantitatively, the model predicts a yearly customer turnover of about 6%. The unconditional frequency of exit from the customer base in our data is 14% on a yearly basis. Thus, price variation arising from idiosyncratic cost shocks explains almost half of customer dynamics observed in the data.[28]

Our baseline model also features distinctive implications with respect to the shape of the price distribution. This is interesting for two reasons. First, we argue that the shape of the price distribution is an indicator of the relevance of customer markets. Therefore, comparing the predicted distribution with the one from our data we provide an external validation of our model. Second, it allows us to relate to a recent literature documenting features of the

[28]It can be noticed that net customer base growth increases in productivity at a decreasing pace. This is dictated by the asymmetry between the retention and attraction margins in our model. For instance, allowing for an advertising technology would enable the firm to affect the mass of customers arriving and reinforce the link between the arrival rate of customers and firm productivity.

Figure 1: Customer base growth and productivity



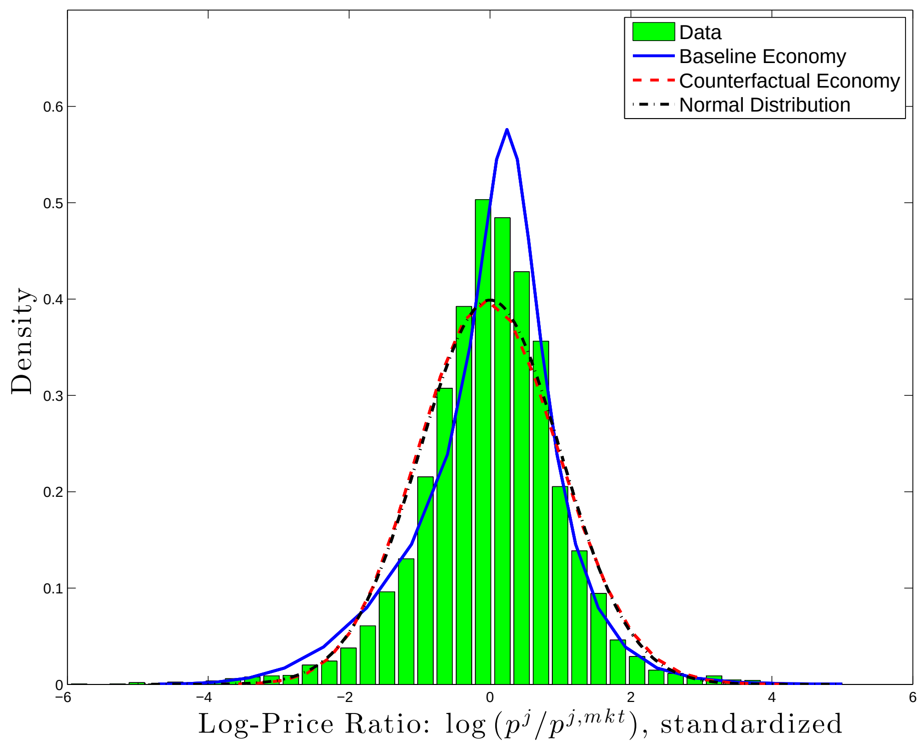
Notes: The figure plots net customer base growth as a function of a firm's idiosyncratic productivity, for the baseline and the counterfactual economy. The baseline economy is simulated using the parameter estimates in Table 2. The counterfactual economy's productivity process is obtained matching the same moments (autocorrelation and volatility of the prices of store baskets) as in the baseline estimation but search is shut down ($\lambda \to \infty$). Therefore, in the counterfactual economy there is no extensive margin of demand. The parameter governing the intensive elasticity of demand is chosen for the counterfactual economy so that it matches the same *overall* elasticity of demand (intensive plus extensive margin) featured by the baseline economy.

price distribution (Kaplan and Menzio (forthcoming)).

Figure 2 plots the distribution of prices in the baseline and counterfactual economies and compares it with the empirical distribution emerging from the data. The figure plots the distribution of the standardized (log-) ratio between the price set by a firm and the average price in the market, $\tilde{p}_t^j \equiv \log(p_t^j / p_t^{j,mkt})$.[29] The price distributions from our baseline model and the counterfactual are markedly different. Even though we impose that the two economies have the same dispersion in prices, the baseline model price distribution displays a larger mass

[29]In the stationary equilibrium of the model, the market price ($p_t^{j,mkt}$) does not vary over time, and there is only one market. However, we construct the ratio to make the output of the model comparable with the data, where the market price can vary through time and controlling for it is necessary to isolate the price variation driven by idiosyncratic shocks.

Figure 2: The distribution of standardized prices: model and data

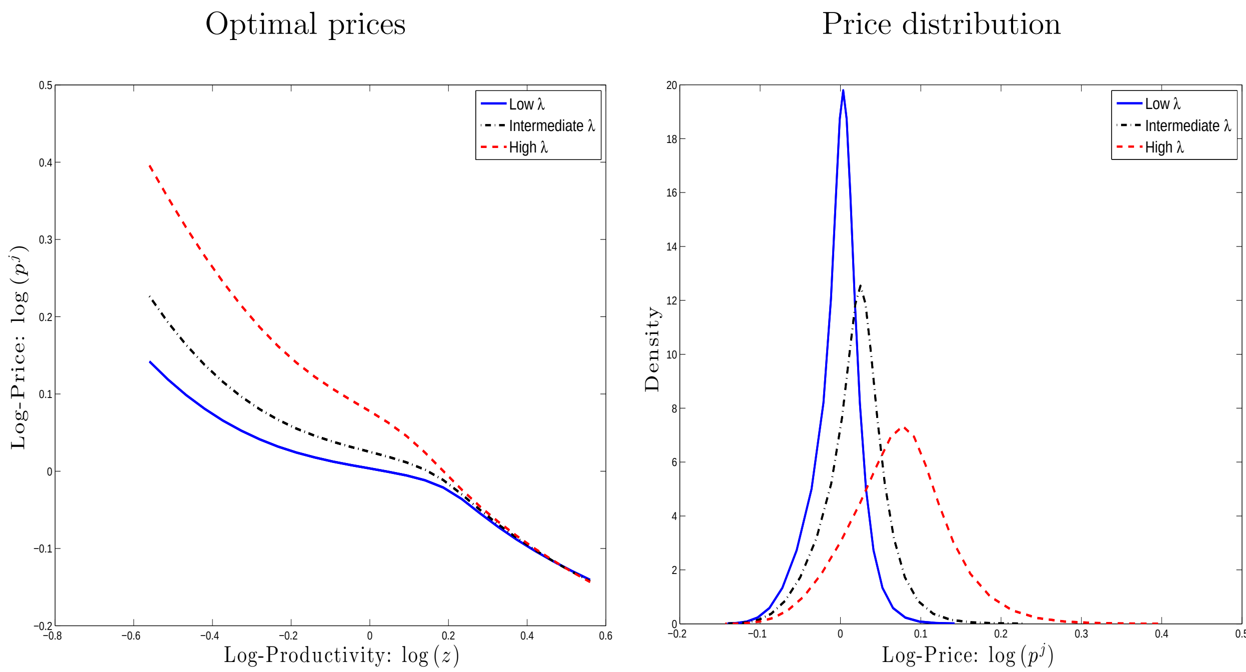


Notes: The figure plots the distribution of the ratio between the price set by a firm and the average price in the market, $\log(p^j/p^{mkt})$. The price ratio is standardized (i.e. reported in deviations from its mean and divided by its standard deviation) to make the outcomes from the baseline and the counterfactual models comparable. The blue solid line refers to our baseline economy with customer markets at parameters estimated in Section 5. The counterfactual economy (dashed red line in the plot) features parameters of the productivity process chosen targeting the same moments (autocorrelation and volatility of the prices, and the intensive margin demand elasticity) as in the baseline estimation, but search is shut down ($\lambda \to \infty$). The green histogram portrays the empirical distribution of the ratio of the price index of each store of the retail chain to the average price index in the Metropolitan Statistical Area where the store is located. Both the numerator and the denominator of this ratio are normalized by their respective averages. Stores whose coefficient of variation for the ratio exceeds 1 are trimmed.

of prices clustered together around the mean that reflects into a more pronounced peakedness of the price distribution relative to the counterfactual economy, whose price distribution is instead nearly normal. Quantitatively the fraction of prices within half a standard deviation from the mean is 46% in the baseline model and 38% in the counterfactual. Another way of summarizing this is to note that only the baseline model displays excess kurtosis (around 4.2).

The increase in the clustering of prices around the mean, with respect to a normal distribution, derives from the strategic complementarity in pricing introduced by customer markets. To illustrate this point we refer to Figure 3, which plots the results from a comparative static exercise where we simulate the model varying only the scale of the search cost λ. Unlike in Figure 2, we are not forcing dispersion and persistence of the price process to be the same

Figure 3: Equilibrium prices as a function of the scale of search costs, λ



Notes: The left panel plots the optimal log-prices as a function of productivity. The right panel figure plots the distribution of the log-price set by a firm. The blue solid line refers to our baseline economy with customer markets at parameters estimated in Section 5 ($\lambda = 0.03$). The black dotted line refers to our baseline economy where however we set $\lambda = 0.08$. The red dashed line refers to our baseline economy where however we set $\lambda = 0.12$.

across the different simulations, so that the other parameters are kept constant at the values of Table 2. More competition for customers (lower λ) increases incentives of each firm to price closer to firms with higher productivity, resulting in a shift of mass from the right to the left of the price distribution. This incentive to reduce prices weakens as productivity grows. In fact, the firm with the highest productivity always charges the same price (the one maximizing profits per customer), independently of λ. It follows that the stronger the competition for customers, the more prices cluster together.[30]

We compare the model prediction with the data by computing the price index for store j in each week t as the average of the prices of the UPCs sold by the outlet, weighted for the share of total revenues they generate in the all sample. We then use the IRI data to obtain the average market price, $p_t^{j,mkt}$, given by the period t average price index for the same basket of goods posted by retailers operating in the same Metropolitan Statistical Area where store

[30]Notice that the shape of the price distribution in our model significantly departs from that of other models featuring equilibrium price dispersion like, for instance, Burdett and Judd (1983). The difference is not only due to the presence of customer retention concerns but also to other divergences in the modeling approach, as for instance allowing for idiosyncratic variation in productivity.

j is located.[31] The statistics plotted in the histogram in Figure 2 is the (standardized) ratio of the store and the market price index. To remove permanent cross-market heterogeneity, we normalize the numerator and the denominator of the ratio by their averages computed over time. The decision to consider the distribution of the store price index, as opposed, for instance, to that of the price of individual UPC's, implicitly assumes that a manager cares about the overall price level at the store for the "average" customer.[32]

The distribution obtained from our data also features high mass around the mean and is well fitted by our baseline model: The fraction of prices within half a standard deviation is 45.5%, and excess kurtosis is 4.6. This is remarkable, given that we did not target at all the shape of the price distribution in our estimation and that our underlying productivity innovations in the model are drawn from a Normal distribution. It follows that the leptokurtic distribution of prices delivered from the model is not the product of ad-hoc assumptions but derives from the strategic interaction that is at its core.[33]

A final difference between our setup and a model without customer markets relates the extent of pass-through. Our calculation for the baseline model implies an average pass-through of idiosyncratic cost shocks equal to 13%, well below the 79% predicted in the counterfactual economy.[34] In the presence of competition for customers, a price increase leads to a persistent loss of customers; this dynamic incentive is not present in the counterfactual economy. This implies that, when experiencing an increase in production cost, the firm has a strong incentive to reduce the pass-through to the price by compressing its margin. Furthermore, as we showed in equation (10), customer markets compress firms' margins with respect to the margin that would maximize profits per customer. As a consequence, when the firm

[31] The procedure requires the price index of the store to be computed on the subset of UPCs for which we have price information both in the retailer's data and for each store in the IRI data for every week in the sample. This substantially reduces the size of the store basket: In our data, the average store price index is computed using about 1,000 UPCs. On the upside, the procedure naturally selects the best-selling products (for which price information is more likely to appear continuously for all stores).

[32] Notice that in the case of Section 4 we used the individual customer's basket price as our main regressor. In that context we were analyzing customers' behavior and it was therefore more appropriate to consider the price the customer cares about, that of its own basket.

[33] Kaplan and Menzio (forthcoming) use Nielsen data to document the features of the price distribution of both single UPCs and of bundles of goods bought by the consumers. They find that the former displays high kurtosis; whereas the latter is nearly normal. Our finding does not contrast with theirs. They analyze the ratio of the grocery expenditure by a household and the expenditure she would have incurred had she purchased each item at the average market price. As such, the figure at the numerator can derive from a bundle of goods bought in different stores. Our leptokurtik distribution refers instead to the ratio between a bundle of goods sold at a given store and the average market price of that same bundle. In Appendix E, we show that we can replicate their findings on the distribution of UPC prices using our data.

[34] Note that the pass-through is incomplete even in the counterfactual economy because, with CES preferences, the demand of good i depends on the relative price p_i/P. With a finite number of goods in the basket of the customer, an increase in p_i also increases the price of the basket, P, thus reducing the overall increase in p_i/P and effect on demand. The effect on P is larger, the higher the weight of good i in the basket, that is the lower the price p_i and the higher its demand. Therefore, the elasticity of demand $\varepsilon_d(p)$ increases in p.

experiences a decrease in production cost, it can increase profits per customer without losing more customers. Therefore, the pass-through is incomplete also in this direction. The store data provided by the retailer contain a measure of cost. Although this measure is imperfect and does not precisely capture the marginal cost, we can use it to check the model's predictions regarding pass-through. The results from this exercise are reported in Appendix F: The pass-through measured in the data is in line with the predictions of a customer markets model and much lower than what the counterfactual economy would imply.[35]

7 The dynamics of demand: short vs. long run

So far we have analyzed the dynamics of prices and customers in response to idiosyncratic shocks in the presence of customer markets. In this section we broaden our scope, exploring the relevance of customer markets for the propagation of a shock affecting a *subset* of the firms in the economy with an emphasis of the dynamics of demand. A shock to the effective cost of a subset of the players in the industry is the salient characteristic of a number of real world scenarios. For instance, variations in state sales tax would affect local sellers but not online ones located out-of-state, as they cannot be compelled to collect it. A similar effect is generated by a shock to the real exchange rate affecting the competitiveness of foreign producers, or by the introduction of size-contingent employment protection legislation.[36] Exploring cost shocks that affect firms *asymmetrically* is useful to highlight one of the main differences between our setup and the standard monopolistic competition models. In fact, such shocks create price dispersion and, therefore, incentivize customers to search for a new supplier. In the presence of customer markets, this leaves scope for customer reallocation to impact persistently the response of demand and output, creating a distinctive difference between long- and short-run response.

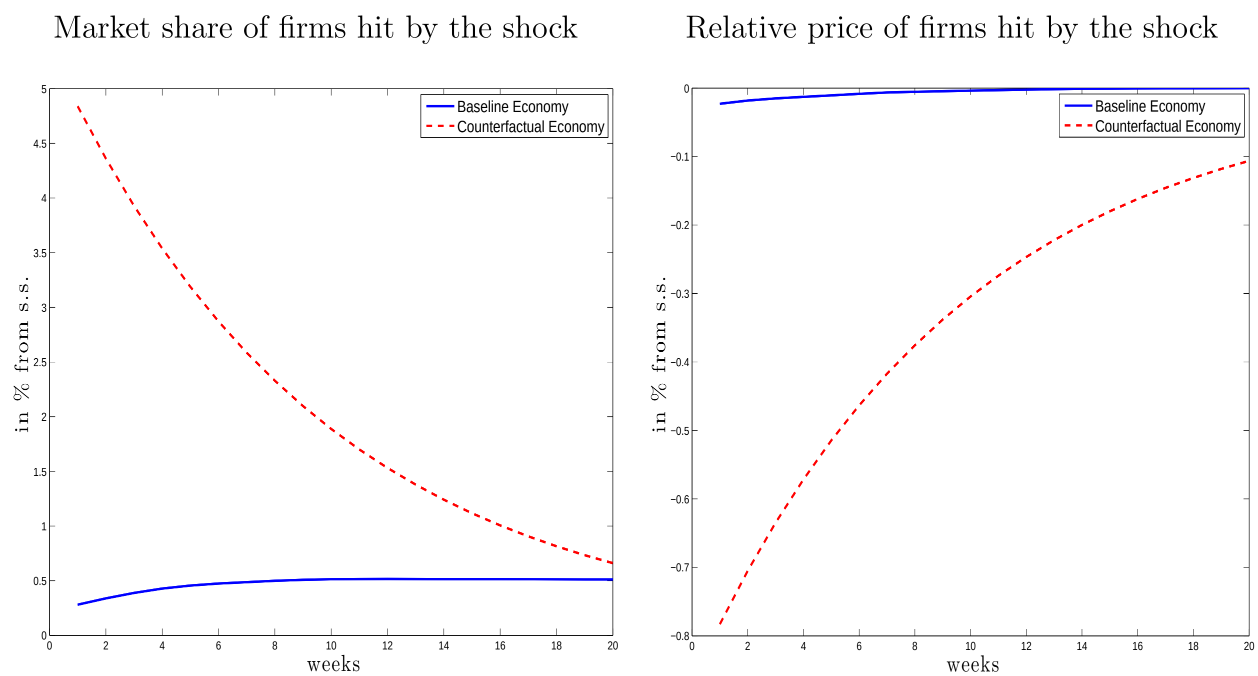
The specifics of the experiment we perform are as follows. We consider the economy calibrated in Section 5 in steady state at period t_0. We assume that 10% of the firms in the economy are hit by an unexpected and unforeseen shock to production cost in the form of a scaling factor τ_t, so that the marginal cost of production of a firm hit by the shock goes from $w_t/z_t^{j^*}$ to $\tau_t\, w_t/z_t^{j^*}$, where j^* denotes a firm being hit by the shock. The productivity

[35]This result is not inconsistent with evidence of complete pass-through presented by Eichenbaum et al. (2011) using the same data. First, they measure pass-through conditional on price adjustment; whereas we look at the unconditional correlation between prices and costs. Second, they deal with UPC-level pass-through while we measure pass-through of a basket of goods. If retailers play strategically with the pricing of different products, for example lowering margins on some UPC to compensate the cost increase they experienced on others, we can obtain both high UPC-level pass-through and low basket-level pass-through.

[36]Introducing nominal rigidities to our framework, a similar exercise could also be used to study the effects of nominal shocks.

shock is realized after the firm has learned about idiosyncratic productivity z_t, but before pricing and customer's exit decisions are taken, and dies out according to an AR(1) process, $\tau_t = \rho_\tau \tau_{t-1}$ for $t > t_0$.[37]

Figure 4: The response of market share and relative price to an aggregate shock



Notes: The figure plots the impulse response of market share of those firms being hit by the aggregate shock and relative price of affected to unaffected firm, for both our baseline economy and a counterfactual one where customer markets are not present. The baseline economy is simulated using the parameter estimates in Table 2. In the counterfactual economy the parameter governing the intensive elasticity of demand is chosen so that it matches the same *overall* elasticity of demand (intensive plus extensive margin) featured by the baseline economy.

In Figure 4 we plot the responses of the market shares of firms hit by the shock (left panel) and relative average price (right panel) of firms hit by the aggregate shock to that of unaffected firms.[38] The plot refers to a parameterization where the shock leads to a 1% increase in productivity with a persistence parameter $\rho_\tau = 0.9$, so that the half-life of the aggregate shock is approximately a quarter. The solid line plots the responses in the economy with customer markets, while the dotted line refers to the response in the alternative economy

[37]Since the shock implies aggregate dynamics, we augment our economy with a simple equilibrium model of the labor market to capture the general equilibrium effects of the shock on wages and income. More details on this extension are provided in Section C.

[38]The market share of the firms hit by the shock is defined as $\int m_t^{j^*} d_t^{j^*} dj^* / (\Gamma \int d_t^j dj)$, where j^* denotes a firm being hit by the shock, and j denote any firm.

where customer markets are shut down. As usual, we make sure that the two economies are comparable, fixing the total average elasticity of demand to be the same.

The difference in the propagation of the same shock in the two economies is striking. In the baseline economy, the effect of the shock is persistent and the long-run impact is larger than the short-run one. In the counterfactual economy, the short-run effect is larger than in a world with customer markets but the response is purely transitory. The reaction of prices is also quite different: relatively little movement in the baseline economy and much more marked changes in the alternative one.

The response pattern in the alternative economy is easy to understand and similar to what would happen in static models of monopolistic competition. Both the response of the market share and relative price follow closely the process for the productivity shock, and thus are transitory and their order of magnitude depends on the size of the shock. The baseline economy has two distinctive characteristics that deliver the very different response path. First, as we have shown, lower levels of search cost imply less pass-through. Therefore, the immediate effect on prices is smaller in the baseline economy. This, in turn, leads to more contained effect on demand in the short run. The general equilibrium effect compounds this mechanism: even firms not hit by the shock have an incentive to decrease their prices, as they experience an increase in the extensive margin elasticity. The second force at play is connected to the process of customer reallocation. After the unexpected shock has hit, firms that were affected are better than those that were not and customers would want to shop there. Because of the search friction, the reallocation process takes time and therefore does not immediately boost the market share of the firms hit by the shock. However, as time goes by, the firms made more productive by the shock gain customers that they will not lose even when the effect of the shock has completely faded away. In fact, at that point the productivity processes of all firms will be the same and there will be no extra incentive for customers to search.

This example showcases the flexibility of our setup: Different levels of search cost can originate stark differences in the response to aggregate shocks. This implies that the possibility of empirically assessing the relevance of customer markets in an economy is key to predict the response of demand to shocks. At our parameter estimates, the shock generates a stronger impact in the long than in the short run and the effect will be persistent. Evidence from the international macro literature provides some support for these predictions: Ruhl (2008) documents that the elasticity of the share of imports to exchange rate shocks is indeed larger in the long run than in the short run.

8 Conclusions

Across a broad range of industries, being able to retain customers and attract new ones is key to firms' success and survival. This is increasingly recognized by scholars, as witnessed by the growing number of studies attempting to incorporate this feature and exploring its implications. In this paper, we combined a formal model and novel data to study and quantify the consequences of the presence of competition for customers on firms' pricing.

Our first contribution is the introduction of a rich yet tractable model of customer markets. We generate stickiness in the customer base of a firm by positing that customers must pay a search cost when they wish to look for a new supplier. We allow this cost to be heterogeneous across customers, and we also let firms differ in their idiosyncratic productivity. We show the existence of a Markov Perfect Equilibrium where optimal pricing are decreasing in productivity, whereas the customer base growth is increasing in it. This implies that our equilibrium features both price and customer dynamics. Another important result from the model states that the fiercer the competition for customers the lower optimal markups will be. This implies that markups in our model will be lower than in a classic static demand model, which does not contemplate customer markets.

Empirically, we exploited detail data from a retail chain to document a relationship between a firm's pricing and its customers' decision to leave its customer base. Retrieving this elasticity and using the data to form other appropriate empirical moments, we were able to estimate the key parameters of the model: those pinpointing the distribution of the search costs and those governing the productivity process. This allowed us to highlight two important implications of our model. First, the incentive to attract and retain customers introduces strategic complementarities pushing firms to set similar prices. This results in a price distribution where a large fraction of prices lies close to the mean, generating a shape in line with the one documented by the available empirical evidence. Second, we presented an application that highlights how a customer market model may have important implications for the response of demand to shocks. In particular, our counterfactual exercise showed that frictions in customer reallocation contribute to magnify the size and the persistence of the long-run effects of shocks.

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A Proofs

A.1 Proof of Lemma 2

The proof of Lemma 2 follows from the assumption of $v(p)$ being strictly decreasing in p so that $\bar{V}(p,z)$ is decreasing in p. If $\hat{V}(z)$ is increasing in z, $\bar{V}(p,z)$ increases with z because of the assumptions that the productivity process is persistent. Finally, notice that $\frac{\hat{\psi}(p,z)}{\partial p} = -v'(p)\,\left(1 - H(V(p,z))\right)\, \geq 0$ and that $\frac{\partial\hat{\psi}(p,z)}{\partial z} = -\frac{\partial\bar{V}(p,z)}{\partial z}\,\left(1 - H(V(p,z))\right)\, \leq 0$.

A.2 Proof of Proposition 1

Let $\bar{p}(z)$ be the level of price at which no customer matched with a firm with productivity z searches. Then $\bar{p}(z)$ satisfies $\bar{V}(\bar{p}(z),z) = \max_{z\in[\underline{z},\bar{z}]}\{\bar{V}(\mathcal{P}(z),z)\}$. First, given the definition of $p^*(z)$ and the fact that $\Delta(p,z)$ is strictly decreasing in p for all $p > \bar{p}(z)$, and constant otherwise, it immediately follows that $\hat{p}(z) \in [\bar{p}(z), p^*(z)]$ if $\bar{p}(z) < p^*(z)$, and $\hat{p}(z) = p^*(z)$ otherwise. Next, we show that $\hat{p}(z) < p^*(z)$ if $\bar{p}(z) < p^*(z)$. Given the definition of $\bar{p}(z)$ and the assumptions made on G, at $p = \hat{p}(z)$: i) $W(p,z)$ is strictly decreasing in p; ii) $\Delta(p,z)$ is strictly decreasing in p. Therefore; $p = \hat{p}(z)$ cannot be a maximum and the result follows.

A.3 Proof of Proposition 2

Monotonicity of prices. We first show that optimal prices $\hat{p}(z)$ are non-increasing in z. Given, that productivity is i.i.d. and that we look for equilibria where $\hat{p}(z) \geq p^*(\bar{z})$, we have that $\bar{p}(z) = p^*(\bar{z})$ for each z. From Proposition 1 we know that, for a given z, the optimal price $\hat{p}(z)$ belongs to the set $[p^*(\bar{z}),\ p^*(z)]$. Over this set, the objective function of the firm,

$$W(p,z) = \Delta(p,z)\,(\pi(p,z) + \beta\,\text{constant})\ , \tag{13}$$

is supermodular in $(p,-z)$. Notice the i.i.d. assumption implies that future profits of the firm do not depend on current productivity as future productivity, and therefore profits, are independent from it. Similarly, $\Delta(p,z)$ does not depend on z, as the expected future value to the customer does not depend on the productivity of the current match as future productivity is independent from it. Abusing notation, we replace $\Delta(p,z)$ by $\Delta(p)$. To show that $W(p,z)$ is supermodular in $(p,-z)$ consider two generic prices p_1, p_2 with $p_2 > p_1 > 0$ and productivities $z_1, z_2 \in [\underline{z},\bar{z}]$ with $-z_2 > -z_1$. We have that $W(p_2,z_2) - W(p_1,z_2) \leq W(p_2,z_1) - W(p_1,z_1)$ if and only if

$$\Delta(p_2)d(p_2)(p_2 - w/z_2) - \Delta(p_1)d(p_1)(p_1 - w/z_2) \leq \Delta(p_2)d(p_2)(p_2 - w/z_1) - \Delta(p_1)d(p_1)(p_1 - w/z_1),$$

which, using $\Delta(p_2)d(p_2) < \Delta(p_1)d(p_1)$ as $d(p)$ is strictly decreasing and $\Delta(p)$ is non-increasing, is indeed satisfied if and only if $z_2 < z_1$. Thus, $W(p, z)$ is supermodular in $(p, -z)$. By application of the Topkis Theorem we readily obtain that $\hat{p}(z)$ is non-increasing in z.

Existence of equilibrium. Next we prove existence of an equilibrium. The fixed point problem is a mapping from candidate functions of equilibrium prices, $\mathcal{P}(z)$, to the firm's optimal pricing strategy, $\hat{p}(z)$, where an equilibrium is one where $\hat{p}(z) = \mathcal{P}(z)$ for each z. Differentiability of $v(p)$ implies that $W(p, z)$ is continuously differentiable in p, so that the operator that maps $\mathcal{P}(\cdot)$ into $\hat{p}(\cdot)$ is given by the first order condition in equation (8). Moreover, notice that $W(p, z)$ in equation (13) is continuous in (p, z). By the theorem of maximum, $\hat{p}(z)$ is upper hemi-continuos and $W(\hat{p}(z), z)$ is continuos in z. Given that $\hat{p}(z)$ is non-increasing in z it follows that $\hat{p}(z)$ has a countably many discontinuity points. We thus proceed as follows. Let $\hat{\mathcal{P}}(z)$ be the set of prices that maximize the firm problem. Whenever a discontinuity arises at some $\tilde{z}$ (so that $\hat{\mathcal{P}}(\tilde{z})$ is not a singleton), we modify the optimal pricing rule of the firm and consider the convex hull of the $\hat{\mathcal{P}}(\tilde{z})$ as the set of possible prices chosen by the firm with productivity $\tilde{z}$. The constructed mapping from z to $\hat{\mathcal{P}}(z)$ is then upper-hemicontinous, compact and convex valued. We then apply Kakutani's fixed point theorem to this operator and obtain a fixed point. Finally, notice that since the convexification procedure described above has to be applied only a countable number of times, the set of convexified prices has measure zero with respect to the density of z. Hence, they do not affect the fixed point.

Necessity of the first order condition. We show that Q and H are almost everywhere differentiable, so that Proposition 1 implies that equation (8) is necessary for an optimum. We guess that $\hat{p}(z)$ is strictly decreasing and almost everywhere differentiable. It immediately follows that $\hat{V}(z)$ is strictly increasing in z and almost everywhere differentiable. Then, given the assumption that F is differentiable, we have that K is differentiable. From $H(x) = K(\hat{V}^{-1}(x))$ it follows that H is also almost everywhere differentiable. Given that G and H are differentiable, so is Q. Then the first order condition in equation (8) is necessary for an optimum, which indeed implies that $\hat{p}(z)$ is strictly decreasing and differentiable in z in any neighborhood of the first order condition. Finally, given that $\hat{p}(z)$ has a countably many discontinuity points, it has countably many points where it is not differentiable, and the first order condition does not apply at those points, but applies everywhere else. These points have measure zero with respect to the density of z and therefore $\hat{p}(z)$ is almost everywhere differentiable.

Point (i). We already proved that $\hat{p}(z)$ is non-increasing in z. The proof that $\hat{p}(z)$ is strictly decreasing follows by contradiction. Consider that $\hat{p}(z_1) = \hat{p}(z_2) = \tilde{p}$ for some $z_1, z_2 \in [\underline{z}, \bar{z}]$. Also, without loss of generality, assume that $z_1 < z_2$. Given that we already established the necessity of the first order condition presented in equation (8) when prices are monotonic, suppose that it is satisfied at the duple $\{z_2, \tilde{p}\}$. Notice that, because of the assumed i.i.d. structure of productivity shocks together with $\pi_z(p,z) < 0$, it is not possible that the first order condition is also satisfied at the duple $\{z_1, \tilde{p}\}$. Moreover, because the first order condition is necessary and we already established that $\hat{p}(z)$ cannot be increasing at any z, we conclude that the optimal price at z_1 is strictly larger than at z_2. That is, $\hat{p}(z_1) > \hat{p}(z_2)$. Notice that this verifies the conjecture used to prove the necessity of the first order condition, which in turn validates the use of equation (8) here.[39]

Notice that, because $\hat{p}(z)$ is strictly decreasing in z, the fact that $v'(p) < 0$ together with i.i.d. productivity, implies, through an application of the contraction mapping theorem, that $\hat{V}(z) = \bar{V}(\hat{p}(z), z)$ is increasing in z.

Point (ii). $\hat{\psi}(p,z) \geq 0$ immediately follows its definition. The fact that $\hat{V}(z)$ is strictly increasing in z, together with Lemma 2, immediately implies that $\hat{\psi}(\hat{p}(\bar{z}), \bar{z}) = 0$ and that $\hat{\psi}(\hat{p}(z), z)$ is strictly increasing in z. Finally, Lemma 3 implies that $\Delta(\hat{p}(z), z)$ is increasing in z. Because of price dispersion, some customers are searching, which guarantees that $\Delta(\hat{p}(\bar{z}), \bar{z}) > 1$. Likewise, $\Delta(\hat{p}(\underline{z}), \underline{z}) < 1$.

A.4 Thought experiment of Section 3

We show that $\mu(p,z)$ is increasing in $\varepsilon_q(p,z)$. Notice that equation (10) can be rewritten as

$$\mu(p,z) = \frac{\varepsilon_q(p,z) + \varepsilon_m(p,z)\tilde{x}(p,z)}{\varepsilon_q(p,z) - 1 + \varepsilon_m(p,z)\tilde{x}(p,z)},$$

where $\tilde{x}(p,z) \equiv \Pi(p,z)/\pi(p,z)$. From the equation above we obtain

$$\frac{\partial \mu(p,z)}{\partial \varepsilon_m(p,z)} = \frac{\tilde{x}(p,z)}{\varepsilon_q(p,z) - 1 + \varepsilon_m(p,z)\tilde{x}(p,z)}(1 - \mu(p,z)).$$

A direct implication of nonnegative prices is that $\varepsilon_q(p,z) - 1 + \varepsilon_m(p,z)\tilde{x}(p,z) \geq 0$, so that $\text{sign}\left[\partial \mu(p,z)/\partial \varepsilon_m(p,z)\right] = \text{sign}[(\tilde{x}(p,z))(1 - \mu(p,z))]$. There are two cases to consider. The first one is when $\pi(p,z) > 0$, which occurs if and only if $\mu(p,z) > 1$. It implies $\tilde{x}(p,z) > 0$

[39] If prices are not strictly decreasing, this argument cannot be used as the first order condition is not necessary. However, it is possible to prove that $\hat{p}(z)$ is strictly decreasing in z for some region of z. The argument follows by contradiction. Suppose that $\hat{p}(z)$ is everywhere constant in z at some $\tilde{p}$. Then $\bar{p}(z) = \tilde{p}$ for all z. If $\tilde{p} > p^*(\bar{z})$, then $\tilde{p}$ would not be optimal for firm with productivity $\bar{z}$, which would choose a lower price. If $\tilde{p} = p^*(\bar{z})$, then continuous differentiability of G together with $H = G = Q = 0$ at the conjectured constant equilibrium price imply that the first order condition is locally necessary for an optimum, and a firm with productivity $z < \bar{z}$ would have an incentive to deviate according to equation (8), and set a strictly higher price than $\tilde{p}$. Finally, the result that $\hat{p}(z) < p^*(z)$ for all $z < \bar{z}$ and that $\hat{p}(\bar{z}) = p^*(\bar{z})$ follows from applying Proposition 1, and using that $\hat{p}(z) \geq \hat{p}(\bar{z})$ and $\bar{p}(z) = \hat{p}(\bar{z})$ for all z.

and, therefore, $\partial\mu(p,z)/\partial\varepsilon_m(p,z) < 0$. The second case is when $\pi(p,z) < 0$, which occurs if and only if $\mu(p,z) < 1$. It implies $\tilde{x}(p,z) < 0$ and, therefore, $\tilde{x}(p,z) < 0$. As a result, $\partial\mu(p,z)/\partial\varepsilon_m(p,z) < 0$.

A.5 Proof of Remark 1

Part (1). Start by noticing that, because the mean of $G(\psi)$ is positive, the expected value of searching diverges to $-\infty$ as n diverges to infinity. Because prices are finite for all $z \in [\underline{z}, \bar{z}]$, the value of not searching is bounded. As a result, customers do not search so that firms do not face customer base concerns. Formally, $\bar{p}(z) \to \infty$ for all $z \in [\underline{z}, \bar{z}]$. Because $p^*(z)$ is finite for all $z \in [\underline{z}, \bar{z}]$, it follows immediately that $p^*(z) < \bar{p}(z)$ for all $z \in [\underline{z}, \bar{z}]$. Then, using Proposition 1 we obtain that $\hat{p}(z) = p^*(z)$ for all $z \in [\underline{z}, \bar{z}]$.

Part (2). From Proposition 2 we have that, in equilibrium, the highest price is $\hat{p}(\underline{z})$. Moreover, under the assumptions of Proposition 2, the first order condition is a necessary condition for optimality of prices. We use this to show that, as n approaches zero, $\hat{p}(\underline{z})$ has to approach $\hat{p}(\bar{z}) = p^*(\bar{z})$.

In equilibrium, it is possible to rewrite equation (8), evaluated at $\{\hat{p}(\underline{z}), \underline{z}\}$, as $LHS(\hat{p}(\underline{z}), n) = RHS(\hat{p}(\underline{z}), n)$, where

$$\begin{aligned}
LHS(\hat{p}(\underline{z}), n) \;&\equiv\; G'\left(\frac{\hat{\psi}(\hat{p}(\underline{z}), \underline{z})}{n}\right)\frac{\hat{\psi}_p(\hat{p}(\underline{z}), \underline{z})}{n} \\
&\quad + \left(G\left(\frac{\hat{\psi}(\hat{p}(\underline{z}), \underline{z})}{n}\right)H'(\bar{V}(\hat{p}(\underline{z}), \underline{z})) + \frac{1}{\Gamma}Q'(\bar{V}(\hat{p}(\underline{z}), \underline{z}))\right)\bar{V}_p(\hat{p}(\underline{z}), \underline{z}) \;, \\
RHS(\hat{p}(\underline{z}), n) \;&\equiv\; -\frac{\pi_p(\hat{p}(\underline{z}), \underline{z})}{\Pi(\hat{p}(\underline{z}), \underline{z})}\left(1 - G\left(\frac{\hat{\psi}(\hat{p}(\underline{z}), \underline{z})}{n}\right)\right) \;,
\end{aligned}$$

given that $H(\bar{V}(\hat{p}(\underline{z}), \underline{z})) = Q(\bar{V}(\hat{p}(\underline{z}), \underline{z})) = 0$.

Suppose that as $n \downarrow 0$, $\hat{\psi}(\hat{p}(\underline{z}), \underline{z})$ does not converge to zero. Then, $G\left(\frac{\hat{\psi}(\hat{p}(\underline{z}), \underline{z})}{n}\right) \uparrow 1$ as $n \downarrow 0$. This implies that $\lim_{n\downarrow 0} RHS(\hat{p}(\underline{z}), n) > 0$.

Consider now the function $LHS(\hat{p}(\underline{z}), n)$. Again, suppose that as $n \downarrow 0$, $\hat{\psi}(\hat{p}(\underline{z}), \underline{z})$ does not converge to zero. Notice that the second term of the function approaches a finite number as $\bar{V}_p(\hat{p}(\underline{z}), \underline{z})$ is bounded by assumptions on $v(p)$ and $H'(\bar{V}(\hat{p}(\underline{z}), \underline{z}))$ and $Q'(\bar{V}(\hat{p}(\underline{z}), \underline{z}))$ being bounded as a result of Proposition 2. Moreover, as long as $\hat{p}(\underline{z}) > \bar{p}(z) = p^*(\bar{z})$, we have that $\hat{\psi}_p(\hat{p}(\underline{z}), \underline{z}) > 0$ so that $\hat{\psi}_p(\hat{p}(\underline{z}), \underline{z})/n$ diverges as n approaches zero. This means that $G'\left(\frac{\hat{\psi}(\hat{p}(\underline{z}), \underline{z})}{n}\right)\frac{\hat{\psi}_p(\hat{p}(\underline{z}), \underline{z})}{n}$ is divergent, and therefore the first order condition cannot be satisfied.

This analysis concluded that, if $\hat{\psi}(\hat{p}(\underline{z}), \underline{z})$ does not converge to zero as n becomes arbitrarily small, the first order condition, i.e. equation (8), cannot be satisfied. This occurs because $LHS(\hat{p}(\underline{z}), n)$ would diverge to infinity, while $RHS(\hat{p}(\underline{z}), n)$ would remain finite. It then follows that, as n approaches zero, a necessary condition is that $\hat{\psi}(\hat{p}(\underline{z}), \underline{z})$ also approaches zero. This condition can be restated as requiring that $\hat{p}(\underline{z})$ approaches $\bar{p}(z)$ as n approaches zero. Moreover, given the assumptions of Proposition 2, $\bar{p}(z) = \hat{p}(\bar{z}) = p^*(\bar{z})$.

In the end, if $\hat{p}(\underline{z})$ approaches $p^*(\bar{z})$ as n becomes arbitrarily small (so that $\hat{\psi}(\hat{p}(\underline{z}), \underline{z}) \to 0$ and $\hat{\psi}_p(\hat{p}(\underline{z}), \underline{z}) \to 0$), we have that $\lim_{n\downarrow 0} LHS(\hat{p}(\underline{z}), n) < \infty$ and $\lim_{n\downarrow 0} RHS(\hat{p}(\underline{z}), n) < \infty$ as $\pi_p(p^*(\bar{z}), \underline{z})$ is bounded as $\pi(p^*(\bar{z}), \underline{z}) > 0$. However, if $\hat{p}(\underline{z})$ does not approach $p^*(\bar{z})$ as n becomes arbitrarily small, we have that $LHS(\hat{p}(\underline{z}), n)$ diverges as n approaches zero, while $LHS(\hat{p}(\underline{z}), n)$ remains finite. As the first order condition has to be satisfied in equilibrium, a necessary condition is that, as n approaches zero, the highest price in the economy, i.e. $\hat{p}(\underline{z})$, has to approach the lowest price in the economy, i.e. $p^*(\bar{z})$.

B Data sources and variables construction

B.1 Data and selection of the sample

The empirical evidence presented in Section 4 is based on two data sources provided by a large supermarket chain that operates over 1500 stores across the United States. This implies that we can observe our agents behavior only when they shop with the chain; on the other hand, cash register data contain significantly less measurement error than databases relying on home scanning (Einav et al. (2010)).

The main data source contains information on grocery purchases at the chain between June 2004 and June 2006 for a panel of over 11,000 households. For each grocery trip made by a household, we observe date and store where the trip occurred, the collection of all the UPCs purchased with quantity and price paid. The data include information on the presence and size of price discounts but do not generally report redemption of manufacturer coupons. Data are collected through usage of the loyalty card; purchases made without using the card are not recorded. However, the chain ensures that the loyalty card has a high penetration by keeping to a minimum the effort needed to register for one. Furthermore, nearly all promotional discount are tied to ownership of a loyalty card, which provides a strong incentive to use it.

Household-level scanner data report information on the price paid conditional on a certain item having been bought by the customer. Therefore, if we do not observe at least one household in our sample buying a given item in a store in a week, we would not be able to infer the price of the item in that store-week. This has important implications as our definition of basket requires us to be able to attach a price to each of the item composing it in every week, even when the customer does not shop. The issue can be solved using another dataset with information on weekly store revenues and quantities between January 2004 and December 2006 for a panel of over 200 stores. For each good (identified by its UPC) carried by the stores in those weeks, the data report total amount grossed and quantity sold. Exploiting this information, we can calculate unit value prices every week for every item in stock in a given store, whether or not that particular UPC was bought by one of the households in our main data. Unit value prices are computed using data on revenues and quantities sold as

$$UVP_{stu} = \frac{TR_{stu}}{Q_{stu}} ,$$

where TR represent total revenues and Q the total number of units sold of good u in week t in store s.

As explained in Eichenbaum et al. (2011), this only allows us to recover an average price for goods that were on promotion. In fact the same good will be sold to loyalty card carrying customers at the promotional price and at full price to customers who do not have or use a loyalty card. Without information on the fraction of these two types of customers it is not possible to recover the two prices separately. Furthermore, since prices are constructed based on information on sales, missing values can originate even in this case if no unit of a specific item is sold in a given store in a week. This is, however, an unfrequent circumstance and involves only rarely purchased UPCs, which are unlikely to represent important shares of the basket for any of the households in the sample. For the analysis, we only retain UPCs with at most two nonconsecutive missing price observations and impute price for the missing observation interpolating the prices of the contiguous weeks.

On top of reporting revenues and quantities for each store-week-UPC triplet, the store-level data also contain a measure of cost. This variable is constructed on the basis of the estimated markup imputed by the retailer for each item and includes more than the simple wholesale cost of the item (the share of transportation cost, etc.). Eichenbaum et al. (2011) suggest to think about it as a measure of replacement cost, i.e. the cost of placing an item on the shelf to replace an analogous one just grabbed by a consumer. We use this measure to construct our instrument of the basket price.

It is important to notice that the retail chain sets different prices for the same UPC in different geographic areas, called "price areas." The retailer supplied store-level information for 270 stores, ensuring that we have data for at least one store for each price area. In order to use unit value prices calculated from store-level data to compute the price of the basket of a specific household, we need to determine to which price area the store(s) at which she regularly shops belong. This information is not supplied by the retailer that kept the exact definition of the price areas confidential. A possible solution is to infer in which price areas the store(s) visited by a household are located by comparing the prices contained in the household panel with those in the store data. In principle the household data should give information on enough UPC prices in a given week to identify the price area representative store whose pricing they are matching. However, even though two stores belonging in the same price area should have the same prices, they may not have the same unit value prices if the share of shoppers using the loyalty card differs in the two stores. Therefore, we choose to restrict our analysis to the set of customers shopping predominantly (over 80% of their grocery expenditure at the chain) in one of the 270 stores for which the chain provided complete store-level data. This choice is costly in terms of sample size: Only 1,336 households (or 12% of the original sample) shop at one of the 270 stores for which we have store-level price data. However, since the 270 representative stores were randomly chosen, the resulting subsample of households should not be subject to any selection bias.

A final piece of the data is represented by the IRI-Symphony database. We use store-level data on quantities and revenues for each UPC in 30 major product categories for a large sample of stores (including small and mom & pop ones) in 50 Metropolitan Statistical Areas in the United States. The data allow to construct unit value prices for all the stores competing with the chain who provided the main dataset. However, the coarse geographic information prevents us from matching each customer with the stores closer to her location (in the same zip code, for instance) and forces us to adopt the MSA as our definition of a market.

B.2 Variables construction

Exit from customer base. The dependent variable in the regression presented in equation (12) is an indicator for whether a customer is exiting the customer base of the chain. With data on grocery purchases at a single retail chain it is hard to definitively assess whether a household has abandoned the retailer to shop elsewhere or is simply not purchasing groceries in a particular week, for instance because she is just consuming its inventory. In fact, we observe households when they buy groceries at the chain but do not have any information on their shopping at competing grocers. Our choice is to assume that a customer is shopping at some other store when she has not visited any supermarket store of the chain for at least eight consecutive weeks. The *Exit* dummy is then constructed so that it takes value of one in correspondence to the last visit at the chain before a spell of eight or more weeks without shopping there. Table 3 summarizes shopping behavior for households in our sample. It is immediate to notice that an eight-week spell without purchase is unusual, as customers tend to show up frequently at the stores. This strengthens our confidence that customers missing for an eight-week period have indeed switched to a different retailer.

Table 3: Descriptive statistics on customer shopping behavior

	Mean	*Std.dev.*	*25th pctile*	*75th pctile*
Number of trips	150	127	66	200
Days elapsed between consecutive trips	4.2	7.5	1	5
Expenditure per trip ($)	69	40	40	87
Frequency of exits	0.003	0.065		

Composition of the household basket and basket price. The household scanner data deliver information on all the UPCs a household has bought through the sample span. We assume that all of them are part of the household basket and, therefore, the household should care about all of those prices. Some of the items in the household's basket are bought regularly, whereas others are purchased less frequently. We take this into account when constructing the price of the basket by weighting the price of each item by its expenditure share in the household budget. The price of household i's basket purchased at store j in week t is computed as:

$$p_{ijt} = \sum_{k \in K_i} \omega_{ik} \, p_{kjt} \ , \qquad \omega_{ik} = \frac{\sum_t E_{ikt}}{\sum_k \sum_t E_{ikt}} \ ,$$

where K^i is the set of all the UPCs (k) purchased by household i during the sample period, p_{kjt} is the price of a given UPC k in week t at the store j where the customer shops. E_{ikt} represents expenditure by customer i in UPC k in week t and the ω_{ik}'s are a set of household-UPC specific weights. There is the practical problem that the composition of the consumer basket cannot vary through time; otherwise basket prices for the same customer in different weeks would not be comparable. This requires that we drop from the basket all UPCs for which we do not have price information for every week in the sample. However, the price information is missing only in instances where the UPC registered no sales in a particular week. It follows that only low market-share UPCs will have missing values and, therefore, the UPCs entering the basket computation will represent the bulk of each customer's grocery expenditure. The construction of the cost of the basket follows the same procedure where we substitute the unit value price with the measure of replacement cost provided by the retailer.

We choose to calculate the weights using the total expenditure in the UPC by the household over the two years in the sample. This can lead to some inaccuracy in identifying the goods the customer cares for at a given point in time. For example, if a customer bought only Coke during the first year and only Pepsi during the second year of data, our procedure would have us give equal weight to the price of Coke and Pepsi throughout the sample period. If we used a shorter time interval, for example using the expenditure share in the month, we would correctly recognize that she only cares about Coke in the first twelve months and only about Pepsi in the final 12 months. However, weights computed on short time intervals are more prone to bias induced by pricing. For example, a two-weeks promotion of a particular UPC may induce the customer to buy it just because of the temporary convenience; this would give the UPC a high weight in the month. The effect of promotion is instead smoothed when we compute weights using expenditure over the entire sample period.

The construction of the price of the competitors occurs in two steps. First, we use the IRI data and the same procedure described above to obtain a price for the basket of each consumer at every store located in her same MSA. Next, we average those prices across stores to obtain the average market price of the consumer basket. In particular, the price is computed as:

$$p_{it}^{mkt} = \sum_{z \in M^i} s_z \sum_{k \in K_i} \omega_{ik} p_{kzt}, \quad \omega_{ik} = \frac{\sum_t E_{ikt}}{\sum_k \sum_t E_{ikt}} \ , \quad s_z = \frac{\sum_t R_{zt}}{\sum_{z' \in M} \sum_t R_{z't}}$$

where M^i is the MSA of residence for customer i and R_{zt} represents revenues of store z in week t. In other words, in the construction of the competitors' price index, stores with higher (revenue-based) market shares weight more.

Composition of the store basket and basket price. The construction of the price (and cost) index for the store is conceptually analogous to that described above for the household basket. In principle, we would want to compute the store price index including all the UPCs sold at a store throughout the sample period, weighted by the share of revenues they generated. However, to keep the composition of the store basket constant through time, we must restrict ourselves to the UPCs for which we have no missing price information in any of the weeks in the sample span. This severely reduces the size of the store basket. At the same time, goods without missing information are the best sellers, which are those the store is likely to care more about.

C A simple model of the labor market

In this appendix we provide details on how the model can be extended to use it to evaluate the role of aggregate shocks.

We assume that each household is divided into a mass Γ of shoppers/customers and a representative worker. The preferences of the household are given by

$$E_t \left[\int_0^\Gamma V_t(p_t^i, z_t^i, \psi_t^i)\, di - J_t \right] \quad , \tag{14}$$

where $V_t(p_t^i, z_t^i, \psi_t^i)$ is defined as in equation (1) and it is the value function that solves the customer problem in Section 2.1. We denote as $J_t \equiv \phi \sum_{T=t}^{\infty} \beta^{T-t} \ell_T$ with $\phi > 0$ the disutility from the sequence of labor ℓ_T. The aggregate state for the household includes the distribution of prices, the distribution of customers over the different firms and the level of income, the wage, and their laws of motion. Given that we allow for aggregate shocks, we have to consider the possibility that the aggregate state varies over time. We index dynamics in the aggregate state through the time subscript t for the value function.

The worker chooses the path of ℓ_t that maximizes household preferences in equation (14). The search problem of each customer is as described in Section 2.1. As for the consumption decision, each customer allocates her income across consumption of the good sold in the local market, the demand of which we denote by d, and another supplied in a centralized market by a perfectly competitive firms, the demand of which we denote by n, to solve the following problem

$$v_t(p_t) = \max_{d,\ n} \ \frac{\left(d^{\frac{\theta-1}{\theta}} + n^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}(1-\gamma)}}{1-\gamma} \tag{15}$$

$$\text{s.t.} \quad p_t\, d + q_t\, n \leq I_t, \tag{16}$$

where $\theta > 1$ and $I_t \equiv (w_t\, \ell_t + D_t)/\Gamma$ is nominal income, which the customer takes as given. Nominal income depends on the household labor income ($w_t \ell_t$) and dividends from firms ownership (D_t). The first order condition to the problem in equations (15)-(16) delivers the following standard downward sloping demand function for variety d

$$d_t(p_t) = I_t\, \frac{p_t^{-\theta}}{p_t^{1-\theta} + q_t^{1-\theta}} \ . \tag{17}$$

Without loss of generality we use the price q_t as the numeraire of the economy. From the first order conditions for the household problem, we obtain that the stochastic discount factor is given by $\beta\,\Lambda_{t+1}/\Lambda_t$, where $\Lambda_{t+s} = \int_0^\Gamma \left(c^i_{t+s}\right)^{-\gamma}/P^i_{t+s}\,di$ is the household marginal increase in utility with respect to nominal income; c^i_{t+s} denotes customer i's consumption basket in period $t+s$, and $P^i_{t+s} = ((p^i_{t+s})^{1-\theta} + (q_{t+s})^{1-\theta})^{\frac{1}{1-\theta}}$ is the associated price.

The production technology of the perfectly competitively sold good (good n) is linear in labor, so that its supply is given by $y^n_t = Z_t\,\ell^n_t$, where Z_t is aggregate productivity, and ℓ^n_t is labor demand by this firm. The production technology of the other good (good d) is also linear in labor, so that its supply is given by $y^j_t = Z_t\,z^j_t\,\ell^j_t$, where Z_t is aggregate productivity, and ℓ^n_t is labor demand by this firm, where j indexes one particular producer. Perfect competition in the market for variety n and in the labor market implies that workers are paid a wage equal to the marginal productivity of labor so that $w_t = q_t\,Z_t$. Equilibrium in the labor markets requires $\ell_t = \ell^n_t + \int_0^1 \ell^j_t\,dj$.

There are two exogenous driving processes in our economy: aggregate productivity Z and the numeraire q. We consider an economy in steady state at period t_0 where expectations are such that $Z_t = 1$ and $q_t = 1$ for all $t \geq t_0$. Notice that in this case the economy coincides with the economy described in Section 2.

D Numerical solution of the model

In order to solve the model, we start by setting the parameters. The parameters $\beta, w, q,$ and I are constant throughout the numerical exercises. For the set of estimated parameters $\Omega_n = [\lambda_n,\,\zeta_n,\,\rho_n,\,\sigma_n]'$, we set a search grid. The grid is different for each parameter, as they differ both in their levels and in the sensitivity of the statistics of interest to their variation. We consider a grid with an interval of 0.01 for σ, 0.05 for ρ, 0.5 for ζ, and 0.01 for λ. Each Ω_n corresponds to a particular combination of parameters among these grids. For each Ω_n we set θ to obtain $E[\varepsilon_d(z)] = 7$.

We next describe how we solve for the equilibrium of the model for a given combination of parameters. We start by discretizing the AR(1) process for productivity to a Markov chain featuring $N = 25$ different productivity values. We then conjecture an equilibrium function $\mathcal{P}(z)$. Given our definition of equilibrium and the results of Proposition 2, we look for equilibria where $\mathcal{P}(z) \in [p^*(\bar{z}), p^*(\underline{z})]$ for each z, and $\mathcal{P}(z)$ is decreasing in z. Our initial guess for $\mathcal{P}(z)$ is given by $p^*(z)$ for all z. We experiment with different initial guesses and found that the algorithm always converges to the same equilibrium.

Given the guess for $\mathcal{P}(z)$, we can compute the continuation value of each customer as a function of the current price and productivity, i.e. $\bar{V}(p,z)$, and solve for the optimal search and exit thresholds as described in Lemma 1. Given $\mathcal{P}(z)$ and the customers' search and exit thresholds we can solve for the distributions of customers $Q(\cdot)$ and $H(\cdot)$ as defined in

Definition 1. Notice that the latter also amounts to solve for a fixed point in the space of functions. Here, standard arguments for the existence of a solution to invariant distribution for Markov chains apply. Therefore, the assumption that $F(z'|z) > 0$ and $\Delta(\hat{p}(z), z) > 0$ ensure the existence of a unique $K(z)$ that solves equation (9). Finally, given $Q(\cdot)$, $H(\cdot)$, $\mathcal{P}(z)$ and $\bar{V}(p, z)$, we solve the firm problem and the obtain optimal firm prices given by the function $\hat{p}(z)$. We use $\hat{p}(z)$ to update our conjecture about equilibrium prices $\mathcal{P}(z)$, and iterate this procedure until convergence to a fixed point where $\mathcal{P}(z) = \hat{p}(z)$ for all $z \in [\underline{z}, \bar{z}]$.

Once we have solved for the equilibrium of the model at given parameter values, we construct the statistics to be matched to their data counterpart as follows.

- Log-price dispersion:

$$\hat{\sigma}_p \equiv \sqrt{\sum_j K(z_j)(\log(\hat{p}(z_j)) - M_p)^2}$$

  where $M_p = \sum_j K(z_j)\log(\hat{p}(z_j))$ and $K(z_j)$ is the equilibrium fraction of customers buying from firms with productivity z_j.

- Average comovement between the probability of exiting the customer base and the price:

$$\hat{b}_1 = Cov(E(z), \log(\hat{p}(z)))/(\sigma_p)^2$$

  where $E(z) \equiv G(\hat{\psi}(\hat{p}(z), z))(1 - H(\bar{V}(\hat{p}(z), z)))$, and $Cov(E(z), \log(\hat{p}(z))) = \sum_i K(z_j)(\log(\hat{p}(z_j)) - M_p)(E(z_j) - M_E)$ and $M_E = \sum_j K(z_j)\, E(z_j)$.

- Dispersion in the marginal effect of the price on the probability of exiting the customer base:

$$\hat{\sigma}_{b_1} = \sqrt{\sum_j K(z_j)(\hat{b}_1(z_j) - M_{\hat{b}_1})^2}$$

  where $\hat{b}_1(z_j) = G'(\hat{\psi}(\hat{p}(z), z))/G(\hat{\psi}(\hat{p}(z), z))(1 - H(\bar{V}(\hat{p}(z), z)))^2$ and $M_{\hat{b}_1} = \sum_i K(z_j)\hat{b}_1(z_j)$.

The autocorrelation of prices, $\hat{\rho}_p$ coincides with the parameter ρ governing the persistence and autocorrelation of productivity. Thus the model-predicted statistics used to estimate the parameters are given by the vector $v(\Omega_n) = [\hat{\rho}_p, \sigma_p, \hat{b}_1, \hat{\sigma}_{b_1}]'$. We then evaluate the objective function $(v_d - v(\Omega_n))'\ (v_d - v(\Omega_n))$ at each iteration. We select as estimates the parameter values from the proposed grid that minimize the objective function and check that the optimum in the interior of the assumed grid.

E Price distribution of individual UPCs

Kaplan and Menzio (forthcoming) perform a thorough study of the properties of the distribution of prices in the grocery sector which is highly related to ours. However, our analysis in section Section 6 focuses on a normalized store-level price index; whereas theirs considers an index of dispersion of households' expenditure in grocery stores (not necessarily at a same store or chain). As such, our results on store baskets and their evidence on price distribution and dispersion for bundles of goods cannot be directly compared.

However, Kaplan and Menzio (forthcoming) also present evidence at the single good (UPC) level. Although this is not the relevant level of observation for our study, we use our data to replicate their findings and establish that any difference between our and their results on bundles of goods comes from the choice of a different object of interest, rather than from some dishomogeneity in the underlying data.

In Figure 5 we plot a distribution comparable to the one Kaplan and Menzio (forthcoming) report in their Figure 2, panel (a). In particular, we take the set of all the UPCs used to compute the store-level price index whose distribution we depict in Figure 2. For each UPC k sold in store j belonging to Metropolitan Statistical Area m, we take the price posted by the store in week t ($P_{kt}^{j(m)}$) and normalize it dividing it by the mean of the prices posted in the same week for the same UPC by the stores active in the same MSA ($\overline{P_{kt}^{m}}$). In computing the MSA average, we weight the different stores by their market shares. Formally, we define the normalized price as follows

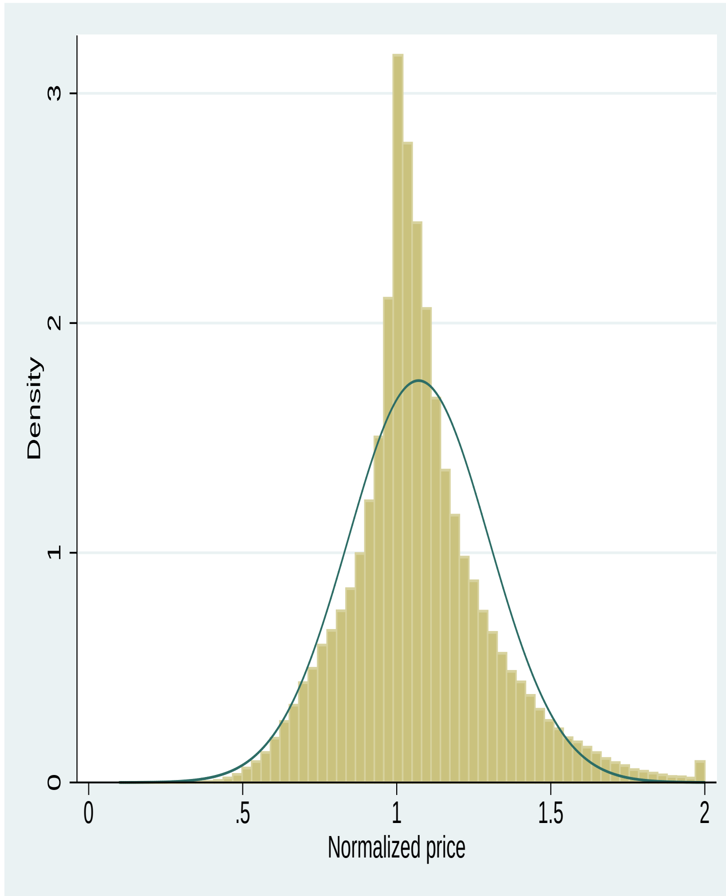
$$p_{kt}^{j(m)} = \frac{P_{kt}^{j(m)}}{\overline{P_{kt}^{m}}}$$

In Figure 5 we plot the distribution of the normalized price across UPCs, stores and weeks. Just as the comparable figure in Kaplan and Menzio (forthcoming), the distribution exhibits excess kurtosis. It is unimodal, has a peak close to the mean, and thicker tails than a normal distribution with the same mean and variance.

F Pass-through of idiosyncratic shocks

To measure pass-through of idiosyncratic shocks, we regress the log-price index of each store in a given week on its log-cost index. The price index $p_t^{j,mkt}$ is constructed as described in Section 6 and the cost index is analogously computed using the data on replacement cost provided by the retailer. To avoid inflating the short-term (weekly) pass-through due to the persistence of both price and cost variables, we include in the specification lagged values of the independent variable. We experiment with an alternative way to deal with the persistence of the dependent variable by measuring the short-term pass-through using first differences. Finally, we include time and market fixed effects to control for aggregate trend (e.g. demand

Figure 5: Distribution of normalized UPC prices



Notes: The histogram plots the distribution of normalized prices across UPCs, stores, and weeks. The normalized price of a UPC in a week is defined as the ratio of the weekly price of the UPC at a store of the chain that shared data with us to the average price of the same UPC in the Metropolitan Statistical Area where the store is located. The latter is computed using the IRI Marketing database. The set of UPCs considered is that used to compute the store-level price index whose distribution is presented in Figure 2; we discard UPCs whose coefficient of variation is larger than 1. The solid line plots the density of a normal with the same mean and variance as the empirical distribution of the normalized prices.

shocks) that can move prices independently from cost shifts. The results are reported in Table 4 and deliver a consistent picture. The weekly pass-through ranges between 13% and 24%, in line with the customer markets model predictions.

Table 4: Pass-through of idiosyncratic shocks

Dep. variable	**(1)** $\log(p_t^j)$	**(2)** $\log(p_t^j)$	**(3)** $\Delta\log(p_t^j)$
$\log(cost_t^j)$	0.17***	0.24***	
	(0.04)	(0.09)	
$\log(cost_{t-1}^j)$	0.04	0.06	
	(0.03)	(0.04)	
$\log(cost_{t-2}^j)$	-0.01	0.02	
	(0.05)	(0.07)	
$\log(cost_{t-3}^j)$	0.06***	0.05*	
	(0.02)	(0.03)	
$\log(cost_{t-4}^j)$	0.07	0.07	
	(0.05)	(0.05)	
$\Delta\log(cost_t^j)$			0.13*
			(0.07)
Observations	12,915	8,295	8,295
MSA f.e.	No	Yes	Yes
Time f.e.	No	Yes	Yes

Notes: An observation is a store(j)-week(t) pair. The dependent variable is the price index of the store and the independent variables are the cost index of the store and its lags. Standard errors are in parenthesis and are clustered at the store level. ***: Significant at 1% **: Significant at 5% *: Significant at 10%.