ENTRY AND PROFITS IN AN AGING ECONOMY: THE ROLE OF CONSUMER INERTIA

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Abstract

Over the past four decades, the share of young firms in the U.S. has declined while the share of profits in GDP has increased. This paper explores the role of *consumer inertia*—persistence in households' consumption choices—as a driver of these twin phenomena. The hypothesis is that more consumer inertia makes it more difficult for entrants to establish a customer base, incentivizes large incumbents to raise markups, and shifts production toward large, high-markup firms. Using micro data on consumer behavior, I estimate the degree of consumer inertia across different age groups and find that young households are significantly less inertial. I develop and estimate a model of firm dynamics with consumer inertia. Through the lens of the model, the aging-induced rise in consumer inertia accounts for about 10%–30% of the twin phenomena between the late 1980s and late 2010s. Reduced-form evidence exploiting variation across states and across product categories are consistent with the model's prediction.

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1 Introduction

Over the past four decades, the U.S. corporate sector has become older and more profitable. The share of young businesses in the economy, defined as businesses which are 5 years old or younger, has declined from 50% in the late 1980s to 30% today. The share of workers employed by young businesses fell from 20% to 10%.[1] Strikingly, over the same period, the share of profits in GDP rose substantially.[2] It is challenging for traditional models of firm dynamics to account for the twin phenomena of declining entry and rising profits. Other things equal, higher profits should stimulate firm entry.

In this paper, I study the role of consumer inertia as a driver of these twin phenomena. By consumer inertia, I mean the tendency of consumers to choose the same products over time for reasons other than the fundamental attributes of those products. That is, not switching a product produced by one firm to one produced by a different firm. The prevalence of consumer inertia has been extensively documented in the industrial organization and marketing literatures.[3] I argue that consumer inertia has increased in the past three decades due to the aging of the U.S. population. I show that the aging-induced rise in consumer inertia accounts for a substantial proportion of the twin phenomena.

The hypothesis is that a rise in consumer inertia leads to higher profits of large incumbent firms while discouraging entry. I develop my argument in four steps. First, I develop and estimate a model of firm dynamics with consumer inertia. I use a static version of the model to illustrate the logic of the hypothesis. Second, I use detailed micro data to identify how consumer inertia varies with household age. I find that younger households display considerably less inertia than older ones. According to my estimates, young households are almost twice as likely to switch their consumption products relative to older ones. Building on this result, I argue that population aging in the U.S. has led to a rise in aggregate consumer inertia. Third, I use the estimated dynamic model to study the implications of a rise in consumer inertia. The model predicts that the aging-induced rise in consumer inertia accounts for about 10%–30% of the twin phenomena between the late 1980s and late 2010s. Finally, I provide supportive empirical evidence on a causal negative link between consumer inertia and firm formation. I find that U.S. states which experienced a larger increase in consumer inertia, have also experienced a larger decline in the share of young firms. And that product categories with a relatively more inertial consumer base display lower entry rates.

[1] See Decker, Haltiwanger, Jarmin and Miranda (2014a), Decker et al. (2014b), Hathaway and Litan (2014), and Pugsley and Şahin (2015).

[2] See Barkai (2016), Gutierrez (2017), and Barkai and Benzell (2018).

[3] Some examples include Luco (2017) and Illanes (2016), which document consumer inertia in the market for pension plans, Handel (2013) and Nosal (2012), which document it in the market for health insurance plans, Anderson, Kellogg, Langer and Sallee (2015), which documents it in the automobile market, Hortaçsu, Madanizadeh and Puller (2015), which documents it in the residential electricity markets, as well as Dubé, Hitsch and Rossi (2010) and Bronnenberg, Dubé and Gentzkow (2012), which document it for consumer packaged goods.

Consumer inertia can reflect a variety of forces. The marketing literature tends to stress psychological and emotional factors, as well as inattention. The industrial organization literature tends to emphasize learning costs, contractual obligations, transaction costs, incomplete information, and search frictions. In my model, I capture consumer inertia in a parsimonious way á la Calvo. Consumers are confronted with a variety of product types (e.g., phones). Each product type consists of a variety of products (e.g., iPhone, Galaxy, Nexus, etc.). In every period, each household consumes a single product from each product type. Households have idiosyncratic preferences over the different products. So when choosing which product to consume, a household takes into account its preferences and the price of the product. Within every product type, the household is locked into its previous choice with some exogenous probability. This simplification allows me to derive an analytic expression for the demand function faced by each firm.

I first study a static economy with two types of firms, incumbents and entrants. There is a measure one of incumbents and an endogenous measure of entrants. The only difference between incumbents and entrants is that incumbents have an initial customer base, i.e., the measure of households who purchased their product in the previous period. Absent consumer inertia, incumbents and entrants behave identically. In the presence of consumer inertia, a fraction of each incumbent's customers will continue to purchase their product regardless of price. Of course, the quantity that they purchase will depend on the price. It follows that the price elasticity of locked-in customers is lower than the price elasticity of unattached customers. Therefore, in equilibrium, incumbents choose a higher price and have higher markups than entrants.

I use the static model to analyze the effects of a rise in consumer inertia. The key result is that more consumer inertia leads to higher aggregate profits, higher incumbent markups, and less entry. So the model qualitatively accounts for the twin phenomena. An increase in consumer inertia reduces the potential customer base of entrants. As a result, the measure of entrants in equilibrium falls. At the same time, incumbents raise their markups as the demand for their products is less elastic. The average markup in the economy goes up both because incumbents raise their markups and because the market share of incumbents goes up. This result is consistent with a growing body of evidence that the average markup has been increasing over time (e.g., De Loecker, Eeckhout and Unger, 2020; Hall, 2018).

While the static model provides intuition on the workings of an increase in consumer inertia, it abstracts from the life-cycle of the firm, and from dynamic considerations. To quantify the effects of a rise in consumer inertia, I construct a general equilibrium firm dynamics model where households display consumer inertia. Consumer inertia gives rise to life-cycle dynamics in a firm's customer base and markups. A new firm has no initial customer base, and builds it over time. The firm's optimal markup reflects both a harvesting motive and an investing motive.[4] The harvesting motive refers to firms' incentive to take advantage of their customer base by increasing markups. The investing motive refers to firms' incentive to increase their customer base by

[4]These terms go back to Klemperer (1987b), which studies a two period model with switching costs.

lowering markups. The firm's optimal markup reflects the balance between the harvesting and investing motives.

The balance between the two motives varies over the life-cycle of the firm. When a firm enters the economy, it has no initial customer base. As a result, the harvesting motive is muted and the investing motive induces the firm to set a relatively low markup. As a firm builds its customer base over its life-cycle, the harvesting motive becomes more dominant and the investing motive becomes weaker. The investing motive weakens because lowering markups in order to attract new customers reduces the profits coming from locked-in customers. So the optimal markup of a firm is increasing in the customer base it carries from the previous period.

To model firm entry, I assume that a firm must pay a fixed cost in order to begin operation. The measure of entrants in equilibrium is determined by a zero-profit condition. In each period, firms are subject to persistent idiosyncratic productivity shocks. So the two firm-level state variables are their customer base and their productivity level. To model firm exit, I assume that firms need to pay a stochastic fixed operating cost in every period. It may be optimal for them to exit, rather than pay this cost.

I calibrate the model's structural parameters to match key features of the U.S. economy in the late 1980s. I match the age distribution of firms, the employment share of firms of different ages, job turnover rates by firm age, and the share of total profits in GDP. I choose the late 1980s period as it is the first period with data moments conditional on firm's age. The estimated degree of consumer inertia implies that households re-optimize about 17% of their consumption choices every year. The high lock-in probability allows the model to match the large difference in size between young and old firms in the data. A productive young firm cannot immediately take over a market, but instead needs to build its customer base over time.

The ultimate use of the estimated model is to study the transition dynamics starting from an equilibrium with a low degree of consumer inertia to a one with more inertia. Focusing on the share of young firms and the share of profits in the economy. To do so, I feed into the model the aggregate degree of consumer inertia in every period. Let me now discuss how I identify the change in the degree of consumer inertia over time.

I focus on changes in consumer inertia arising from changing demographics. To study the degree of consumer inertia and how it depends on household age, I use Nielsen's Consumer Panel dataset. The dataset includes longitudinal panel information on the purchases of approximately 160,000 households in the U.S. between 2004 and 2015. I merge the dataset with the GS1 U.S. dataset. This allows me to link products in Nielsen to the firms which produce them.

Nielsen divides the products in the dataset into 100 product groups which span 1,000 different product modules. The merged dataset allows me to construct an annual panel dataset of the customer base at the firm-module-state level. That is, I construct information on the size of the customer base of each firm, in every year, in each product module, and in every state in the US.

The constructed panel data allows me to estimate the structural customer base evolution equation in the model. The estimation procedure takes advantage of the form of this equation. The customer base in each period is the sum of two terms. The first is the share of locked-in customers the firm carries with it from the previous period. This share is governed by the degree of consumer inertia. The second term is the share of new customers the firm attracts. This term is the product of market conditions, such as the measure of operating firms, with product characteristics, such as the price of the product. As a result, the customer base evolution equation takes the form of an interactive fixed effects model, in which market conditions are interactive with product characteristics. I follow the approach of Bai (2009) in the estimation procedure.

I group households into four groups, according to the age of the household head: 20–34, 35–49, 50–64, and older than 64. I estimate the degree of consumer inertia for each group and in every product group. I find that younger households display significantly less consumer inertia than any other age group across more than 95% of the product groups. According to my estimates, a young household (20–34) is, on average, about 20 percentage points more likely to re-optimize its product choice relative to older age groups.

I combine the micro-estimates on consumer inertia across different age groups together with data on the age composition in the U.S. to measure the change in the aggregate degree of consumer inertia over time. The share of young households in the U.S. economy has started declining in the 1980s, going from a peak of 38% of adult population to 28% in 2015. As these group of households are estimated to be substantially less inertial than other age groups, this decline is associated with a rise in aggregate consumer inertia.

To assess the quantitative impact of the aging-induced rise in consumer inertia, I consider an unexpected deterministic shock that moves the level of consumer inertia from its late 1980s through 2050. I then study the transition dynamics of the economy from the initial stationary equilibrium to the new one.

An increase in the level of consumer inertia strengthens both the harvesting motive and the investing motive. As a result, firms with a relatively small customer base, particularly entrants, choose to reduce their markups. On the other hand, firms with a relatively large customer base, for which the harvesting motive dominates the investment motive, choose to raise their markups. So more consumer inertia increases markup dispersion between small and large firms in the economy.[5] Firms become less profitable at the beginning of their life-cycle, and more profitable later in their life-cycle. The changes in profitability across the life-cycle of a firm affect the present value of entrants. In the calibrated model, holding fixed the measure of operating firms, a rise in consumer inertia reduces the present value of entrants. As a result, the measure of entrants in equilibrium falls. In the transition dynamics following a rise in consumer inertia, the rate of entrants in the economy declines.

My key results are as follows. First, the model captures qualitatively the twin phenomena.

[5] De Loecker et al. (2020) and Baqaee and Farhi (2020) provide empirical evidence that markup dispersion in the U.S. has been increasing since the 1980s.

Second, the model accounts for about 30% of the decline in the share of workers employed by young firms and 12% of the rise in the aggregate profits share between the late 1980s and 2015–2019.

This paper is not the first to study the impact of population aging on the decline in firm formation. Karahan, Pugsley and Şahin (2019), Hopenhayn, Neira and Singhania (2018), Peters and Walsh (2019), Liang, Wang and Lazear (2014), and Engbom (2019) provide theory and evidence that supply forces due to population aging partially account for the declining firm formation. The first three papers focus on the labor force growth rate, while the last two focus on the age composition of the workforce. Differently from these papers, I focus on the impact of population aging due to demand forces. In the final part of the paper, I provide empirical evidence on the effects of consumer inertia on firm formation. My approach allows me to identify the *demand* effects of population aging.

First, I use a panel dataset of U.S. states to study the effect of consumer inertia on firm formation. I use annual data on the age composition of each state and an instrumental variable approach to identify a causal impact. I find that an increase in consumer inertia at the state level leads to a significant and substantial decline in firm formation. My regression specifications account for the labor force growth rate as well as the age composition of the workforce to mitigate a potential omitted variable bias.

Second, I study how entry rates vary across product categories. I construct a measure of consumer inertia for each product category based on the age composition of its customers. I find that there is a significant negative relation between the level of consumer inertia and the firm entry rate into a product category. Other things equal, product categories with a lower level of consumer inertia, i.e., with a relatively younger customer base, have higher entry rates. Focusing on the age composition of customers isolates the demand effects of population aging from possible supply effects.

Related literature. This paper is related to several strands of literature. First, it is related to a recent literature which studies the causes for the decline in business dynamism. The explanations unrelated to population aging include changes in the regulatory environment (Davis and Haltiwanger, 2014), skill-biased technical change (Jiang and Sohail, 2017; Kozeniauskas, 2017; and Salgado, 2017), and rising business entry costs (Gutierrez Gallardo et al., 2019).

Second, my paper is related to an emerging literature that studies the reasons for the rise in corporate profits and the decline in the labor share.[6] Autor, Dorn, Katz, Patterson and Van Reenen (2020) argue that the rise of profits is the result of a rise in *superstar* firms. Grullon, Larkin and Michaely (2019), on the other hand, argue that the rise in profits is an inefficient outcome, resulting

[6]The magnitude of the rise in profits during the past three decades is the subject of an ongoing debate. See Karabarbounis and Neiman (2018) and the discussion of Rognlie (2018) for the challenges in computing the share of economic profits in GDP. Barkai and Benzell (2018) argue that the rise in profits is robust even when addressing these challenges.

from a rise in concentration. Gutierrez and Philippon (2017) provide evidence to support the latter explanation. My model also suggests that the rise in profits is associated with a rise in concentration. The reason is that more consumer inertia leads to a decline in entry rates and incentivizes incumbents to raise their markups.

My paper is also related to a vast theoretical literature in industrial organization that studies how switching costs affect the pricing decision of firms. For a review of this literature, see Farrell and Klemperer (2007). Several papers in the literature have studied how switching costs affect firm entry and profits (e.g., Klemperer, 1987a; Farrell and Shapiro, 1988; Gabszewicz et al., 1992). These papers restrict attention to duopoly markets and are partial equilibrium in nature. My analysis embodies the channels they stress but focuses on a general equilibrium analysis with a large number of atomistic firms.

Different forms of consumer inertia have also been studied in a macroeconomic context. Early examples include Winter and Phelps (1970) and Rotemberg and Woodford (1991). More recently, Ravn, Schmitt-Grohé and Uribe (2006) studies a dynamic stochastic general equilibrium model where the demand function faced by each firm features inertia, the *deep habits* model. Gourio and Rudanko (2014) studies a firm dynamics model where the matching between customers and firms is subject to search frictions. These frictions give rise to consumer inertia. Relative to these papers, the main advantage of my modeling approach is that it allows me to identify the degree of consumer inertia directly from the micro data.[7]

Layout. The paper proceeds as follows. Section 2 presents a static model of consumer inertia. In Section 3 I lay out the structural quantitative model, and its estimation. In Section 4, I estimate the degree of consumer inertia for different age groups. Section 5 quantifies the contribution of the rise in consumer inertia to the observed change in profitability and firm formation. I first present empirical evidence on the effect of consumer inertia on firm formation, and then study the implications of the aging-induced rise in consumer inertia using the quantitative model. Section 6 concludes.

2 Static Model of Consumer Inertia

I start by analyzing a static economy in which households display consumer inertia. There are two types of firms, incumbents and entrants. Incumbents start the period with an existing customer base, while entrants have no initial customer base upon entry. Firms cannot price discriminate, i.e., they must charge the same price to all their customers.

The static model serves two purposes. First, it allows me to introduce the way I model con-

[7] Other macroeconomic models which include inertia in firm-level demand include Luttmer (2006), Arkolakis (2010), Nakamura and Steinsson (2011), Drozd and Nosal (2012), Moreira (2016), Sedláček and Sterk (2017),Gilchrist, Schoenle, Sim and Zakrajšek (2017), and Perla (2019).

sumer inertia in a simple framework. I take a similar modeling approach when incorporating consumer inertia in the dynamic model and when estimating consumer inertia using the micro data. Second, it provides intuition for how consumer inertia alters the behavior of firms.

Consumer inertia can reflect a variety of forces. Examples for such forces include psychological and emotional costs, learning costs, contractual obligations, transaction costs, incomplete information, or search frictions. I model consumer inertia in a parsimonious way á la Calvo. There is a continuum of products, and each household buys only a single product. There is a constant probability that a household cannot freely choose what product to buy and is locked into the product it purchased in the previous period.[8]

The main result of the static model is that more consumer inertia leads to higher aggregate profits, higher incumbent markups, and less entry. The intuition is as follows. Higher consumer inertia leads to a fall in the measure of entrants' potential customers. As a result, the measure of entrants in equilibrium goes down. In addition, the fraction of locked-in customers of incumbents goes up. The elasticity of demand of locked-in customers is lower than the demand elasticity of customers who can re-optimize their choice. So the optimal markup set by incumbents is increasing in the level of consumer inertia. Finally, since a larger share of customers are buying from incumbents, which charge higher markups than entrants, aggregate profits rise.

2.1 Demand

The economy is populated by a measure one of ex-ante identical households. Each household consumes a single product out of a variety of products indexed by $j \in (0, J)$, where J is the measure of products in the economy. The utility of household i from consuming product j is given by

$$U_i = u\left(\exp\left(\frac{1}{\sigma - 1}\epsilon_j\right) c_j\right) , \tag{1}$$

where $u(\cdot)$ is a strictly increasing function, c_j is the quantity consumed of product j, and ϵ_{j_i} is the idiosyncratic taste of household i for product j.[9] Taste shocks follow a Gumbel distribution and are drawn independently across households and products. As I show below, the parameter σ governs the price elasticity of demand in the demand function faced by the firm.

Households' consumption decision features consumer inertia. There is a probability θ that a household can choose freely which product to buy. With probability $1 - \theta$, the household is locked into the product it purchased in the previous period. i.e., it must consume the same product it has bought in the previous period. I assume that the previous product consumed by households is

[8]In appendix section B.1, I discuss in details how this modeling assumption relates to other structural models of consumer inertia in the literature.

[9]To dispense with notation, I omitted the i superscript in all variables in equation (1) as well as in all subsequent equations. Note that due to different taste shocks, individual households do differ in their consumption behavior ex-post.

uniformly distributed across incumbents. The re-optimization draw is independent across households.

The household's problem can be written as follows,

$$
\begin{aligned}
U_i = \max_{\{j,c_j\}} u\left(\exp\left(\frac{1}{\sigma-1}\epsilon_j\right)c_j\right)\ , \\
\text{s.t.} \qquad p_j c_j \leq w\ , \\
j = j_i^0\ , \quad \text{if}\ \ \xi_i = 0\ ,
\end{aligned}
$$

where the first constraint is the budget constraint and the second constraint is the consumer inertia constraint. The household's sole income is its salary. It supplies a unit of labor and receives a wage w. The household needs to choose which product to purchase (j), and how much of it to consume (c_j). ξ^i is an indicator variable that takes the value 0 if the household cannot re-optimize its product choice and is locked into its previous purchased product. This product is denoted by j_i^0. The probability that a household can re-optimize its choice, $\xi_i = 1$, is equal to θ. I refer to households who can re-optimize their product choice as *unattached*.

Before turning to the supply side of the economy, it is useful to derive the demand function faced by the firm. Each firm in the economy produces a single product. To achieve an analytic expression for the demand function faced by firms, I need to derive the optimal consumption decision of households. I start by showing what is the product chosen by an unattached household, given the distribution of prices and taste shocks.

Lemma 1. *If the household is unattached, it chooses the product that maximizes* $-(\sigma-1)\ln p_j + \epsilon_j$ *for* $j \in (0, J)$*. That is,*

$$
j_i = \arg\max_{j\in(0,J)} -(\sigma-1)\ln p_j + \epsilon_j\ . \tag{2}
$$

The proof of Lemma 1, as well as of all other proofs in the paper, is presented in Appendix A. The intuition of the result above is straightforward. When a household compares between two different products, it values a lower price, as it allows it to buy a larger quantity of the good, and higher taste shock, as it lets it derive higher utility from each good consumed. As taste shocks are assumed to be drawn from a Gumbel distribution, Lemma 1 shows that the consumption choice of *unattached households* follows a multinomial logit.

Using Lemma 1 and the distributional assumption of the taste shocks, I can aggregate the optimal consumption decision of individual households to arrive at the customer-base function faced by the firm. The following proposition presents this result, characterizing the customer base of a firm as a function of its relative price and initial customer base. I denote the customer base of a firm, i.e., the measure of households who purchase a product from the firm, as B, and the initial customer base of a firm by B_0.

Proposition 1. *The customer base of a firm with price* p *is given by*

$$
B = (1-\theta)\,B_0 + \frac{\theta}{J}\left(\frac{p}{P}\right)^{1-\sigma}\ , \tag{3}
$$

where B_0 is the initial customer base of the firm, and P is the price index, given by

$$P = \left[\frac{1}{J} \int_0^J p_j^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}} . \tag{4}$$

The first term in equation (3) consists of the locked-in customers, those who were customers of the firm in the previous period and cannot re-optimize. For incumbents, the measure of locked-in customers is equal to $1-\theta$, as their initial customer base is equal to one. Entrants do not have any locked-in customers.

The second term of equation (3) consists of the measure of households who actively choose to buy the firm's good. This term is increasing in the measure of unattached households, θ, decreasing in the measure of operating firms, J, and decreasing in the firm's relative price. Furthermore, it is isoelastic in the firm's relative price. The aggregation of individual multinomial logit consumption decision into an isoelastic demand function faced by the firm goes back to Anderson et al. (1987). Differently from their result, consumer inertia implies that the demand function faced by firms also includes a relatively inelastic term coming from the firm's locked-in customers.

Each household spends w on the product it consumes. As a result, the total revenues of a firm is given by wB. From the firm's perspective, the demand for its good is given by $y = \frac{wB}{p}$. Using the law of motion for a firm's customer base, we have that the demand function faced by the firm is given by

$$y = \left[(1-\theta) B_0 + \frac{\theta}{J} \left(\frac{p}{P} \right)^{1-\sigma} \right] \frac{w}{p} . \tag{5}$$

2.2 Supply

Each firm in the economy sells a single product, and the measure of firms is equal to J. A measure one of these firms are incumbents and an endogenous measure E are entrants, so that $1 + E = J$. The only difference between incumbents and entrants is their initial customer base. An entrant joins the economy with no initial customer base, while incumbents' initial customer base is equal to one. As mentioned above, a fraction $1-\theta$ of an incumbent's initial customer base is locked-in.

Firms use a linear technology in labor to produce their goods. The firm's problem is given by,

$$\begin{aligned} V(B_0) = \max_{\{p,y,l\}} \quad & py - wl , \\ \text{s.t.} \quad & y = (1-\theta) B_0 w p^{-1} + \frac{\theta}{J} P^{\sigma-1} w p^{-\sigma} , \\ & y = l , \end{aligned}$$

where $V(B)$ is the operating profits of a firm with initial customer base B_0. p is the price the firm sets, y is the quantity sold, l is the labor used for production, and P is the price index defined in equation (4). The first constraint is the demand function faced by the firm, and the second constraint is the firm's technology.

In addition to production costs, entrants need to hire f_e units of labor to pay the fixed cost of entry. So the profits of an entrant, net of the fixed entry costs, are given by $V(0) - f_e w$. In equilibrium, a free-entry condition holds so that $V(0) = f_e w$, if the measure of entrants is positive.

Solving the firm's problem, I obtain an equation that implicitly defines the firm's optimal markup.

Proposition 2. *The markup charged by the firm, $\mu \equiv p/w$, satisfies the following equation,*

$$\mu = \frac{\sigma}{\sigma - 1} + B_0 \frac{1}{\sigma - 1} \frac{1 - \theta}{\theta} J \left(\frac{P}{w} \right)^{1-\sigma} \mu^{\sigma - 1} \, . \tag{6}$$

I assume that $\sigma < 2$, a sufficient condition which ensures that equation (6) uniquely pins down the firm's markup as a function of P and J.[10]

Proposition 2 reveals how the firm's markup is set. The demand function faced by the firm consists of two terms: a relatively inelastic one coming from its locked-in customers, and a more elastic one coming from customers who actively choose the firm's product. In its choice of markup, the firm is balancing between these two opposing forces. If the firm only has locked-in customers, it has an incentive to raise its markup as high as possible. While if the firm only has unattached customers, it has an incentive to lower its markup to $\frac{\sigma}{\sigma-1}$. The latter is the markup set by entrants, as those do not have any locked-in customers.

Incumbents markup is increasing in the level of consumer inertia, $1 - \theta$, as higher consumer inertia implies a higher share of locked-in customers and a lower share of unattached customers. Incumbents markup is also increasing in the measure of operating firms. The higher is the measure of operating firms, the harder it is for an incumbent to attract unattached customers. As a result, it chooses to increase its markup and harvest the benefits of having a locked-in customer base. Finally, incumbents markup is decreasing in the price index P. Similar to the measure of operating firms, a lower price index makes it harder for incumbents to attract unattached customers and incentivizes them to increase their markup.

2.3 Equilibrium and Comparative Statics

Without loss of generality, I choose the wage as the numeraire and set it to 1. A firm's price is therefore equal to its markup. I denote the price charged by entrants as μ_E and that of incumbents by μ_I.

Definition 1 (Equilibrium)**.** An equilibrium is a set of prices $\{\mu_E, \mu_I, P\}$, consumption policy functions, and a measure of operating firms J such that: (i) consumption policy functions solve the household's problem, (ii) prices solve the firms' problems, (iii) free entry condition holds, and (iv) the price index P satisfies equation (4).

[10] To see that equation (6) uniquely pins down the level of markup, note that the LHS is linear and increasing in μ and that the RHS is concave and increasing in μ. When $\mu = 0$ the RHS is greater than the LHS, so there exists a unique value of μ which solves the equation.

As the households' policy functions take an explicit form derived in section 2.1, finding an equilibrium boils down to finding a set of four endogenous variables, $\{\mu_E, \mu_I, P, J\}$, such that: (i) P satisfies equation (4), (ii) μ_E solves equation (6) with $B_0 = 0$, (iii) μ_I solves that equation with $B_0 = 1$, and (iv) free entry condition holds.[11]

Proposition 3. *There exists a unique equilibrium. In addition, there is a cutoff $\bar{f}_e$ such that if and only if $f_e < \bar{f}_e$ then the measure of entrants is strictly positive.*

Having established that an equilibrium exists and is unique, I can study how it depends on the different structural parameters. In particular, I study how the measure of entrants, the markup charged by entrants and incumbents, and the share of profits in the economy, depend on the level of consumer inertia, $1-\theta$, and on the fixed entry costs, f_e.[12]

Proposition 4. *[Comparative statics] Consider two economies, A and B. Suppose the two economies differ by only one structural parameter. The following comparative statics hold:*

Parameter	*Entrants' markup*	*Incumbents' markup*	*Profits share*	*Entry rate*
$\theta_A < \theta_B$	$\mu_E^A = \mu_E^B$	$\mu_I^A > \mu_I^B$	$\Pi_A > \Pi_B$	$E_A < E_B$
$f_e^A > f_e^B$	$\mu_E^A = \mu_E^B$	$\mu_I^A < \mu_I^B$	$\Pi_A > \Pi_B$	$E_A < E_B$

Proposition 4 presents the main result of this section. An increase in the level of consumer inertia (a lower θ) leads to an increase in incumbents markup, an increase in profitability, and a decline in the entry rate. Incumbents choose to increase their markups as the share of locked-in customers relative to unattached customers increases. This results in higher profits for incumbents. Entrants charge the same markup but their customer base shrinks. As a result, if the measure of firms hadn't changed they would make lower profits. The measure of entrants in equilibrium goes down so that the free-entry condition holds.

The proposition above also sheds light on the difference between an increase in entry costs and an increase in consumer inertia. Under both cases, the share of profits in the economy goes up and the entry rate goes down. However, when entry costs increase, incumbents markup goes down. The increase in entry costs leads to a lower measure of entrants. As a result, it is easier for incumbents to attract new customers. Incumbents set a lower markup, as a larger share of their customer base are unattached customers. Since the environment in which incumbents operate is less competitive, despite setting a lower markup, incumbents profits go up.

[11] If the set of parameters that solves these four conditions yields $J < 1$, then the measure of entrants in equilibrium is equal to zero. In that case, we have that $J = 1$, $P = \mu_I$, and μ_I is set so that it solves equation (6) with $B_0 = 1$.

[12] I denote the share of profits in equilibrium by Π. In equilibrium, the share of profits in the economy is equal to the profits earned by incumbents. That is, $\Pi = V(1)$. Entrants profits are equal to the entry cost paid in order to operate, as implied by the free-entry condition.

3 Dynamic Model

In this section, I develop a quantitative general equilibrium model of entry, exit, and firm dynamics that features consumer inertia. The model differs from the static model along three dimensions. Most importantly, as opposed to the static model, the quantitative model is dynamic. This introduces an investment motive in the firm's choice of markup. In particular, the firm has an incentive to lower its markup and increase the measure of its locked-in customers in the following period. Second, households' final consumption good is combined of a continuum of product types. In each product type, a household consumes a single product out of a variety of options. So even if a household is locked into a product in a specific product type, it can shift its expenditure toward other product types. As a result, the elasticity of demand coming from locked-in customers is higher than one, its value in the static model, but lower than the demand elasticity coming from unattached customers. Finally, firms are subject to persistent idiosyncratic productivity shocks and stochastic fixed operating costs. The latter gives rise to endogenous exit. The stationary equilibrium of the economy features a time-invariant distribution of firms over the two dimensions of heterogeneity: the size of the customer base and the productivity level.

I abstract from explicitly modeling households of different ages. Instead, I study an economy populated by ex-ante identical households who display the same level of consumer inertia. I then study the transition dynamics of the economy in response to an unanticipated and deterministic rise in the level of consumer inertia. The goal of the quantitative model is to study how a rise in consumer inertia affects the economy, regardless of the driver of this rise.

I calibrate the stationary equilibrium of the model to match key features of the U.S. economy in the late 1980s, such as the age distribution of firms and the aggregate share of profits. The estimated degree of consumer inertia implies that households re-optimize 17% of their consumption basket every year. The model needs a high degree of consumer inertia to match a key feature of the data, young firms tend to be substantially smaller than older firms. A high degree of consumer inertia allows the model to match this fact, as firms need to build their customer base over time.

3.1 Environment

There is a continuum of product types. Each product type consists of a continuous measure of operating firms. In every period, households consume only one product from each product type. Consumer inertia is modeled as introduced in section 2. In each product type, there is an exogenous probability $1-\theta$ that a household is locked into its previous consumption product and cannot re-optimize.

The supply side of the economy builds upon Hopenhayn (1992). The economy is populated by a continuum of firms who differ along two dimensions: their productivity level and the size of their customer base.[13] New firms can enter the economy by paying a fixed entry cost. Entrants

[13]Firms also differ by the product type in which they operate. This distinction, however, is not important, as I study

start with no initial customer base, and build it along their life-cycle. In addition, firms are subject to persistent idiosyncratic productivity shocks. Finally, incumbents need to pay a stochastic fixed operating cost in every period. This gives rise to endogenous exit.

I start by describing the demand side of the economy, and derive the equilibrium demand function for individual firms. I then turn to the supply side of the economy, and lay out the firm's problem.

3.1.1 Demand

There is a continuum of measure one of ex-ante identical households in the economy, indexed by $i \in (0,1)$. The lifetime utility of household i is given by

$$U_i = \sum_{t=0}^{\infty} \beta^t \ln C_{it} \ ,$$

where C_{it} is the aggregate consumption good household i consumes at time t. To ease notation, I omit both the household index i and the time index t from all equations below. The aggregate consumption good is composed of a variety of product types using a Dixit-Stiglitz aggregator,

$$C = \left\{ \int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \epsilon_{j_m} \right) c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}} \ , \tag{7}$$

where $j_m \in (0, J_m)$ denotes the product the household is consuming in product type m, and c_{j_m} is the quantity consumed of that product. J_m is the measure of products in product type m. ϵ_{j_m} is an idiosyncratic taste shock for consuming product j_m. Taste shocks are independent across products, product types, and households. I describe the distribution of taste shocks after introducing the household's problem below. The budget constraint of the household is given by

$$\int_0^1 p_{j_m} c_{j_m} dm = w + \Pi \ , \tag{8}$$

where p_{j_m} is the price of the chosen product from product type m. I assume household inelastically supply a unit of labor so that their salary is equal to the wage, w. I assume that aggregate profits, Π, are rebated to households as a lump sum transfer.

Households are subject to consumer inertia. There is a probability $1-\theta$ that the household cannot re-optimize its consumption choice in product type m and is locked into an existing product. The re-optimization draw is iid across households and product types. The Law of Large Numbers implies that each household is locked into products in a share $1-\theta$ of product types and is free to choose which products to consume in a share θ of product types.

I farther assume that households do not internalize the lock-in possibility. So when a household chooses which product to purchase, it only considers its current relative price and not its expected relative price in future periods.

a symmetric equilibrium in which all product types are identical.

The household's problem is given by

$$\max_{\{\{j_{mt},c_{j_{mt}}\}_{m=0}^{1}\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty}\beta^t \ln\left[\int_0^1\left(e^{\frac{1}{\sigma-1}\epsilon_{j_{mt}}}c_{j_{mt}}\right)^{\frac{\eta-1}{\eta}}dm\right]^{\frac{\eta}{\eta-1}}, \tag{9}$$

$$\text{s.t.} \qquad \int_0^1 p_{j_{mt}}c_{j_{mt}}dm = w_t + \Pi_t\;, \quad \text{for all } t\;, \tag{10}$$

$$j_{mt} = \quad j^*_{mt-1}, \quad \text{if} \quad \xi_{mt} = 0\;. \tag{11}$$

The household is maximizing its discounted lifetime utility (9), subject to two constraints. The first constraint (10) is the budget constraint of the household, and the second constraint (11) is the consumer inertia constraint. ξ_{mt} is an indicator variable that takes the value 1 in case the household can re-optimize its choice in product type m at time t. ξ_{mt} takes the value 1 with probability θ, drawn independently across product types and households. j^*_{mt-1} is the product the household is locked into, in case it cannot re-optimize. If the product the household is locked into is not available at time t, as the firm which produced it is not longer operating, then the price of that product is infinite.

In equilibrium, the product to which the consumer is locked into is the one consumed by the household in the previous period. The household, however, does not internalize that it may be locked into its current product choices in the future. To formalize that, I use the $*$ superscript, implying that the household does not directly choose j^*_{mt-1}. j^*_{mt} is defined as follows,

$$j^*_{mt} = \begin{cases} j^*_{mt-1}, & \text{if} \quad (\xi_{mt}=0) \\ \arg\max_{j\in(0,J_{mt})}\left[-(\sigma-1)\ln p_{jt}+\epsilon_{jt}\right], & \text{otherwise.}\end{cases} \tag{12}$$

The expression for j^*_{mt} implies that, in equilibrium, $j^*_{mt} = j_{mt}$ for all m and t.

If households were to internalize the possibility of lock-in, they would need to take into account not only the current price of a product but also its expected future prices. A forward-looking consumer would put more weight on a firm's relative price than a myopic consumer. This is because, in equilibrium, relative prices are serially correlated – a firm with a lower relative price this period is likely to have a lower relative relative price also in following periods. In Appendix B.2, I consider a dynamic version of the static model presented in Section 2 where household internalize the possibility of lock-in. By imposing a structure on household belief formation regarding future prices, I show that the behavior of a forward-looking household is identical to that of a myopic household with a different elasticity of substitution. In particular, if the serial correlation of prices is positive, then the demand elasticity of forward-looking household is higher. I conclude that the estimated value of the elasticity of substitution, σ, is likely a combination of the fundamental elasticity of substitution between products and of the persistence of prices over time.

An alternative assumption is that when a household cannot re-optimize its choice, it is not locked into its own previously consumed product, but into a product previously chosen by another random consumer in the economy. That is, rather than *internal* lock-in there is *external* lock-in.[14] While individual consumption behavior differs under this assumption as households will switch products more frequently, the demand function faced by the firm as well as the customer base evolution equation remain unchanged. This assumption is also consistent with the micro-data estimation performed in Section 4. Under the external lock-in assumption, households have no incentive to take into account the future expected prices of the products they choose. This assumption is similar to the one made in Luttmer (2006), who assumes consumers switch to the product of another random consumer in the economy with some Poisson intensity.

I assume that if the household can re-optimize its consumption choice, then its taste shocks follow a Gumbel distribution with location parameter $-\ln J_m$ and unit scale. The assumption on the location parameter implies that there is no love-of-variety in the model. If, instead, the household is locked into its previous consumption choice, I assume that the taste shock satisfies $e^{\frac{\eta-1}{\sigma-1}\epsilon} = \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right)$, where $\Gamma(\cdot)$ is the Gamma function. As Lemma 4 shows below, this assumption implies that if all firms charge the same price, the household spends the same amount on a product which it is locked into and on a product which it chooses freely.

It is useful to derive the optimal consumption behavior of households before turning to the firm's problem. As in the static model, I am able to derive an analytic formula for the firm's demand function. Some results are similar to the ones derived in section 2. However, the presence of imperfectly substitutable product types adds an aspect to the consumption behavior of households. Households do not only need to choose which product to purchase in every product type, but also how much of their expenditure to allocate toward different products.

First, I show that the household consumption choice can be represented as a multinomial logit discrete choice problem. The following lemma also implicitly implies that in equilibrium $j_{mt} = j^*_{mt}$, for all m and t. In the following lemmas, whenever appropriate, I omit both the time and product type subscripts to ease notation.

Lemma 2. *If the household is not locked into a product, it chooses the firm which maximizes*

$$j_m \equiv \arg \max_{j \in (0, J_m)} -(\sigma - 1) \ln p_j + \epsilon_j \ .$$

Using Lemma 2 and the distributional assumption on the taste shocks, I can derive the equation describing the evolution of a firm's customer base over time.

Proposition 5. *The customer base of a firm with price p is given by*

$$B' = (1-\theta)B + \frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma} , \tag{13}$$

where B is the customer base it starts the period with, θ is the measure of unattached households, and P_m is the price index of the product type, given by

$$P_m = \left[\frac{1}{J}\int_j p_j^{1-\sigma}\right]^{\frac{1}{1-\sigma}} . \tag{14}$$

[14] Such assumption is similar in spirit to the *external* deep habits model of Ravn et al. (2006).

Both the Proposition above and the preceding Lemma are identical to the ones derived in the static model. Differently from the static model, the presence of imperfectly substitutable product types makes the elasticity of demand of locked-in customers greater than 1. The following Lemma presents the demand of a household conditional on its taste shock toward the chosen product.

Lemma 3. *The demand of a household for the chosen product in product type m is given by*

$$c^i_{j_m} = \exp\left(\frac{\eta-1}{\sigma-1}\epsilon^i_{j_m}\right)\left(\frac{p_{j_m}}{P}\right)^{-\eta} C \ ,$$

where p_{j_m} is the price of the chosen product, $\epsilon^i_{j_m}$ is the idiosyncratic taste shock of the household for this product, and P is the aggregate price index given by

$$P = \left[\int_0^1 \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right)(p_{j_m})^{1-\eta}\, dm\right]^{\frac{1}{1-\eta}} \ .$$

Lemma 3 shows that the demand elasticity for the chosen product is equal to η. In addition, the amount of expenditure allocated to purchase the product depends on the relative taste toward the product. The distribution of tastes toward all other chosen products appears in the aggregate price index P.

As I study a symmetric equilibrium of the economy, I turn my focus to the case where the joint distribution of prices and tastes across products is identical across all product types. By assumption, the taste of a household toward a product it is locked into satisfies $e^{\frac{\eta-1}{\sigma-1}\epsilon} = \Gamma\left(1-\frac{\eta-1}{\sigma-1}\right)$. The following lemma derives the average adjusted taste of a household toward a product it chooses freely, conditional on the price of that product and the distribution of prices of other products in the same product type.

Lemma 4. *The average adjusted taste shock of a household that freely chooses to consume a product with price p is given by,*

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\middle| j_m = j, p_j = \bar{p}\right] = \left(\frac{p}{P_m}\right)^{\eta-1}\Gamma\left(1-\frac{\eta-1}{\sigma-1}\right) \ ,$$

where $\Gamma(\cdot)$ is the Gamma function.

Lemma 4 shows how the average taste shock among consumers depends on the firm's price. A firm with a low price attracts consumers with a relatively low taste shock, while a firm that sets a high price only attracts households with relatively higher tastes toward their good. Note that, as mentioned earlier, if all prices are equal then the expected taste toward products chosen freely is equal to the taste of the household toward products it is locked into. Using Lemma 4 and the symmetry of product types, I derive the aggregate price index of households as a function of the price distribution across firms. This result is presented in the following Lemma.

Lemma 5. *The aggregate price index P is given by,*

$$P = \Gamma \left(1 - \frac{\eta - 1}{\sigma - 1}\right)^{\frac{1}{1-\eta}} \left[\theta P_m^{1-\eta} + (1-\theta) P_B^{1-\eta}\right]^{\frac{1}{1-\eta}} ,$$

where P_m is the product type price index defined above, and P_B is the initial-customer-base-weighted price index given by

$$P_B = \left[\int_0^J B_j p_j^{1-\eta} dj\right]^{\frac{1}{1-\eta}} .$$

Note that even though different households are locked into different products across different product types, the continuum of products and product types together with the symmetry of product types implies that all households face the same aggregate price index. The explicit formula for the aggregate price index allows me to aggregate household-level demand to obtain the demand function faced by the firm.

Proposition 6. *The demand function faced by each firm is given by*

$$y_j = \left[(1-\theta) B p_j^{-\eta} + \frac{\theta}{M} P_m^{\sigma-\eta} p_j^{-\sigma}\right] \frac{1}{\theta P_m^{1-\eta} + (1-\theta) P_B^{1-\eta}} (w + \Pi) . \tag{15}$$

The proof of Proposition 6, which is included in the Appendix, reveals that a firm needs to take into account three key trade-offs when choosing its price level. First, its choice of price affects the size of its customer base as indicated in Lemma 5. Second, its price relative to the product-type price index affects, through selection, the average taste shock of its customers toward its product. Third, its price relative to the aggregate price index affects the share of expenditure households allocate to the purchase of its product. With the firm's demand function derived, I can turn to the supply side of the economy.

3.1.2 Supply

Each firm produces a single product in a specific product type. Firms use a linear technology, with labor as the sole input of production. The production of firm j is given by,

$$y_j = a_j l_j ,$$

where a_j is the idiosyncratic productivity of firm j and l_j is the labor used for production. Productivity follows an AR(1) process in logs, so that

$$\ln a_j = \rho_a \ln a_j^L + \sigma_a \zeta_j ,$$

where ρ_a is the persistence parameter, a_j^L is the productivity level in the previous period, and ζ_j is an iid productivity shock drawn from a standard normal distribution. I denote the conditional productivity distribution by $H(a'|a)$. In the remainder of this section, I omit the j subscript for the individual firm to save on notation.

In each period the firm operates, it needs to pay a fixed operating cost x_o. The operating cost is stochastic and follows an iid log-normal distribution with mean μ_o and standard deviation σ_o. I denote this distribution by $G_o(\cdot)$. After observing the fixed operating cost, the firm can choose to exit the economy instead of paying it.

The timing is as follows. At the beginning of each period, a firm observes its fixed operating cost and productivity level for the period. It then decides whether to pay the cost and operate, or whether to exit the economy. Finally, if the firm decides to operate, it chooses production, labor, and the price it charges. Firms cannot price discriminate, and must charge the same price from all their customers.

A firm has two state variables, its current productivity level (a) and its customer base it carries from the previous period (B). It discounts future profits according to the endogenous interest rate, r. The Bellman equation for the firm's present value, after paying the fixed cost for the current period, is given by

$$
\begin{aligned}
V(B,a) = \max_{\{p,y,B'\}} &\ py - \frac{w}{a}y + \frac{1}{1+r}\mathbb{E}\left[\max\left\{V\left(B',a'\right) - x_o'w', 0\right\}\right] \\
\text{s.t.} \quad & B' = (1-\theta)B + \frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma} , \\
& y = \left[(1-\theta)Bp^{-\eta} + \frac{\theta}{J}{P_m}^{\sigma-\eta}p^{-\sigma}\right]\frac{1}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}(w+\Pi) ,
\end{aligned}
$$

where J is the measure of operating firms in the product type. P_m and P_B are the price indicies defined in the previous subsection.

Entrants. Potential entrants can join the economy for a fixed entry cost f_e. Upon paying this cost, a potential entrant draws a productivity level from the distribution $H_e(a)$ and observes its stochastic operating cost for the period. It then decides whether to enter the economy and begin operating or not. Entrants join the economy with no initial customer base ($B = 0$). A free entry condition implies that

$$
f_e w = \int\int \max\left\{V(0,a) - x_o w, 0\right\} dG_o(x_o) dH_e(a) ,
$$

if the measure of potential entrants is positive.[15] In the estimation of the model, I assume that entrants' initial prodcutivity is drawn from a log-normal distribution with mean 0 and variance σ_a^2. So an entrant productivity distribution is the same as an incumbent with a previous productivity equal to 1.

To close the model, I assume that a mutual fund holds the shares of all firms in the economy. The mutual fund discounts payoffs with the discount factor of households in the economy. So the

[15] The entry cost can be higher than the value of being a potential entrant in equilibrium in case the measure of entrants is equal to zero. In the stationary equilibrium, however, the measure of entrants is positive regardless of the parameter specification.

interest rate satisfies the following equation,

$$\frac{1}{1+r} = \beta \left(\frac{w+\Pi}{w'+\Pi'}\right)\left(\frac{P'}{P}\right) \ ,$$

where I have used $C = \frac{w+\Pi}{P}$ and the assumption of $\ln$ utility. The profits (or losses) of the mutual fund, denoted by Π, are rebated in a lump-sum fashion to households.[16] The aggregate profits are defined as follows,

$$\Pi = \int_0^1 \int_0^J \pi_{jm} dj dm - J_e f_e w \ , \tag{16}$$

where J_e is the measure of potential entrants which pay the entry costs. π_{jm} denotes the operating profits of firm jm which are given by $\pi_{jm} = \left(p_{jm} - \frac{w}{a_{jm}}\right) y_{jm} - x_o^{jm} w$, where x_o^{jm} is the fixed operating cost firm jm incurs.

Solving the firm's problem, I derive an implicit characterization of the firm's markup, defined by $\mu \equiv \frac{p}{w/a}$, as a function of its state variables.

Proposition 7. *The markup of a firm with customer base B and productivity a is implicitly defined by the following equation,*

$$\mu = \frac{\sigma}{\sigma-1} + \underbrace{\alpha\left(\frac{\eta}{\eta-1} - \frac{\sigma}{\sigma-1}\right)}_{\textit{harvesting motive}} - \underbrace{(1-\alpha)\sum_{\tau=1}^{\infty} (\beta(1-\theta))^{\tau}\, \mathbb{E}\left[\mathbb{1}\left(\overline{T} > \tau\right)\gamma_{+\tau}\right]}_{\textit{investing motive}} \ , \tag{17}$$

where $\overline{T}$ is the stopping time indicating that the firm exits the economy in $\overline{T}$ periods. $\mathbb{1}\left(\overline{T} > \tau\right)$ is an indicator that takes the value 1 if the firm still operates τ periods ahead. The variables α and γ_τ are given by

$$\alpha = \frac{(\eta-1)(1-\theta)B}{(\eta-1)(1-\theta)B + (\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{\eta-\sigma}}, \qquad \gamma_{+\tau} = \frac{w_{+\tau}}{a_{+\tau}}\frac{a}{w}\left(\frac{p_{+\tau}}{P_{+\tau}}\right)^{-\eta}\left(\frac{p}{P}\right)^{\eta}(\mu_{+\tau}-1) \ ,$$

where a variable with subscript $+\tau$ corresponds to the variable τ periods ahead.

The Proposition above sheds light on the trade-off a firm faces when choosing its markup. The first term in equation (17), $\frac{\sigma}{\sigma-1}$, is the markup a firm would charge if the economy did not feature consumer inertia. The second term corresponds to the *harvesting motive*. The firm has an incentive to exploit its locked-in customer base and raise its markup. α is between 0 to 1 and is increasing in the share of locked-in costumers of the firm. When the firm does not have any locked-in customers $\alpha = 0$, and when the firm only sells to locked-in customers $\alpha = 1$. The higher the share of locked-in customers of a firm, the stronger the harvesting motive is. If the firm could only sell to locked-in customers, it would charge a markup of $\frac{\eta}{\eta-1} > \frac{\sigma}{\sigma-1}$. Note that even locked-in customers have the option to shift away their expenditure to other product types, which limits the ability of firms to exploit them.

[16]This assumption is isomorphic to one where households can buy and hold directly claims to the profits of firms.

Finally, the third term in equation (17) is the *investing motive*. Firms have an incentive to lower markups in order to attract customers. The customers the firm carries with it allow it to set higher markups and increase profits in following periods. In every period, the firm losses a fraction θ of its locked-in customer base, the customers who get to re-optimize their choice. So the benefits from building a customer base are discounted at rate $\beta(1-\theta)$. The higher the share of locked-in customers of a firm, the weaker is the investing motive. This is because firms cannot price discriminate, and pushing down their markups to attract new customers lowers their profit gains from locked-in customers. So the investing motive is strongest for entrants, who have no initial customer base.

3.2 Stationary Markov-Perfect Equilibrium

I restrict attention to a symmetric equilibrium where all product types are identical. The measure of operating firms in each product type is equal to J, and the price index in each product type is denoted by the scalar P_m.

When describing the environment in the previous section, I referred to firms by their index j. For the equilibrium definition, it is useful to formally define the joint distribution of firms over the two dimensions of heterogeneity: the customer base and productivity levels.

I denote the joint distribution of incumbents across customer base and productivity levels at the beginning of the period, prior to making their exit decision, by $\Lambda\left(B,a\right)$. Four components characterize the law of motion for this joint distribution: (i) the exit decision of firms, (ii) the pricing decision of firms, (iii) the measure of entrants, and (iv) the exogenous law of motion for productivity. The law of motion for the joint distribution is defined as follows. For all Borel sets $\mathcal{B}\times\mathcal{A}\subset\mathbb{R}^{+}\times\mathbb{R}^{+}$,

$$\Lambda'\left(\mathcal{B}\times\mathcal{A}\right)=\int_{x_o}\int_{\mathscr{B}(B,a,x_o)}\int_{a'\in\mathcal{A}}dH(a'|a)d\Lambda(B,a)dG_o(x_o)+\mathbb{1}\left(0\in\mathcal{B}\right)J'_e\int_{a'\in\mathcal{A}}dH_e(a')\,, \tag{18}$$

and

$$\mathscr{B}\left(B,a,x_o\right)=\big\{(B,a)\quad \text{s.t.}\quad V(B,a)\geq x_o\quad\text{and}\quad B'\left(B,a\right)\in\mathcal{B}\big\}\,,$$

where $B'(B,a)$ is the chosen customer base of a firm with initial customer base B and productivity a.

In the stationary equilibrium, the distribution $\Lambda(B,a)$ is constant over time. The definition of the stationary Markov-perfect equilibrium is as follows.

Definition 2 (Equilibrium)**.** A stationary Markov-perfect equilibrium is a set of prices $\{P_m,P_b,P,w\}$, aggregate allocations $\{\Pi,C\}$, policy functions, and a distribution of firms over customer base and productivity levels, $\Lambda(B,a)$, such that:

1. Consumption policy functions solve the household's problem.

2. Pricing policy functions solve the firm's problem.

3. Free entry condition holds.

4. Price indicies equations hold.

5. Markets clear.

6. The distribution of firms is stationary.

3.3 Calibration

The model contains nine structural parameters: The discount factor β; The re-optimization probability θ; The parameters that govern the elasticity of substitutions between products within the same product type and across product types, σ and η, respectively; The two parameters that shape the distribution of fixed operating cost, μ_o and σ_o; The two parameters that shape the productivity distribution, ρ_a and σ_a; And the entry cost f_e. I normalize the measure of firms in the stationary equilibrium to 1, and calibrate f_e so that the free entry condition holds.[17] This leaves me with eight structural parameters.

I assume a period in the model corresponds to a year and calibrate the discount factor β to 0.97. The seven remaining parameters are calibrated so that the stationary economy matches features of the U.S. economy between 1987–1991. I choose this 5 year period as some of the moments I use for the calibration are only available beginning in 1987.

I calibrate the structural parameters to match four features of the U.S. business sector in 1987–1991: (i) the share of firms by firm age, (ii) the share of employment by firm age, (iii) the job turnover rate by firm age, and (iii) the aggregate profitability share in the economy. For the first three sets of moments, I use the Business Dynamics Statistics dataset. I categorize firms into four age groups: 0–1, 2–5, 6–10, 11+.[18] I match the average firm share and average employment share in each age category, resulting in six moments. For each age category, I target the job turnover rate. This is the ratio between the sum of job creation and destruction to the total level of employment. This results in four additional moments. These ten moments are presented in Table 1. Finally, I target the profits share of GDP which I take from the BEA. The average hp-filtered aggregate profits share for that time period is 4.1%. The weighting matrix I use is diagonal, with the diagonal elements equal to the inverse of the squared targeted moments. That is, I minimize the sum of the squared percentage deviations from each moment. I discuss identification in the next subsection, after presenting the model fit.

[17] I normalize the measure of firms as there is one degree of freedom in the selection of the structural parameters. Scaling f_e, μ_o, and σ_o by a constant only alters the average size of firms and the total measure of firms. It does not change the pricing decision of firms, the exit probability of firms, the entry rate in the economy, or any other endogenous variable.

[18] The division between 6–10 and 11+ can only be done beginning in the year 1987. For this reason, I use the period 1987–1991 to calibrate the model.

The model implied moments are displayed next to the data moments in Table 1. We see that the model does a good job matching the data moments, considering that there are 11 moments to be matched and 7 estimated parameters.[19] Table 2 presents the estimated values of the different structural parameters.

Table 1: Data and model moments

	Data				Model			
Moment \ Firm Age	0–1	2–5	6–10	11+	0–1	2–5	6–10	11+
Employment share	7%	12%	12%	69%	6%	13%	16%	65%
Firm share	21%	26%	20%	34%	18%	23%	17%	42%
Job turnover rate	76%	45%	36%	27%	74%	40%	37%	27%
Agg. profits share	4.1%				4.1%			

Notes: This table presents the targeted data moments and the model implied ones. The time period for the data moments is 1987–1991. For the first two rows, the estimation procedure targets only the first three moments in each column, as columns sum to 100%.

Table 2: Parameter Values

Parameter	Description	Value
θ	Re-optimization probability	0.17
η	Elasticity of sub. between product types	2.75
σ	Elasticity of sub. within a product type	5.44
μ_o	Average ln fixed operating costs	-4.04
σ_o	Std of ln fixed operating costs	2.7
ρ_a	Idiosyncratic productivity persistence	0.99
σ_a	Std of productivity shocks	0.06

Notes: This table presents the value of the estimated structural parameters.

Identification. While the seven structural parameters are jointly estimated via GMM, it is useful to discuss which moments help pin down each parameter. I follow Andrews, Gentzkow and Shapiro (2017) and compute the elasticity of the targeted moments to the structural parameters as well as the elasticity of the estimated structural parameters to the targeted moments. These two sets of elasticities are reported in Table 3.

[19] Since the sum of employment shares and firm shares sum to one, I don't target the share of firms older than 10 years old.

Table 3: Identification of Structural Parameters

A. Elasticity of model-implied moments to parameters

	θ	η	σ	e^{μ_o}	σ_o	ρ_a	σ_a
s^f_{0-1}	0.10	0.10	0.09	0.27	1.70	-0.87	-0.05
s^f_{2-5}	0.13	0.01	-0.06	0.15	1.30	-1.31	-0.14
s^f_{6-10}	0.10	-0.05	-0.19	0.02	0.60	-1.52	-0.18
s^e_{0-1}	0.19	-0.45	0.13	0.71	2.93	-3.42	-0.73
s^e_{2-5}	0.18	0.14	0.31	0.90	2.71	-2.85	-0.33
s^e_{6-10}	-0.07	-0.05	2.02	1.10	2.76	-1.82	0.44
JT_{0-1}	-0.14	-0.30	0.31	0.07	-0.05	-0.23	-0.09
JT_{2-5}	-0.36	-0.66	1.77	0.10	0.40	0.20	0.75
JT_{6-10}	-0.88	-3.74	6.49	0.06	0.24	-0.56	1.29
JT_{10+}	-0.74	-3.15	7.92	1.07	1.12	0.17	2.12
π	-0.19	-0.47	-0.32	0.15	-1.17	1.85	0.80

B. Elasticity of estimated parameters to targeted moments

	θ	η	σ	e^{μ_o}	σ_o	ρ_a	σ_a
s^f_{0-1}	0.75	-0.35	-0.07	-0.78	0.73	0.51	-0.04
s^f_{2-5}	1.37	-0.19	-0.08	-0.73	0.18	-0.09	0.77
s^f_{6-10}	1.06	0.15	-0.09	-0.41	-0.50	-0.77	1.42
s^e_{0-1}	0.10	-0.48	-0.12	0.41	0.15	0.20	-0.58
s^e_{2-5}	-0.31	0.10	-0.04	0.46	-0.23	-0.24	0.11
s^e_{6-10}	-1.47	0.46	0.03	0.25	0.01	-0.08	0.01
JT_{0-1}	-2.16	0.17	-0.02	0.68	-0.13	0.02	-0.77
JT_{2-5}	-2.17	0.39	-0.16	-0.58	0.22	-0.15	0.53
JT_{6-10}	-0.86	-0.17	-0.07	-0.31	0.08	-0.04	-0.11
JT_{10+}	1.69	-0.08	0.20	0.28	-0.13	0.07	0.07
π	0.01	-0.53	-0.44	0.52	-0.02	0.00	0.62

Notes: This figure presents the elasticities of model-implied moments to structural parameters in the left panel, and the elasticity of estimated parameters to targeted moments in the right panel. This follows the approach of Andrews et al. (2017). s^e_a denotes the employment share of firms of age group a, s^f_a denotes the share of firms of age group a, and JT_a denotes the job turnover rate of firms of age group a.

The estimated re-optimization probability is 0.17. This implies that households re-optimize 17% of their consumption basket every year. From the firms' perspective, even if they set their price to zero, they cannot capture more than 17% of the market in a single year.

The first column of panel A in Table 3 displays the elasticity of model-implied moments to the re-optimization probability, θ, holding other parameters constant. A lower degree of consumer inertia (higher θ) alters the stationary equilibrium in four key ways. First, as more customers are re-optimizing their choices, young firms can reach a larger share of the market, and, as a result, the share of 10-years or younger firms in the economy increases. Second, the larger share of economic activity of young firms leads to an increase in their employment share. In particular, the employment share of 5-years or younger firms increases. Third, a lower degree of consumer inertia reduces job turnover rates. Absent of consumer inertia, firms reach their optimal size instantaneously and job turnover rates are only the result of idiosyncratic productivity shocks. With consumer inertia, the life-cycle employment dynamics of a firm raises job turnover rates. Finally, a lower degree of consumer inertia reduces aggregate profits as a share of output. Note that these qualitative predictions are consistent with comparative statics results of the static model (Proposition 4).

The first column of panel B in Table 3 displays the elasticity of the estimated degree of consumer inertia to the different targeted moments. The column reveals the three sources of identification. First, the higher the share of 10-years or older firms, the higher is the estimated degree of consumer inertia (lower θ). Second, the higher is the share of workers employed by older firms, the higher is consumer inertia. Finally, higher job turnover rates of young firms lead to a higher estimated degree of consumer inertia. Note that despite the effect consumer inertia has on aggregate profits, changes in aggregate profits do not lead to large changes in the estimated degree of consumer inertia. The model is able to match the share of aggregate profits in output by altering the elasticity of substitution across and within product types, η and σ.

The estimated elasticities of substitution across product types (η) and within product types (σ) are equal to 2.75 and 5.44, respectively. These elasticities of substitution are within the range of elasticities estimated in Foster, Haltiwanger and Syverson (2008). The second and third columns of panel B in Table 3 display the effects of the data moments on the estimated elasticities of substitution. A key moment that identifies the degree of these elasticities is the profits share. Higher profits imply lower estimated elasticities. The second and third columns in panel A confirm that lower elasticities of substitution lead to higher share of profits in output. A set of moments that identifies the difference between σ and η are the relative size of firms of different ages.[20] As young firms become relatively larger, the estimated difference between η and σ grows. A higher difference in elasticities implies that young firms charge a relatively lower markup. As the markup of young firms is lower, they attract more unattached consumers, and their relative size grows.

The two fixed cost parameters μ_o and σ_o are estimated to be -4.04 and 2.7, respectively. The parameter μ_o governs the average exit rate. A higher average fixed operating costs, other things equal, increases the exit probability of all firms. Since firms build their customer base over their life-cycle, the present value of older firms is higher. As a result, older firms can absorb higher operating cost shocks and survive with higher probability. The parameter σ_o governs the shape of the survival probability as a function of age. A low volatility of operating costs implies that the survival probability of old firms is much higher than of young firms. Taking the limit of $\sigma_o \to \infty$, the survival probability becomes independent of age. In the stationary equilibrium, the age distribution of firms is determined by the survival probability of firms of different ages. So these moments help determine the values of μ_o and σ_o. These parameters imply that young firms fixed operating costs are equal to between 12%–14% of their sales. For firms older than 10 years old, the average fixed costs amount to about 8% of sales.

Finally, I discuss the productivity parameters ρ_a and σ_a. The persistence parameter ρ_a governs the average productivity by age. The survival probability is increasing in the level of productivity and customer base. Since the customer base increases along a firm's life-cycle, the productivity threshold for exiting the economy decreases with age. As a result, if $\rho_a = 0$, then the average productivity of an operating firm is decreasing with age. Since only the more productive firms survive, higher productivity persistence can turn this result and imply that the average productivity is increasing with age. The relative size of firms by age, helps pin down the persistence parameter ρ_a. The persistence parameter is also important for determining the shape of the survival probab-

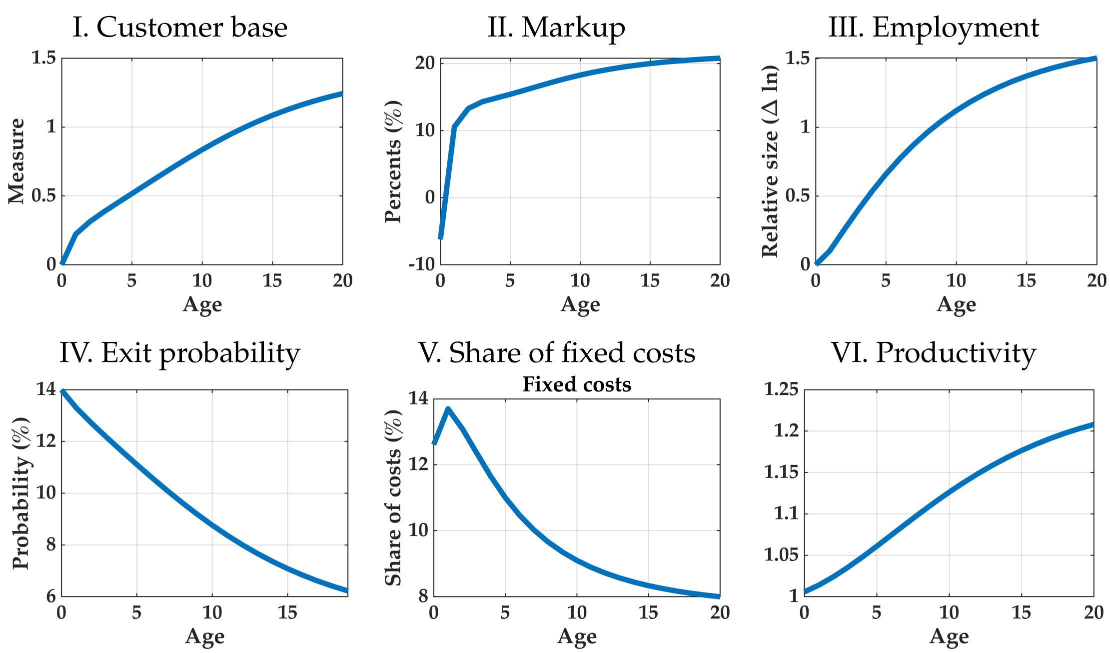
[20] Note that a change in the share of workers employed by firms of a certain age (s_a^e), holding constant the share of firms (s_a^f), is equivalent to changes in the relative size of firms of different ages.

ility by age. Higher persistence leads to higher difference between the survival probability of old and young firms. The standard deviation of productivity shocks is also important for determining the average productivity of firms by age. Trivially, without productivity shocks the productivity of all firms is the same. But also very high productivity shocks lead to a small difference in the average productivity by age. A combination of high persistence ($\rho_a = 0.99$) and relatively small volatility ($\sigma_a = 0.06$) imply that the average productivity is increasing with age, helping the model match the increasing relative size of firms with age.

3.4 The Calibrated Stationary Economy

I now describe the properties of the calibrated stationary economy. Figure 1 presents the life-cycle of an average firm in the economy over the first 20 years of its life. A firm enters the economy with no initial customer base. It sets a relatively low markup in order to build its customer base. As it builds its customer base, the harvesting motive becomes stronger while the investing motive becomes weaker. As a result, the average markup a firm sets is increasing with its age. Despite higher markups, the average size of a firm is growing with age as it sells its product to a larger number of customers.

Figure 1: The Life-Cycle of a Firm



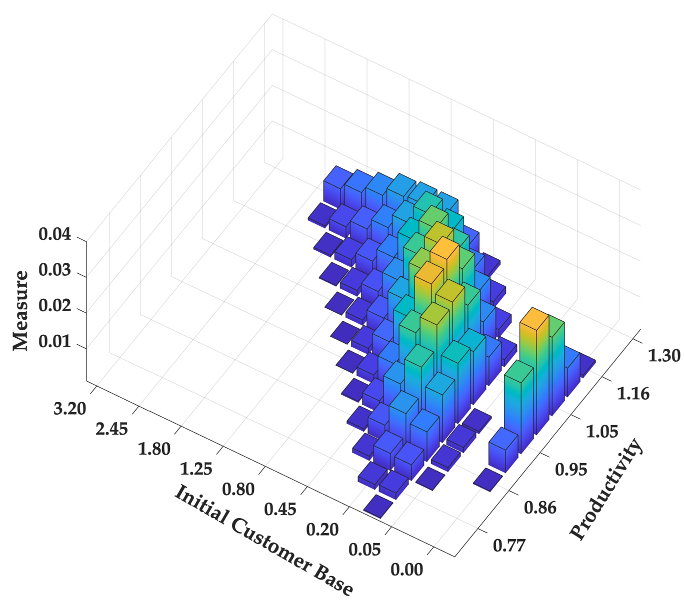
Notes: This figure presents the properties of the average firm across the first 20 years of its life. A firm joins the economy with no customer base and builds it over time. As its customer base grows, the harvesting motive becomes more dominant and the firm raises its markup. Employment is relative to the average firm aged 0–1. Share of fixed costs is with respect to sales.

As a firm builds its customer base, its present value increases. It can absorb larger fixed operating costs, and so its exit probability is decreasing with age. However, as a fraction of sales, younger firms are willing to pay more than older firms. This can be seen in Panel V of Figure 1. Young firms are willing to pay a large fraction of their sales as they expect their profits to rise in the future. Old firms do not expect their profits to increase further, so they are willing to pay a lower fraction of their sales.[21]

Finally, as discussed in the previous section, the high persistence of idiosyncratic productivity implies that the average productivity is increasing with the firm's age.

Figure 2 presents the stationary distribution of firms along the two heterogeneity dimensions, the initial customer base and productivity levels. For better visualization, I collapse the state space into bins and present the measure of firms in each bin.[22] The firms with initial customer base equal to 0 are the entrants. Depending on their productivity level, entrants set their markup and decide how many customers to attract. More productive firms decide in equilibrium to attract more customers, so we see a positive correlation between the productivity level of a firm and its initial customer base.

Figure 2: The Stationary Distribution of Firms

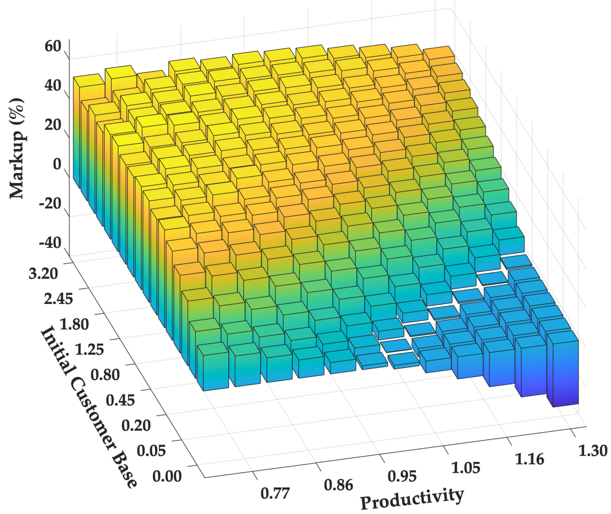


Notes: This figure presents the stationary distribution of firms along the two heterogeneity dimensions:eize the initial customer base and productivity levels. I collapse the state space into bins, and present the measure of firm in each bin. On average, more productive firms have a higher number of customers.

[21]The decreasing relationship between the ratio of fixed costs to sales and age is true for all ages except for entrants. Entrants are not willing to pay as much as 1-year old firms, because the high exit probability they face is stronger than the expected rise in their profits.

[22]The model is solved on a grid containing 501 customer base points and 15 productivity levels.

Figure 3: Markup Policy Function



Notes: This figure presents the equilibrium markup as a function of the firm's customer base and productivity levels. The markup is increasing with the firm's customer base, and decreasing with the firm's productivity.

Figure 3 presents the optimal markup of a firm as a function of its two state variables. Recall that the markup satisfies equation (17). In setting its markup, the firm trades off the harvesting motive and the investing motive. Entrants have no initial customer base, so the harvesting motive is shut down for them. As a firm builds its customer base, a larger fraction of its customer base are locked-in, and the harvesting motive becomes more dominant. As a result, we see that markups are increasing with a firm's customer base.

From equation (17), we see that the harvesting motive is independent of the productivity level of the firm. This is not the case for the investing motive. A more productive firm has a lower exit probability, due to the persistence in productivity. Since the investing motive is increasing in the survival probability, it is also increasing in the productivity level of the firm. Consequently, the optimal markup of a firm is decreasing in a firm's productivity level.

4 Consumer Inertia Across Age Groups

To study how consumer inertia changed over time, I use Nielsen's Consumer Panel dataset. The Nielsen dataset spans the years 2004 to 2015, so I cannot directly estimate how the degree of consumer inertia changed over the past three decades. Instead, I study how the degree of consumer inertia varies with the age of the household. The resulting estimates, together with the demographic composition in the U.S. over time, allow me to construct a time-series of the changes in the aggregate degree of consumer inertia.

I find that young households, household with a family head younger than 35 years old, are significantly and substantially less inertial than older households. Consumer inertia of older households does not vary substantially with age. The results suggest that the decline in the share of young households in the U.S. economy during the past decades have led to a rise in the aggregate degree of consumer inertia.

4.1 Data

The main dataset I use for the analysis is Nielsen Homescan Consumer Panel Data provided by the Kilts-Nielsen Data Center at the University of Chicago, Booth School of Business. The dataset includes longitudinal panel information on the purchases of approximately 160 thousand households in the U.S. between 2004 and 2015. Households receive a barcode scanner from Nielsen and are directed to scan the barcodes of all consumer packaged goods they purchase. The dataset covers both food and non-food items across all retail outlets in the US.[23]

For each shopping trip of a household, I observe the date of the shopping trip, the products purchased at the Universal Product Code (UPC) level, and the stores in which these goods were purchased. An example of a product at the UPC level is a 16 fl oz plastic bottle of Coca-Cola. Nielsen organizes products at the UPC level into product modules, product categories, and departments. Product modules are the most granular, then product categories, and finally departments. For example, a 16 oz can of "Stapleton's California Whole Prunes packed in Pear Juice" is classified into the product module "canned fruit - prunes", the product category "canned fruit", and into the department "dry grocery".

For each household, I observe a vector of demographic and geographic characteristics including the number of family members and their ages, the household's income, education, and race, as well as its zip code, county and state. The panel composition is designed to be projectable to the total United States population.

I supplement the Consumer Panel dataset with the GS1 U.S. dataset. GS1 U.S. is a not-for-profit information standards organization which administers the UPC barcodes of products in the US. Using the GS1 dataset, I link between products at the UPC level from the Nielsen Consumer Panel dataset and the firms producing them.

4.2 Descriptive Statistics: Who is Buying From Entrants

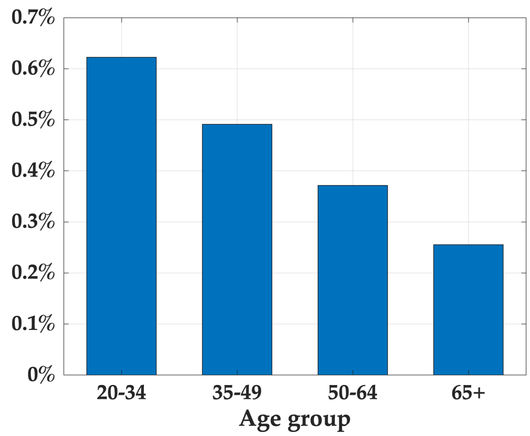
Household who display consumer inertia are less likely to consider buying a product from an entrant firm. As a result, consumer inertia acts as an entry barrier. Prior to structurally estimating the degree of consumer inertia across age groups, I present evidence on the probability of buying from an entrant firm across age groups.

[23]For a validation study of the dataset, see Einav, Leibtag and Nevo (2010).

I divide households into four age categories, according to the family head's age: 20–34, 35–49, 50–64, and 65+. I define an entrant firm in a product module as the first year in which the firm sells a product in that product module.[24] I then compute the share of household purchases from entrants out of all their purchases. Figure 4 presents the results.

There are two key takeaways from Figure 4. First, the share of purchases from entrants is declining with the household age. The group of young households are more than twice as likely to purchase products of entrant firms relative to the oldest household group. And the relationship seems to be monotonic with the age of the household.

Figure 4: Share of purchases from entrants by household age



Notes: The figure presents the share of purchases from entrant firms by household age. There are two key takeaways. First, the share of purchases from entrants is declining with household age. Second, these shares are small for all age groups. On average, households' purchase share of entrants is about 0.5%, while the entry rate is an order of magnitude larger (8.5%).

Second, the share of purchases of households from entrant firms are small for all age groups. The average share of entrant firms in the Nielsen dataset is 8.5%, similar to the average share of entrant firms in the U.S. economy during the same time period (8.7%). Yet their purchase share is less than 0.5%. This suggests that the potential customer base of entrant firms is small.

Under the assumption that the characteristics of entrant products are not different from those of incumbent products, we can back out the degree of consumer inertia by comparing the entrants' relative share of purchases to their share of firms. This calculation results in a very high degree of consumer inertia, suggesting different age groups have a re-optimization probability between 3% to 7%. However, other factors may contribute to the relatively low share of entrants market share. First, entrants may sell their products only in a subset of markets. Second, entrants may introduce their product later in the year. Furthermore, entrants may target younger consumers and introduce products that are particularly appealing to younger households.

[24] I omit the first two years of the sample so that I don't mistakenly identify incumbents as entrants. The patterns are robust to defining an entrant firm as the first year in which the firm sells a product in *any* product module.

4.3 Estimation and Identification

I obtain the degree of consumer inertia for households of different ages by estimating the structural equation that governs the evolution of a firm's customer base, equation (13). To identify the degree of consumer inertia, I use variation in the customer base of a firm across U.S. states. The augmented customer base evolution equation is given by

$$B^a_{fmst} = (1-\theta^a)B^a_{fmst-1} + \frac{F^a_{mst}}{J_{mst}}\left(\frac{p_{fmt}}{P^a_{mst}}\right)^{-\sigma} q^a_{fmt}, \tag{19}$$

where B^a_{fmst} is the customer base of age group a of firm f in product module m in state s at time t. θ^a is the re-optimization probability of households in age group a. F^a_{mst} is the measure of customers of age group a in product module m in state s at time t who are not locked-in to a product, and J_{mst} is the measure of firms operating in product module m in state s at time t. p_{fmt} is the price the firm sets, while P^a_{mst} is the quality-adjusted price index faced by households of age a in product module m in state s at time t. Finally, q^a_{fmt} is the quality of the firm's product.[25] Note that I allow the quality to vary over time, so that it accommodates common changes in consumer tastes across different ages.

Equation (19) implicitly assumes no variation in the price of a product across locations. That is, the price that governs how attractive a product is in each state is the national price of the product. This assumption is motivated by the finding of DellaVigna and Gentzkow (2019), who show that retail chains in the U.S. charge nearly uniform prices across locations.[26] This assumption implies that the customer base evolution equation takes the following form:

$$B^a_{fmst} = (1-\theta^a)B^a_{fmst-1} + \underbrace{\lambda^a_{mst}}_{\text{local market conditions}} \times \underbrace{\gamma^a_{fmt}}_{\text{product characteristics}}, \tag{20}$$

where λ^a_{mst} is a module-state-time fixed effects which represents local market condition such as how many firms are competing for customers, how many customers are looking for a product, and the quality adjusted price index in the market. γ^a_{fmt} is a firm-module-time fixed effect which represents product characteristics, such as the price and quality of the product. This panel data model with interactive fixed-effects can be estimated following Bai (2009).

I study the degree of consumer inertia at an annual level. B^a_{fmst} is defined as the number of customers in age group a who live in state s that have bought a product from firm f in product module m sometime throughout year t. I weight customers according to their projection weights so that the customer base represents the U.S. population. I then divide the customer base of each firm by the total size of customer base so that $\sum_f B^a_{fmst} = 1$, for all a, m, s, and t.

In the estimation, I allow the re-optimization probability, θ^a, to vary by product category. The Bai (2009) estimation technique is computationally demanding, and computing it for all product

[25] While in the model all products are of the same quality, this is not the case in the data.

[26] An alternative justification for including the national price rather than the local price is that the local price may respond to local factors. So the national price acts as an instrument for the local price of the product (e.g., Nevo, 2001).

categories simultaneously is not computationally feasible. By assuming θ^a is heterogeneous across product categories, I can estimate equation (20) separately for each product category.[27]

Before turning to the estimation results, it is useful to discuss how the degree of consumer inertia, $1-\theta^a$, is identified. Suppose, for example, that the price of a product goes up, so that it becomes less attractive. Absent consumer inertia, we expect the market share of the firm to decline by the same magnitude across locations. With consumer inertia, the share of unattached customers should decline but the share of locked-in customers remain unchanged. So the relative decline in customer base should be smaller in markets where the firm has a larger existing customer base.

4.4 Results

I estimate equation (20) separately for each product category and for each age group. Overall, there are 103 product categories across the seven product departments. Across all categories and age groups there are about 18 million observations. The results of all 412 regressions (103 categories $\times$ 4 age groups) are presented in Appendix C. Figure 5 displays the average estimated degree of consumer inertia for each age group in each product department. Each row contains the estimated degree of consumer inertia for each age group. The center of each circle represents the average point estimate across product categories within each department. The length of each confidence interval represents the average length of confidence intervals within each product department. When averaging estimates and standard errors across regressions, I weight each regression by the number of observations.

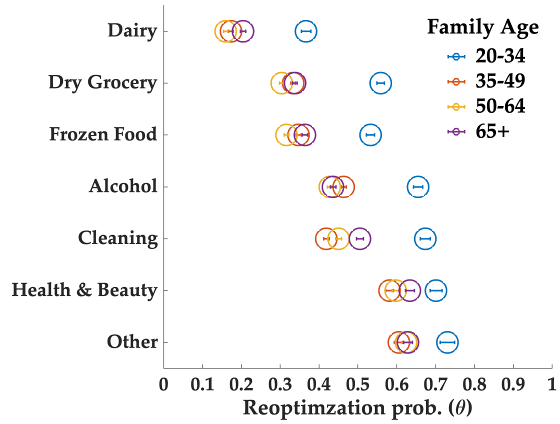
The figure shows that in each product department, the group of young households, those younger than 35 years old, are substantially less inertial. In the dairy department, for example, the re-optimization probability of young households is 37%. That is, in every year, young households are estimated to re-optimize 37% of their consumption basket in the dairy department. The re-optimization probability for older households is 17%, 16%, and 20% for households in the age groups of 35–49, 50–64, 65+, respectively.

The difference between households of different ages not only holds in department averages, but also across individual product categories. In more than 95% of product categories, young households are significantly less inertial than all other age groups.

As the results reveal, there is substantial heterogeneity across different product categories. The carbonated beverages product category, for example, is estimated to have a very strong degree of consumer inertia. The estimation results imply that households above the age of 35 years old almost do not change their consumption decision in this category as the estimated re-optimization probability is about 4%. The estimated re-optimization probability for young households in the carbonated beverages category is 21%. The candy product category, on the other hand, displays low degree of consumer inertia. The estimated re-optimization probability for households above

[27] Estimating the equation product category by product category allows for parallel computing. I use the Julia package *Interactive Fixed Effect Models* in the estimation procedure.

Figure 5: Consumer Inertia by Household Age Across Departments



Notes: This figure displays the average estimated consumer inertia by age groups in each product department. The center of each circle represents the weighted average point estimates, and each confidence interval represent the weighted average confidence interval. Weights are proportional to the number of observations in the regression of each product category.

the age of 35 varies between 47% and 59%. The estimated re-optimization probability for young households in the candy category is 77%.

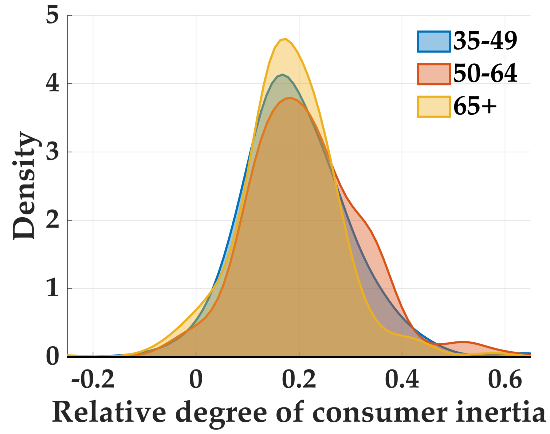
While there is substantial heterogeneity in the absolute degree of consumer inertia across product categories, the difference in the re-optimization probability between households below and above the age of 35 years old is quite stable across product categories. Figure 6 presents the probability density of the difference between the estimated re-optimization probabilities of 20–34 and other age groups across product categories. There is a large mass around 0.2. The average estimated difference is 0.181 for the 35–49 age group, 0.194 for the 50–64 age group, and 0.171 for the 65+ age group. That is, younger households are about 20 percentage points more likely to re-optimize their consumption choice in a product category within one year.

4.5 Implied consumer inertia over time

Using the micro-estimates, I construct a time series of the aggregate re-optimization probability. I start by using data from the World Bank on the observed and predicted age composition of the adult population in the U.S. between 1987 and 2050. I combine the age composition data together with the estimated difference in consumer inertia between households of different ages, presented in the previous subsection, to construct a time series of changes in aggregate consumer inertia. Finally, I choose the average value of re-optimization probability during 1987–1991 to correspond to the one I structurally estimated in Section 3.

The implied aggregate time-series of consumer inertia is displayed in Figure 7. The re-optimization probability fell from about 17% in the late 1980s to almost 15% in the 2010s. This means that the

Figure 6: Consumer Inertia Relative to Young Households Across Product Categories



Notes: This figure displays the probability density of the difference in the degree of consumer inertia between different age groups and the 20–34 age group across different product categories. The relative degree of consumer inertia is defined as $\hat{\theta}^{20\text{–}34} - \hat{\theta}^{a}$.

potential market share entrants can capture has dropped by about 10% during this time period. The degree of consumer inertia is predicted to continue rising in the future, but at a much slower pace. By 2050, the re-optimization probability is predicted to fall to 14.7%.

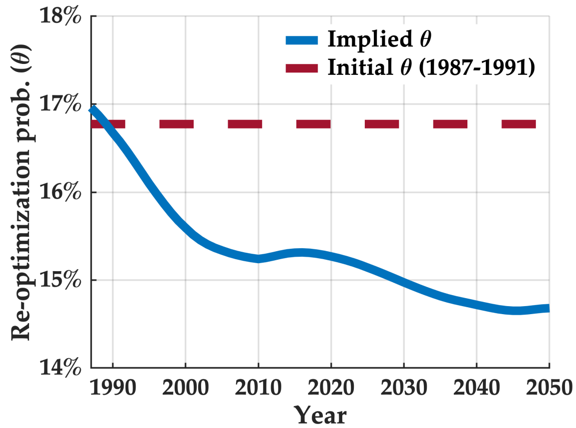
The time series for the aggregate degree of consumer inertia is based on the micro estimates from the Nielsen dataset, which covers only the consumer packaged goods (CPG) sector. As this time series is used in the next section to analyze the impact of the aging-induced rise in consumer inertia on the macroeconomy as a whole, a question on the external validity of the micro estimates arises.

The CPG sector is potentially less inertial than other sectors as consumers need to actively choose the products they buy.[28] To the extent that the difference in consumer inertia across sectors is not correlated with the age of consumers, the heterogeneity in the absolute degree of consumer inertia would not impact external validity. This is because I only use micro estimates of the relative consumer inertia by age to construct the aggregate time series.

In the previous subsection, I've shown that the degree of consumer inertia varies substantially in absolute terms across product categories but is quite stable in relative terms. This fact suggests that using the relative degree of consumer inertia in the CPG sector for the rest of the economy may be a good approximation.

[28]Compared, for example, to insurance services, where consumers may be enrolled in auto-renewal of their contracts.

Figure 7: Aggregate Consumer Inertia Over Time



Notes: This figure presents the aggregate re-optimization probability over time. The series is constructed using the micro-estimates of consumer inertia by households age, the observed and predicted age composition of the adult population in the US, and the estimated degree of re-optimization probabilities in the late 1980s. A decline in re-optimization probability corresponds to higher consumer inertia.

5 Aggregate Impact of the Aging-Induced Rise in Consumer Inertia

In this section, I study the aggregate implications of the aging-induced rise in consumer inertia. I start by providing reduced-form evidence on the impact of consumer inertia on firm formation. I use two research designs. First, I analyze a panel of U.S. states. I find that states that have seen larger increases in consumer inertia over time, as inferred by their demographic composition, have also experienced larger declines in firm formation measures. Second, I analyze the cross-section of product categories in the Nielsen dataset. I find that entry rates are lower in product categories with high degrees of consumer inertia. The point estimates suggest that the effect of consumer inertia on firm formation is not only statistically significant but also quantitatively.

Finally, I study the impact of the rise in consumer inertia using the quantitative model. As observed in the data, the model predicts a decline in firm formation and a rise in the share of profits in aggregate output. Consistent with other empirical studies, the majority of the rise in the profits share is due to a reallocation of production towards large, high-markup firms, and not due to a uniform rise in markups across firms. Quantitatively, the aging-induced rise of consumer inertia in the model accounts for between 10%–30% of the decline in firm formation and rise in aggregate profits between 1987–1991 and 2015–2019.

5.1 Cross-State Analysis of the Impact of Consumer Inertia

The demographic shift was not uniform across U.S. states. Some states have experienced a large decline in the share of young population, while others have experienced only a modest decline.

In this section, I exploit this variation to study the impact of consumer inertia on firm formation.

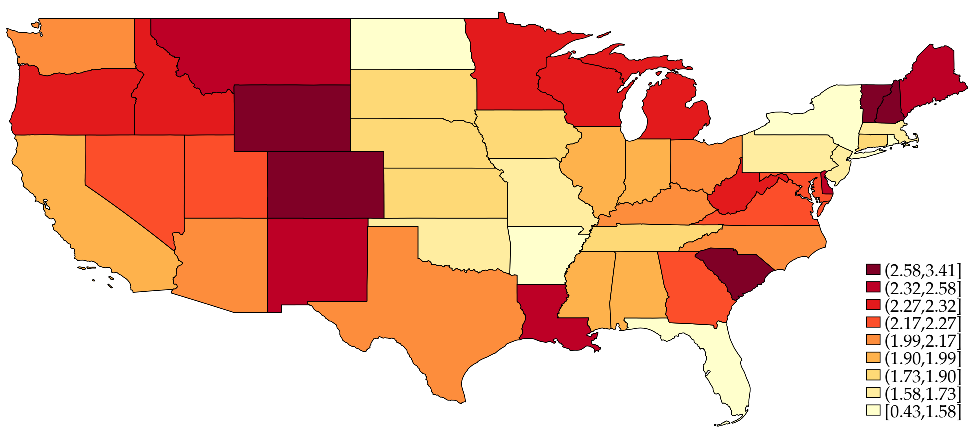
Using the age composition of each state in every year, I construct an annual state-specific consumer inertia index based on the age-specific estimates of consumer inertia presented in the previous section. The consumer inertia index is simply the average degree of consumer inertia among the adult population (20 years and older) of a state. That is,

$$\overline{(1-\theta)}_{lt} = \sum_{a} s_{alt}\left(1-\hat{\theta}_a\right) , \tag{21}$$

where $\overline{(1-\theta)}_{lt}$ is the consumer inertia index in state l at time t, s_{alt} is the share of population in the age group a out of the adult population in state l at time t. Finally, $\hat{\theta}_a$ is the average estimated re-optimization probability of age group a from Section 4.[29]

Figure 8 presents the change in the consumer inertia index across states between 1980–2019. The map reveals that all states have experienced a rise in consumer inertia. But there is substantial variation in these changes. Florida, which had a small share of young households already in 1980, have experienced a small rise in consumer inertia. Vermont and New Hampshire, on the other hand, have experienced a large increase in consumer inertia.

Figure 8: State-Level Change in Consumer Inertia (1980–2019)



Notes: This figure presents the change in the consumer inertia index between 1980 to 2019 for each state. The change is in percentage points. This figure shows that all states have experienced a rise in consumer inertia during this time period and that there is substantial variation across states in the magnitude of this rise.

For the dependent variable, I use two different firm formation indicators. The first is the share of young firms (5 years or younger) in a state. The second is the share of workers employed by young firms in a state. I choose these indicators as they are less affected by business cycle

[29]Note that since all regressions presented in this section include a state fixed-effect, the relevant estimate from the micro data is the degree of consumer inertia of each age group relative to the young age group, $\hat{\theta}^{20-34} - \hat{\theta}^{a}$.

fluctuations. Appendix D includes results also for the share of entrants and the share of workers employed by entrants. The results are robust to these alternative measures of firm formation.

I use the following regression specification.

$$y_{alt} = \alpha_l + \delta_t + \beta\overline{(1-\theta)}_{alt} + \Gamma X_{alt} + \epsilon_{alt} \ , \tag{22}$$

where y_{alt} is one of the firm formation measures, α_l is a state-level fixed-effect, δ_t is a time fixed-effect, and X_{alt} is a vector of controls. The coefficient of interest is β.

There are two potential biases when estimating regression (22). The first is an omitted-variable bias. Since the constructed index of consumer inertia is based on the age composition in each state, I need to control for other demographic channels which can affect firm formation. Otherwise, I may mistakenly attribute the effects of these other channels to consumer inertia. To address this concern, I include other demographic channels that have been raised by the literature as drivers of the decline in firm formation. The two controls I include are the share of old workers in the workforce and the growth rate of the labor force. Liang et al. (2014) and Engbom (2019) argue that the decline in firm formation is driven by an aging workforce. Karahan et al. (2019) and Hopenhayn et al. (2018) argue that a decline in the growth rate of the labor force can explain a substantial proportion of the decline in firm formation.

Before turning to the second potential bias, it is worth pointing out the differences in the age composition of a state which allow me to separately identify the effects of consumer inertia from the other demographic channels I control for. Consumer inertia depends primarily on the share of young households in the *adult population*. The share of older workers, on the other hand, heavily depends on the share of young households in the *working age population*. So the share of old households (65 and older) in the economy allows me to separately identify the demand channel of consumer inertia from the supply channel of an aging workforce. The labor force growth rate depends on the difference between the share of population which moves from the mature to old population (retirees) and the share of young population which joins the workforce. If the two are equal, so that the labor force growth rate is zero, it does not matter how large each of the two components is. For consumer inertia, on the other hand, an increase in the share of young households leads to a decline in consumer inertia regardless of the fraction of mature households that turn old. This is because consumer inertia among the mature and old age groups is fairly similar.

The second potential bias I address is an endogeneity bias. Households can move across states due to economic incentives. In particular, household may choose to move to booming states, which are those that display higher share of young firms. Since moving across states may be correlated with age, such migration flows can lead to an estimation bias. To mitigate this concern, I instrument a state's consumer-inertia index with the 10-year lagged age composition of that state. The approach of using the lagged age composition to control for this potential endogeneity bias is common in the literature and has been used, for example, by Shimer (2001), Karahan et al. (2019), and Engbom (2019). The exclusion restriction is that an individual does not move to a state because she thinks that it will boom in 10 years.[30] The instrument I use is the predicted level of consumer inertia 10-years ahead which is defined as follows,

$$\left[\overline{(1-\theta)}_{lt}^{p}\right]_{t-10} = \sum_{a} \left[s_{alt}^{p}\right]_{t-10} \left(1-\hat{\theta}_a\right) \ , \tag{23}$$

where $\left[\overline{(1-\theta)}_{lt}^{p}\right]_{t-10}$ is the predicted value of consumer inertia 10-years ahead. $\left[s_{alt}^{p}\right]_{t-10}$ corresponds to the predicted share of households that would be in age group a, 10 years into the future. For example, the predicted share of young households 10-years ahead is defined as the share of households aged 10–24 out of the population aged 10–79.[31] This instrument has substantial explanatory power. The R^2 from the first-stage regression is equal to 0.94 and the F-stat is equal to 105.

Table 4 presents the regression results. The top panel of the table considers the share of workers employed by young firms as the dependent variable, and the bottom panel considers the share of young firms. The first three columns include the OLS results and the last three columns include the IV results. The OLS results point at a significant negative relationship between the level of consumer inertia and the two measures of firm formation. The OLS specifications indicate that a one percentage point increase in consumer inertia is associated with about 2.3 percentage points decrease in the share of workers employed by young firms and 5.1 percentage points decrease in the share of young firms.

The IV results lead to a similar conclusion. An increase in the level of consumer inertia leads to a decline in firm formation. A rise of one percentage point in consumer inertia leads to a decline of 3.5 percentage points in the share of workers employed by young firms and a decline of 5.4 percentage points in the share of young firms. A back-of-the-envelope calculation indicates that the aging-induced rise in consumer inertia between the period 1987–1991 and 2015–2019 period is responsible for 58% of the decline in the share of workers employed by young firms observed in the data (5.1pp out of 11.7pp decline). A similar calculation for the share of young firms suggests that the aging-induced rise in consumer inertia is responsible for 68% of the decline observed in the data (7.9pp out of 11.7pp decline).

5.2 Cross-Product-Category Analysis

This section explores the relationship between consumer inertia and firm entry rate across different product categories in the Nielsen dataset. I study how the average consumer inertia among customers in a market affects firm entry rate in that market. To perform the analysis, I construct

[30] Note that if a young household moves to a state because she believes it would boom 10 years into the future, my estimates would suffer from a downward bias. This is because such household would be in the *maturing households* group 10 years following its move, and consumer inertia of maturing households is larger than the average level of consumer inertia.

[31] Similarly, the predicted share of maturing, mature, and old households correspond to the share of households aged 25–39, 40–54, and 55–79, respectively, out of the population aged 10–79.

Table 4: Consumer Inertia and Firm Formation – State Analysis

	Dependent variable: share of workers employed by young firms					
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer inertia index	-2.26^{***}	-2.23^{***}	-2.42^{***}	-3.48^{***}	-3.46^{***}	-3.89^{***}
	(0.72)	(0.71)	(0.83)	(1.26)	(1.24)	(1.47)
Labor-force growth rate		0.037^{***}	0.038^{***}		0.032^{***}	0.037^{***}
		(0.01)	(0.01)		(0.01)	(0.01)
Share of older workers			0.04			0.11
			(0.04)			(0.07)
State and time f.e.	✓	✓	✓	✓	✓	✓
Instrumented	✗	✗	✗	✓	✓	✓
	Dependent variable: share of young firms					
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer inertia index	-5.14^{***}	-5.10^{***}	-5.15^{***}	-5.43^{***}	-5.41^{***}	-5.51^{***}
	(0.84)	(0.84)	(0.87)	(1.36)	(1.34)	(1.57)
Labor-force growth rate		0.053^{***}	0.054^{***}		0.052^{***}	0.054^{***}
		(0.01)	(0.01)		(0.01)	(0.01)
Share of older workers			0.01			0.03
			(0.03)			(0.07)
State and time f.e.	✓	✓	✓	✓	✓	✓
Instrumented	✗	✗	✗	✓	✓	✓

Notes: This table presents the regression results of (22). The sample period is 1982–2019. In the top panel, the dependent variable is the share of workers employed by young firms, defined as firms which are 5 years or younger. The dependent variable in the bottom panel is the share of young firms. Standard errors in parenthesis. Standard errors are clustered at the state level. *** (**) - 99% (95%) confidence interval does not include zero.

an indicator of the average degree of consumer inertia and compute the entry rate in each product category.

The average degree of consumer inertia in a product category is computed using my micro estimates of consumer inertia by age together with the age composition of customers. I compute the share of purchases by households of different ages in every product category across the entire sample (2004–2015). Let the share of purchases by age group a in product category j be denoted by s_{aj}. The consumer inertia index is given by

$$\overline{(1-\theta)}_j = \sum_a s_{aj}\left(1-\hat{\theta}_a\right) \ , \tag{24}$$

where $\overline{(1-\theta)}_j$ is the degree of consumer inertia in product category j, and $\hat{\theta}_a$ is the average estimated re-optimization probability for age category a.

Table 5: Consumer Inertia and Firm Entry Rate Across Product Categories

	(1)	(2)
Consumer inertia index	-1.45***	-1.17**
	(0.49)	(0.50)
Department f.e.	✓	✓
Weighted	✗	✓
Obs.	89	89

Notes: The table presents the cross-product-category regressions. The dependent variable is the entry rate at the product-category level. Standard errors in brackets. If weighted, then weights are equal to the number of operating firms in a product category. *** (**) {*} - 99% (95%) {90%} confidence interval does not include zero.

To compute the annual firm entry rate, I divide the number of firms who sell their product in a product category for the first time by the number of firms who sell products in that category during that year. The firm entry rate used in the analysis is the average annual firm entry rate between 2006–2015.

I regress the firm entry rate on the consumer inertia index, controlling for department fixed effects. I present both non-weighted results as well as weighted by the number of firms in the product category. Naturally, entry rates are more volatile in categories with a lower number of firms. So I weight observations to achieve a precise estimate by correcting for hetroskedasticity.[32] Table 5 presents the regression results.

The benchmark specification is column (2), in which product categories are weighted by the number of operating firms. A one percentage point increase in consumer inertia leads to a decline of 1.17 percentage points in the firm entry rate. If we take the regression specification at face value, the 1.5 percentage points decline re-optimization probability between the period 1987–1991 and 2015–2019 accounts for 1.7 percentage points decline in the entry rate. The entry rate between these two periods declined by 3.2 percentage points. So this rough back-of-the-envelope calculation yields a similar prediction the state-level analysis–the aging-induced rise in consumer inertia accounts for 54% of the observed decline in the entry rate.

5.3 Model Implications of Rising Consumer Inertia

The two empirical results in the previous subsections suggest that the aging-induced rise in consumer inertia is both qualitatively and quantitatively important in accounting for the declining share of young firms in the U.S. economy. But the effect of consumer inertia on the macroeconomy is not static. Both the markup and the entry decision of firms take into account market conditions

[32]The regression excludes outlier categories, defined as the top and bottom 5% of product categories according to their entry rates.

in the future. So extrapolating the regression estimates to understand the contribution of consumer inertia to macroeconomic phenomena over time is bound to be inaccurate. In this section, I use the dynamic model to assess the implications of the aging-induced rise in consumer inertia.

I consider an unexpected deterministic shock that moves the level of consumer inertia from its initial steady state value according to the constructed time series of consumer inertia presented in Figure 7. I assume that the re-optimization probability remains fixed at its 2050 level and that the model converges to the new stationary equilibrium in 2100. I study the transition dynamics from the initial stationary distribution to the new one, taking into account general equilibrium.[33] I focus on the impact of the aging-induced rise in consumer inertia on firm formation as well as on the profits share of output.

Greater consumer inertia changes the optimal markup of firms in two ways. On the one hand, greater inertia implies customers are locked in with firms for an extended period of time, so their value as intangible capital goes up. The investing motive of firms in setting markups is stronger and that incentivizes firms to lower markups. On the other hand, as firms have a larger share of their customers locked in to their products, the effective demand elasticity that they face is lower. The lower demand elasticity incentivizes firms to raise markups. That is, greater consumer inertia strengthens the harvesting motive in setting markups. The magnitude of each of the two forces, the investing and the harvesting motives, varies depending on the initial customer base of the firm. For young firms, which have a small share of locked in consumers, the investing motive dominates and they reduce markups. For old firms, which tend to be larger and have a high share of locked in consumers, the harvesting motive dominates and they raise markups.

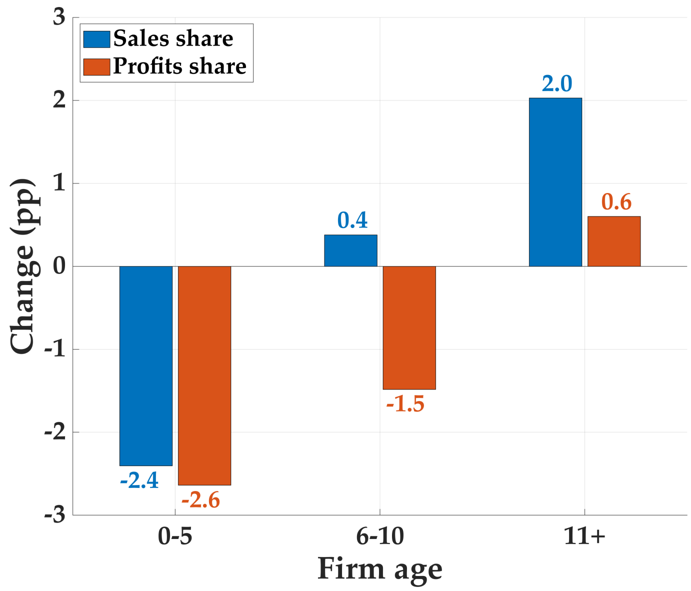
We can see the result of the forces that shape the markup of firms in Figure 9. The orange bars present the change in the profits share of sales within each age group between the initial stationary equilibrium in the late 1980s and the average profits share in the period 2015–2019.[34] The profits share of firms that are younger than 10 years old has declined by about 2 percentage points. The model predicts that firms older than 10 years old have seen a modest rise of 0.6 percentage points in the profits share.

To understand the overall impact on the aggregate profits share in the economy we also need to take into account the change in the sales distribution of firms over this time period. The change in the market share between the initial stationary distribution and the period 2015–2019 is presented by the blue bars in Figure 9. The rise in consumer inertia has reallocated consumers from young firms to older firms. This is the result of two forces. First, greater inertia makes the potential customer base young firms can attract smaller as more consumers are locked in to their existing firms. Thus reducing the measure of consumers buying from young firms. This force is attenuated by the reduction in markups of young firms. Second, the measure of entrant firms declines along the

[33] The numerical algorithm to solve the transition dynamics is presented in Appendix E.

[34] I choose the period 2015–2019 as it represents the most recent data available in the Business Dynamics Statistics dataset.

Figure 9: Change in Sales and Profits Share between 1987–1991 and 2015–2019



Notes: The blue bars in the graph present the change in the market share of firms of different ages between the initial stationary distribution and the period 2015–2019. The orange bars present the change in the profits share of sales within each age group between the two periods. All changes are presented in percentage points.

transition path. If the measure of firms were to remain unchanged, the present value of an entrant firm would be smaller than the entry cost. To maintain the free-entry condition, the measure of firms in the economy goes down.

Overall, the aggregate profits share in the economy between the initial stationary distribution and the period 2015–2019 goes up by 33 basis points. As Figure 9 suggests, the majority of the rise in aggregate profits is not coming from changes in markup at the firm-level, but due to a reallocation of sales towards large, high-markup firms. This result is consistent with a growing body of empirical evidence that the rise in the aggregate profits share and the decline in the labor share is due to reallocation towards large, high-markup firms (see De Loecker et al. 2020, Baqaee and Farhi 2020, and Kehrig and Vincent 2021).

Table 6 presents the main results of the quantitative model. It shows the difference in the aggregate profits share as well as two measures of firm formation between the initial stationary distribution and the period 2015–2019. I contrast the results obtained from the model with the observed changes in the data.

The first row in the table presents the change of the profits share in the model and in the data. Profits in the model increased from a level of 4.3% of output in the stationary equilibrium to 4.6% in the late 2010s, compared to an increase of almost 2.8 percentage points in the data. That is, according to the model, the aging-induced rise in consumer inertia accounts for 12% of the rise

Table 6: The Aggregate Implications of the Rise in Consumer Inertia

	1987–1991 to 2015–2019		
	Model	Data	Contribution
Aggregate profits share	+0.33	+2.78	12%
Emp. share of young firms	-2.43	-8.81	28%
Firm share of young firms	-1.51	-11.68	13%

Notes: This table contrasts the aggregate implications of the rise in consumer inertia in the model with the observed changes in the data. Changes are all in percentage points.

in the aggregate profits share observed in the data. The share of workers employed by young firms (0–5 years old) declined from 21.3% to 18.8%. The model accounts for 28% of the observed decline in the data. Finally, the share of young firms in the economy declined from 40.9% to 39.4%, accounting for 13% of the decline observed in the data. In summary, the model predicts that the aging-induced rise in consumer inertia accounts for 10%–30% of the twin phenomena of declining firm formation and rising profits.

6 Conclusion

In this paper, I study the role of a rise in consumer inertia as a driver of the twin phenomena of declining share of young firms and rising profits during the past three decades. Using micro data on consumer behavior, I find that young households are significantly less inertial. So the aging of the baby-boom generation has led to a rise in the aggregate level of consumer inertia. Empirical evidence using variation across product categories and temporal variation across states indicates that consumer inertia has a negative effect on firm formation.

I develop a model of entry, exit, and firm dynamics in the presence of consumer inertia. I calibrate the model so that the stationary equilibrium corresponds to the U.S. economy in the late 1980s. I then consider an unexpected and deterministic shock to the level of consumer inertia, which moves it according to observed and predicted demographic shifts in the U.S. between the late 1980s and 2050. The model implies that the rise in consumer inertia accounts for about 10%–30% of the declining share of young firms and the rising share of aggregate profits between the late 1980s and late 2010s.

While the model shows how consumer inertia can raise aggregate profits and reduce the share of young firms, several questions remain open for future research. First, what are the welfare costs of rising market power and markup dispersion resulting from an increase in consumer inertia? To answer this question, one needs to take a stand on the fundamental forces underlying consumer inertia. Traditional theory suggests that firms who set a relatively high markup are under-producing, from a social welfare perspective. Suppose, however, that consumer inertia is the result of contractual pecuniary switching costs. Then, a social planner may prefer a low-productive firm with a relatively high markup to cease operation, instead of reallocating production resources toward that firm.

Another question that remains open regards the implication of the declining share of young firms for the growth rate of the economy. Some research argues that young firms are not an important driver of economic growth based on the their small share in aggregate employment (e.g., Garcia-Macia, Hsieh and Klenow 2016). In the presence of consumer inertia, young firms can be small because it takes time to build a customer base. So the employment share of these firms cannot be used as a sufficient statistic to infer their contribution over time to economic growth. Understanding the welfare and growth implications of the rise in consumer inertia is left for future research.

A Mathematical Appendix

A.1 Static Model

Proof of Lemma 1

Lemma 1. *If the household is unattached, it chooses the product that maximizes* $-(\sigma-1)\ln p_j + \epsilon_j$ *for* $j \in (0, J)$. *That is,*

$$j_i = \arg\max_{j\in(0,J)} -(\sigma-1)\ln p_j + \epsilon_j \ . \tag{2}$$

Proof. The household maximizes $u\left(\exp\left(\frac{1}{\sigma-1}\epsilon_j\right)c_j\right)$. Since $u(\cdot)$ is an increasing function, the household's choice, conditional on not being locked-in with its previous product, solves the following problem

$$\max_{\{j,c_j\}} \exp\left(\frac{1}{\sigma-1}\epsilon_j\right)c_j \ ,$$
$$\text{s.t.} \quad c_j p_j = w \ .$$

Substituting the constraint the maximization problem can be rewritten as follows,

$$\max_j \exp\left(\frac{1}{\sigma-1}\epsilon_j\right)\frac{w}{p_j} = w\max_j \exp\left(\frac{1}{\sigma-1}\epsilon_j\right)\frac{1}{p_j} \ .$$

So the optimal product chosen is independent of the level of the wage. Taking logs and multiplying by $\sigma-1>0$, I have that

$$j_i = \arg\max_j -(\sigma-1)\ln p_j + \epsilon_j \ .$$

$\square$

Proof of Proposition 1

Proposition 1. *The customer base of a firm with price* p *is given by*

$$B = (1-\theta)B_0 + \frac{\theta}{J}\left(\frac{p}{P}\right)^{1-\sigma} \ , \tag{3}$$

where B_0 *is the initial customer base of the firm, and* P *is the price index, given by*

$$P = \left[\frac{1}{J}\int_0^J p_j^{1-\sigma}dj\right]^{\frac{1}{1-\sigma}} \ . \tag{4}$$

Proof. The first term of equation (3) is the share of existing customers who cannot re-optimize their consumption choice. It is simply a share $1-\theta$ of the initial customer base of the firm, B_0.

The second term represents the measure of new customers who actively choose the product. Overall, there is a measure θ of customers who can re-optimize their product choice. I start by considering the probability of a single consumer buying the product given the price distribution and a finite number of firms, J. I then take the limit as the number of firms and number of consumers goes to infinity.

Suppose there are J firms operating. The conditional probability of product j being chosen given that its taste shock is equal to $\bar{\epsilon}$ is

$$\begin{aligned} Pr(j_i = j|\epsilon_j = \bar{\epsilon}) &= \prod_{j' \neq j} Pr\left[-(\sigma-1)\ln p_j + \bar{\epsilon} > -(\sigma-1)\ln p_{j'} + \epsilon_{j'}\right] \\ &= \prod_{j' \neq j} Pr\left[\epsilon_{j'} < (\sigma-1)(\ln p_{j'} - \ln p_j) + \bar{\epsilon}\right] \ . \end{aligned}$$

Using the CDF of the Gumbel distribution and the independence of taste draws I obtain

$$Pr(j_i = j|\epsilon_j = \bar{\epsilon}) = \prod_{j' \neq j} e^{-e^{-\left[(\sigma-1)(\ln p_{j'} - \ln p_j)+\bar{\epsilon}\right]}} \ .$$

Using this equation, I can find the unconditional probability product j is chosen:

$$Pr(j_i = j) = \int_{-\infty}^{\infty} \left(\prod_{j' \neq j} e^{-e^{-\epsilon} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} \right) e^{-e^{-\epsilon}} e^{-\epsilon} d\epsilon$$

If $j' = j$ the term that would appear in the product is $e^{-e^{-\epsilon}}$, so I can multiply the product by $e^{e^{-\epsilon}}$ and let it include all terms:

$$\begin{aligned} Pr(j_i = j) &= \int_{-\infty}^{\infty} \left(\prod_{j'} e^{-e^{-\epsilon} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} \right) e^{e^{-\epsilon}} e^{-e^{-\epsilon}} e^{-\epsilon} d\epsilon \\ &= \int_{-\infty}^{\infty} \left(\prod_{j'} e^{-e^{-\epsilon} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} \right) e^{-\epsilon} d\epsilon \ . \end{aligned}$$

The product can be simplified as follows

$$\prod_{j'} e^{-e^{-\epsilon} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} = e^{-e^{-\epsilon} \sum_{j'} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} = e^{-Qe^{-\epsilon}} \ ,$$

where $Q = \sum_{j'} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}$. Substituting into the integral I have

$$Pr(j_i = j) = \int_{-\infty}^{\infty} e^{-Qe^{-\epsilon}} e^{-\epsilon} d\epsilon \ .$$

I use a change of variables: let $x \equiv e^{-\epsilon}$. The inverse transformation is $\epsilon = -\ln x$, and I have $\frac{d\epsilon}{dx} = -\frac{1}{x}$. So that

$$Pr(j_i = j) = \int_{0}^{\infty} e^{-xQ} dx \ .$$

Now I can integrate to obtain

$$Pr(j_i = j) = \Big|_{0}^{\infty} - \frac{1}{Q} e^{-xQ} = \frac{1}{Q} \ .$$

That is, we have that

$$Pr(j_i = j) = \frac{1}{\sum_{j'} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} .$$

Multiplying both the denominator and the numerator by $e^{-(\sigma-1)\ln p_j}$ the expression above simplifies to

$$Pr(j_i = j) = \frac{e^{-(\sigma-1)\ln p_j}}{\sum_{j'} e^{-(\sigma-1)\ln p_{j'}}} = \frac{p_j^{1-\sigma}}{\sum_{j'} p_{j'}^{1-\sigma}} .$$

Taking $J \to \infty$ we have that the density of product j being chosen by the household is

$$f(j_i = j) = \frac{p_j^{1-\sigma}}{\int_0^J p_{j'}^{1-\sigma} dj'} .$$

The result above is well known. Defining the price index P, the density of product j being chosen is

$$f(j_i = j) = \frac{1}{J}\left(\frac{p_j}{P}\right)^{1-\sigma} ,$$

where

$$P = \left(\frac{1}{J}\int_0^{J_m} p_{j'}^{1-\sigma} dj'\right)^{\frac{1}{1-\sigma}} .$$

Since the measure of households who can re-optimize their consumption choice is equal to θ, the measure of households who choose a product with price p is given by

$$\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma} .$$

This is the second term of equation (3), thus completing the proof. □

Proof of Lemma 2

Proposition 2. *The markup charged by the firm, $\mu \equiv p/w$, satisfies the following equation,*

$$\mu = \frac{\sigma}{\sigma-1} + B_0 \frac{1}{\sigma-1}\frac{1-\theta}{\theta} J \left(\frac{P}{w}\right)^{1-\sigma} \mu^{\sigma-1} . \tag{6}$$

Proof. The firm's problem, substituting labor using the linear production technology, is given by

$$\begin{aligned} V(B_0) = \max_{\{p,y\}} \quad & py - wy , \\ \text{s.t.} \quad & y = (1-\theta) B_0 w p^{-1} + \frac{\theta}{J} P^{\sigma-1} w p^{-\sigma} . \end{aligned}$$

The first order conditions are given by

$$\begin{aligned} [y] \qquad & p - w = \lambda , \\ [p] \qquad & \frac{py}{\lambda} = (1-\theta) B_0 w p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} w p^{-\sigma} . \end{aligned}$$

Dividing the second equation by y and using the demand function we have

$$\frac{p}{\lambda} = \frac{(1-\theta)\, B_0 w p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} w p^{-\sigma}}{(1-\theta)\, B_0 w p^{-1} + \frac{\theta}{J} P^{\sigma-1} w p^{-\sigma}} \ .$$

Substituting λ from the first order condition w.r.t y, and simplifying the fraction on the RHS we have

$$\frac{p}{p-w} = \frac{(1-\theta)\, B_0 p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}}{(1-\theta)\, B_0 p^{-1} + \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}} \ .$$

Raising to the power of -1, the expression becomes

$$1 - \frac{w}{p} = \frac{(1-\theta)\, B_0 p^{-1} + \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}}{(1-\theta)\, B_0 p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}} \ ,$$

so that

$$\frac{w}{p} = 1 - \frac{(1-\theta)\, B_0 p^{-1} + \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}}{(1-\theta)\, B_0 p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}} \ .$$

The expression in the RHS can be simplified so that

$$\frac{w}{p} = \frac{(\sigma-1) \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}}{(1-\theta)\, B_0 p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}} \ .$$

Raising again to the power of -1 and defining the markup $\mu = \frac{p}{w}$, we have

$$\mu = \frac{(1-\theta)\, B_0 p^{-1} + \sigma \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}}{(\sigma-1) \frac{\theta}{J} P^{\sigma-1} p^{-\sigma}} \ .$$

Finally the expression on the RHS simplifies to

$$\mu = \frac{\sigma}{\sigma-1} + B_0 \frac{1}{\sigma-1} \frac{1-\theta}{\theta} J \left(\frac{P}{w}\right)^{1-\sigma} \mu^{\sigma-1} \ .$$

□

Proof of Proposition 3

Proposition 3. *There exists a unique equilibrium. In addition, there is a cutoff $\bar{f}_e$ such that if and only if $f_e < \bar{f}_e$ then the measure of entrants is strictly positive.*

Proof. I start by assuming that the entry condition holds with equality. There are four endogenous variables, $\{\mu_E, \mu_I, J, P\}$, that need to satisfy the following four equilibrium equations,

$$\begin{aligned}
&[\mu_E] \qquad \mu_E = \frac{\sigma}{\sigma-1} \ , \\
&[\mu_I] \qquad \mu_I = \frac{\sigma}{\sigma-1} + \frac{1}{\sigma-1} \frac{1-\theta}{\theta} J P^{1-\sigma} \mu_I^{\sigma-1} \ , \\
&[J] \qquad f_e = \frac{1}{\sigma-1} \frac{\theta}{J} P^{\sigma-1} \mu_E^{-\sigma} \ , \\
&[P] \qquad P^{1-\sigma} = \frac{1}{J} \int_0^J \mu_j^{1-\sigma} dj \ .
\end{aligned}$$

The last equation can be simplified to

$$JP^{1-\sigma} = \left[\mu_I^{1-\sigma} + (J-1)\mu_E^{1-\sigma}\right] .$$

Using the free entry condition, $[J]$, together with the expression for μ_E we have that

$$JP^{1-\sigma} = \frac{\theta}{\sigma f_e}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}$$

Plugging into equation $[\mu_I]$ I obtain

$$\mu_I = \frac{\sigma}{\sigma-1} + (1-\theta)\frac{1}{(\sigma-1)\sigma}\frac{1}{f_e}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\mu_I^{\sigma-1} .$$

Multiplying by $\mu_I^{1-\sigma}$ we have

$$\mu_I^{2-\sigma} = \mu_E\mu_I^{1-\sigma} + (1-\theta)\frac{1}{(\sigma-1)\sigma}\frac{1}{f_e}\mu_E^{1-\sigma} . \tag{25}$$

This is an equation that uniquely determines μ_I. The LHS is increasing in μ_I and the RHS is decreasing in it. So there exists a unique equilibrium for μ_I. Note also that $\mu_I > \mu_E = \frac{\sigma}{\sigma-1}$, as when $\mu_I = \mu_E$ we have that the RHS is larger than the LHS.

The equation that determines J is given by

$$\left[\mu_I^{1-\sigma} + (J-1)\mu_E^{1-\sigma}\right] = \theta\frac{1}{(\sigma-1)f_e}\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} .$$

We can rearrange it as follows,

$$(J-1)\mu_E^{1-\sigma} = \theta\frac{1}{(\sigma-1)f_e}\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} - \mu_I^{1-\sigma} .$$

Note that if f_e increases, then μ_I goes down from the implicit equation that determines μ_I. So the LHS increases and RHS decreases. As a result, the equilibrium level of J must decrease. Let $\bar{f}_e$ be the value that makes the resulting $J = 1$. If $f_e < \bar{f}_e$, the measure of entrants is positive as $J > 1$ and we obtained the equilibrium allocations. P is obtained from equation (4).

If $f_e \geq \bar{f}_e$, then there are no entrants in equilibrium. In that case, $P = \mu_I$ and $J = 1$. The equation that pins down μ_I is

$$\mu_I = \frac{\sigma}{\sigma-1} + \frac{1}{\sigma-1}\frac{1-\theta}{\theta} .$$

Thus, also in the case where $f_e \geq \bar{f}_e$ the equilibrium is unique. □

Proof of Proposition 4

Proposition 4. *[Comparative statics] Consider two economies, A and B. Suppose the two economies differ by only one structural parameter. The following comparative statics hold:*

Parameter	Entrants' markup	Incumbents' markup	Profits share	Entry rate
$\theta_A < \theta_B$	$\mu_E^A = \mu_E^B$	$\mu_I^A > \mu_I^B$	$\Pi_A > \Pi_B$	$E_A < E_B$
$f_e^A > f_e^B$	$\mu_E^A = \mu_E^B$	$\mu_I^A < \mu_I^B$	$\Pi_A > \Pi_B$	$E_A < E_B$

Proof. The equation that determines incumbents markup is (25):

$$\mu_I^{2-\sigma} = \mu_E \mu_I^{1-\sigma} + (1-\theta)\frac{1}{(\sigma-1)\sigma}\frac{1}{f_e}\mu_E^{1-\sigma} \; .$$

To see what happens to the measure of entrants we look at J which satisfies,

$$\mu_I^{1-\sigma} + (J-1)\mu_E^{1-\sigma} = \theta\frac{1}{\sigma-1}\frac{1}{f_e}\mu_E^{1-\sigma} \; . \tag{26}$$

Now we can turn to the two different cases:

1. If θ increases, then μ_I goes down as the RHS of (26) goes down. Rearranging equation (26) I obtain,

   $$(J-1)\mu_E^{1-\sigma} = \theta\frac{1}{\sigma-1}\frac{1}{f_e}\mu_E^{1-\sigma} - \mu_I^{1-\sigma} \; . \tag{27}$$

   Rearranging equation (25) I get

   $$\theta\frac{1}{(\sigma-1)}\frac{1}{f_e}\mu_E^{1-\sigma} - \mu_I^{1-\sigma} = \frac{1}{(\sigma-1)}\frac{1}{f_e} - (\sigma-1)\left(\mu_I^{2-\sigma} - \mu_I^{1-\sigma}\right) \; .$$

   Since μ_I decreases, $2-\sigma > 0$, and $1-\sigma < 0$, the RHS is increasing. This implies from equation (27) that J must go up as well.

   Finally, the share of profits in the economy is equal to the profits made by incumbents as entrants make zero profits net of entry costs in equilibrium. We know that in equilibrium $JP^{1-\sigma} = \theta\frac{1}{\sigma-1}\frac{1}{f_e}\mu_E^{1-\sigma}$. So $JP^{1-\sigma}$ increased. This makes incumbents' profits go down for any given price. Similarly, a larger θ makes profits decrease for any given price. So it must be that incumbents' profits in the new equilibrium are lower than in the economy with a lower θ. Thus, the profit share in the economy is lower.

2. Consider an increase in f_e. As the RHS of equation (26) goes down, incumbents' markup in equilibrium is lower. Entrants' markup is unchanged as it only depends on σ. We see that the RHS of equation (27) goes down as f_e increases and $\mu_I^{1-\sigma}$ increases as well. As a result, the measure of firms in equilibrium, J is lower. Recall that $JP^{1-\sigma} = \frac{\theta}{\sigma f_e}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}$. So $JP^{1-\sigma}$ goes down as f_e goes up. Looking at the incumbent's problem, we see that the quantity sold for any given price is now higher. So it must be that incumbents' profits go up. That is, the share of profits in the economy goes up.

□

A.2 Dynamic Model

Proof of Lemma 2

Lemma 2. *If the household is not locked into a product, it chooses the firm which maximizes*

$$j_m \equiv \arg \max_{j \in (0, J_m)} -(\sigma - 1) \ln p_j + \epsilon_j \ .$$

Proof. The household maximizes the taste-adjusted consumption, $\exp\left(\frac{1}{\sigma-1}\epsilon_{j_m}\right) c_{j_m}$. For any given level of expenditure on product type m, E_m, the taste-adjusted consumption level obtained by choosing product j is given by

$$e^{\frac{1}{\sigma-1}\epsilon_j} \frac{E_m}{p_j} \ .$$

By taking logs and multiplying by $(\sigma - 1)$ we obtain that the product which maximizes the taste-adjusted consumption level is the one which maximizes

$$-(\sigma - 1) \ln p_j + \epsilon_j \ .$$

□

Proof of Proposition 5

Proposition 5. *The customer base of a firm with price* p *is given by*

$$B' = (1 - \theta)B + \frac{\theta}{J} \left(\frac{p}{P_m}\right)^{1-\sigma} \ , \tag{13}$$

where B *is the customer base it starts the period with,* θ *is the measure of unattached households, and* P_m *is the price index of the product type, given by*

$$P_m = \left[\frac{1}{J} \int_j p_j^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \ . \tag{14}$$

Proof. The first term of equation (13) is the share of existing customers who cannot re-optimize their consumption choice. It is simply a share $1 - \theta$ of the existing customer base of the firm, B.

The second term represents the measure of new customers of the firm. Overall there is a measure θ of consumers who can re-optimize their choice in product type m. The remainder of this proof proceeds in a similar fashion to the proof of Proposition 1. I want to show that conditional on re-optimizing, the density of households who choose a firm with price p is given by

$$\frac{1}{J} \left(\frac{p}{P_m}\right)^{1-\sigma} \ .$$

Obtaining this, I can multiply this density by the measure of re-optimizing households to obtain the second term of equation (13).

Suppose there are J firms in a product module. Below I show the well-known result about the probability of a household choosing firm j given prices. Using Lemma 2 we know that the household chooses the firm that maximizes $-(\sigma-1)\ln p_j + \epsilon_j$. The conditional probability of firm j being chosen by household i given that the household's taste shock towards the firm is equal to $\bar{\epsilon}$ is

$$\begin{aligned} Pr(j_m = j|\epsilon_i = \bar{\epsilon}) &= \prod_{j' \neq j} Pr\left[-(\sigma-1)\ln p_j + \bar{\epsilon} > -(\sigma-1)\ln p_{j'} + \epsilon_{j'}\right] \\ &= \prod_{j' \neq j} Pr\left[\epsilon_{j'} < (\sigma-1)(\ln p_{j'} - \ln p_j) + \bar{\epsilon}\right] \ . \end{aligned}$$

Using the CDF of the Gumbel distribution with location parameter $-\ln J$ and unit scale as well as the independence of taste draws I obtain[35]

$$Pr(j_m = j|\epsilon_i = \bar{\epsilon}) = \prod_{j' \neq j} e^{-e^{-\left[(\sigma-1)(\ln p_{j'} - \ln p_j) + \bar{\epsilon} + \ln J\right]}} \ .$$

If $j' = j$ the term that would appear in the product is $e^{-e^{-\epsilon - \ln J}}$, so

$$\left(\prod_{j' \neq j} e^{-e^{-\epsilon - \ln J} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}}\right) = \left(\prod_{j'} e^{-e^{-\epsilon - \ln J} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}}\right) e^{e^{-\epsilon - \ln J}} \ .$$

Note that we can rearrange the last term above so that we have,

$$Pr(j_m = j|\epsilon_i = \bar{\epsilon}) = \left(e^{-e^{-\epsilon} \frac{1}{J} \sum_{j'} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}}\right) e^{e^{-\epsilon - \ln J}} = e^{-Qe^{-\epsilon}} e^{e^{-\epsilon - \ln J}} \ , \tag{28}$$

where I define $Q \equiv \frac{1}{J} \sum_{j'} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}$.

Using the equation above, I can find the unconditional probability product j is chosen using the Gumbel distribution of taste shocks:

$$Pr(j_m = j) = \int_{-\infty}^{\infty} e^{-Qe^{-\epsilon}} e^{e^{-\epsilon - \ln J}} e^{-e^{-\epsilon - \ln J}} e^{-\epsilon - \ln J} d\epsilon \ ,$$

which simplifies to

$$Pr(j_m = j) = \frac{1}{J} \int_{-\infty}^{\infty} e^{-Qe^{-\epsilon}} e^{-\epsilon} d\epsilon \ .$$

I use a change of variables: let $x \equiv e^{-\epsilon}$. The inverse transformation is $\epsilon = -\ln x$, and I have $\frac{d\epsilon}{dx} = -\frac{1}{x}$. So that

$$Pr(j_m = j) = \frac{1}{J} \int_{0}^{\infty} e^{-xQ} dx \ .$$

Now I can easily integrate to obtain

$$Pr(j_m = j) = \frac{1}{J} \Big|_{0}^{\infty} - \frac{1}{Q} e^{-xQ} = \frac{1}{J} \frac{1}{Q} \ . \tag{29}$$

[35] The location parameter is actually irrelevant for this result as all taste shocks have the same location parameter.

That is, we have that

$$Pr(j_m = j) = \frac{1}{\sum_{j'} e^{-(\sigma-1)(\ln p_{j'} - \ln p_j)}} \ .$$

Multiplying both the denominator and the numerator by $e^{-(\sigma-1)\ln p_j}$ we have

$$Pr(j_m = j) = \frac{e^{-(\sigma-1)\ln p_j}}{\sum_{j'} e^{-(\sigma-1)\ln p_{j'}}} = \frac{p_j^{1-\sigma}}{\sum_{j'} p_{j'}^{1-\sigma}} \ .$$

Denote $P_m \equiv= \left[\frac{1}{J}\sum_{j'} p_{j'}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$. So we have that the probability of a single consumer to choose product j is

$$Pr(j_m = j) = \frac{1}{J}\left(\frac{p_j}{P_m}\right)^{1-\sigma} \ .$$

I now take both the number of consumers and the number of products to infinity. With a slight abuse of notation, let J be the ratio of the measure of consumers to the measure of products. The density of consumers who choose product j is given by

$$f(j_m = j) = \frac{1}{J}\left(\frac{p_j}{P_m}\right)^{1-\sigma} \ .$$

So if the measure of firms is J and the measure of consumers is 1, then the measure of consumers buying from firm j is $f(j_m = j)$ and we have that $\int_0^J f(j_m = j)dj = 1$. □

Proof of Lemma 3

Lemma 3. *The demand of a household for the chosen product in product type m is given by*

$$c^i_{j_m} = \exp\left(\frac{\eta-1}{\sigma-1}\epsilon^i_{j_m}\right)\left(\frac{p_{j_m}}{P}\right)^{-\eta} C \ ,$$

where p_{j_m} is the price of the chosen product, $\epsilon^i_{j_m}$ is the idiosyncratic taste shock of the household for this product, and P is the aggregate price index given by

$$P = \left[\int_0^1 \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right)(p_{j_m})^{1-\eta}\, dm\right]^{\frac{1}{1-\eta}} \ .$$

Proof. To show this, we start by considering the cost minimization problem of the household. Here, I take as given the joint distribution of prices and taste shocks of chosen products. When deriving the demand faced by the firm, I shall derive this joint distribution explicitly. The cost minimization problem of the household is

$$\min_{\{c_m\}_{m\in(0,1)}} \int_0^1 p_{j_m} c_m dm$$

$$\text{s.t.} \quad \left[\int_0^1 \exp\left(\frac{\eta-1}{\eta(\sigma-1)}\epsilon_{j_m}\right)(c_m)^{\frac{\eta-1}{\eta}}\, dm\right]^{\frac{\eta}{\eta-1}} \geq \bar{C} \ .$$

Taking first order conditions we have

$$p_{j_m} = \lambda \bar{C}^{\frac{1}{\eta}} \exp\left(\frac{\eta - 1}{\eta(\sigma - 1)} \epsilon_{j_m}\right) (c_m)^{-\frac{1}{\eta}} \ .$$

To find the expression for the multiplier λ we first rearrange the equation above as follows. We raise it to the power of $(1 - \eta)$ and rearrange to obtain

$$\exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_{j_m}\right) (p_{j_m})^{1-\eta} = \lambda^{1-\eta} \bar{C}^{-\frac{\eta-1}{\eta}} \exp\left(\frac{\eta - 1}{\eta(\sigma - 1)} \epsilon_{j_m}\right) (c_m)^{\frac{\eta-1}{\eta}} \ .$$

Integrating over all product modules, and simplifying using the formula for aggregate consumption we have

$$\int_0^1 \exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_{j_m}\right) (p_{j_m})^{1-\eta} \, dm = \lambda^{1-\eta} \ ,$$

so that

$$\lambda = \left[\int_0^1 \exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_{j_m}\right) (p_{j_m})^{1-\eta} \, dm\right]^{\frac{1}{1-\eta}} \ .$$

Notice that since λ is the multiplier of the cost minimization problem, it is also the natural price index. We can observe the problem is homothetic by noticing no consumption level enters the equation above. So I define

$$P \equiv \left[\int_0^1 \exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_{j_m}\right) (p_{j_m})^{1-\eta} \, dm\right]^{\frac{1}{1-\eta}} \ .$$

Plugging into the first order condition I obtain the household's demand for the chosen firm from product module m,

$$c_m = \exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon^i_{j_m}\right) \left(\frac{p_{j_m}}{P}\right)^{-\eta} \bar{C} \ .$$

□

Proof of Lemma 4

Lemma 4. *The average adjusted taste shock of a household that freely chooses to consume a product with price p is given by,*

$$\mathbb{E}\left[\exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_j\right) \middle| j_m = j, p_j = \bar{p}\right] = \left(\frac{p}{P_m}\right)^{\eta-1} \Gamma\left(1 - \frac{\eta - 1}{\sigma - 1}\right) \ ,$$

where $\Gamma(\cdot)$ is the Gamma function.

Proof. Let $f_\epsilon\left(\epsilon_j | \, j_m = j, p_j = p\right)$ denote the conditional probability density function of the taste shock ϵ_j given that the price of product j is p and that it was freely chosen by the household. So that,

$$\mathbb{E}\left[\exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_j\right) \middle| j_m = j, p_j = p\right] = \int_0^\infty \exp\left(\frac{\eta - 1}{\sigma - 1} \epsilon_j\right) f_\epsilon\left(\epsilon_j | \, j_m = j, p_j = p\right) d\epsilon_j$$

This density function can be rewritten as follows,

$$f_\epsilon\left(\bar{\epsilon}_j \mid j_m = j, p_j = p\right) = \frac{f_{\epsilon,\,\text{chosen}}\left(\bar{\epsilon}_j, j_m = j \mid p_j = p\right)}{Pr\left(j_m = j \mid p_j = p\right)}$$
$$= \frac{Pr\left(j_m = j \mid \epsilon_j = \bar{\epsilon}_j, p_j = p\right)}{Pr\left(j_m = j \mid p_j = p\right)} e^{-(\bar{\epsilon}_j + \ln J)} e^{-e^{-(\bar{\epsilon}_j + \ln J)}} ,$$

where the last equality uses that the draw of a taste shock is the Gumbel distribution with location parameter $-\ln J$, which is independent of the firm's price. From the proof of Lemma 2 I use equations (28) and (29) to have that,

$$Pr\left(j_m = j \mid \epsilon_j = \bar{\epsilon}_j, p_j = p\right) = e^{-Qe^{-\bar{\epsilon}_j}} e^{e^{-\bar{\epsilon}_j - \ln J}} ,$$
$$Pr\left(j_m = j \mid p_j = p\right) = \frac{1}{JQ} ,$$

where $Q \equiv \frac{1}{J}\int_0^J e^{-(\sigma-1)(\ln p_j - \ln p)} dj$. Combining these together with the PDF of the Gumbel distribution I obtain

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\bigg| j_m = j, p_j = p\right] = JQ \int_{-\infty}^{\infty} e^{\frac{\eta-1}{\sigma-1}\epsilon} e^{-Qe^{-\epsilon}} e^{e^{-\epsilon - \ln J}} e^{-e^{-(\epsilon + \ln J)}} e^{-(\epsilon + \ln J)} d\epsilon ,$$

Canceling out terms I have

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\bigg| j_m = j, p_j = p\right] = Q \int_{-\infty}^{\infty} e^{\frac{\eta-1}{\sigma-1}\epsilon} e^{-Qe^{-\epsilon}} e^{-\epsilon} d\epsilon ,$$

Using a change of variables $x = Qe^{-\epsilon}$, so that $\epsilon = \ln Q - \ln x$ and $\frac{d\epsilon}{dx} = -\frac{1}{x}$. The integral can then be written as

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\bigg| j_m = j, p_j = p\right] = Q \int_0^{\infty} \left(\frac{x}{Q}\right)^{-\frac{\eta-1}{\sigma-1}} e^{-x} Q^{-1} dx ,$$

This can be simplified to

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\bigg| j_m = j, p_j = p\right] = Q^{\frac{\eta-1}{\sigma-1}} \int_0^{\infty} x^{-\frac{\eta-1}{\sigma-1}} e^{-x} dx ,$$

This is an Euler integral of the second kind. We have that

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\bigg| j_m = j, p_j = p\right] = Q^{\frac{\eta-1}{\sigma-1}} \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right) ,$$

where I've used the definition of the Gamma function $\Gamma(z) = \int_0^\infty x^{z-1} e^{-x} dx$.

Using the equality $Q = \left(\frac{p}{P_m}\right)^{\sigma-1}$ we have

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j\right)\bigg| j_m = j, p_j = p\right] = \left(\frac{p}{P_m}\right)^{\eta-1} \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right) .$$

□

Proof of Lemma 5

Lemma 5. *The aggregate price index P is given by,*

$$P = \Gamma\left(1 - \frac{\eta - 1}{\sigma - 1}\right)^{\frac{1}{1-\eta}} \left[\theta P_m^{1-\eta} + (1-\theta) P_B^{1-\eta}\right]^{\frac{1}{1-\eta}} ,$$

where P_m is the product type price index defined above, and P_B is the initial-customer-base-weighted price index given by

$$P_B = \left[\int_0^J B_j p_j^{1-\eta} dj\right]^{\frac{1}{1-\eta}} .$$

Proof. Recall that the definition of the aggregate price index from Lemma 3 is

$$P = \left[\int_0^1 \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right) (p_{j_m})^{1-\eta}\, dm\right]^{\frac{1}{1-\eta}} .$$

Since all product modules are symmetric, the aggregate price index is given by

$$P = \left\{\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right) p_{j_m}^{1-\eta}\right]\right\}^{\frac{1}{1-\eta}} .$$

The expectation term can be split into the fraction of products the household is locked-in with and the ones it chooses freely:

$$P = \left\{(1-\theta)\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right) p_{j_m}^{1-\eta}\middle|\, \text{lock-in}\right] + \theta\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right) p_{j_m}^{1-\eta}\middle|\, \text{unattached}\right]\right\}^{\frac{1}{1-\eta}} . \tag{30}$$

Using the Law of Iterated Expectations together with Lemma 4 I have that

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right) p_{j_m}^{1-\eta}\middle|\, \text{unattached}\right] = \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right) P_m^{1-\eta} .$$

Using the assumption on the taste shock towards locked-in products I have that

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\epsilon_{j_m}\right) p_{j_m}^{1-\eta}\middle|\, \text{lock-in}\right] = \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right) \mathbb{E}\left[p_{j_m}^{1-\eta}\middle|\, \text{lock-in}\right] .$$

I define the last term in the equation to be equal to $P_B^{1-\eta}$. That term is given by,

$$P_B \equiv \mathbb{E}\left[p_{j_m}^{1-\eta}\middle|\, \text{lock-in}\right]^{\frac{1}{1-\eta}} = \left[\int_0^J B_j^L p_j dj\right]^{\frac{1}{1-\eta}} .$$

The subscript B stands for the the fact the P_B is a power mean of product prices weighted by the initial customer-base of each product, B. Plugging in equation (30) I obtain the desired result

$$P = \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right)^{\frac{1}{1-\eta}} \left[(1-\theta) P_B^{1-\eta} + \theta P_m^{1-\eta}\right]^{\frac{1}{1-\eta}} .$$

□

Proof of Proposition 6

Proposition 6. *The demand function faced by each firm is given by*

$$y_j = \left[(1-\theta)Bp_j^{-\eta} + \frac{\theta}{M}P_m^{\sigma-\eta}p_j^{-\sigma}\right]\frac{1}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}(w+\Pi)\ . \tag{15}$$

Proof. Using Lemma 3 we can write the demand of firm j as follows,

$$y_j = \int_{i:j_m^i=j} \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j^i\right)\left(\frac{p_j}{P}\right)^{-\eta} C di\ ,$$

where we integrate over the set of customers who chose firm j out of all firms. Since there is no price discrimination we have

$$y_j = \left[\int_{i:j_m^i=j} \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j^i\right) di\right]\left(\frac{p_j}{P}\right)^{-\eta} C\ .$$

We can split customers who chose firm j to ones who actively chose the it and ones who inertially were locked-in with it. So we have

$$y_j = \left[\int_{i:j_m^i=j,\text{lock-in}} \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j^i\right) di + \int_{i:j_m^i=j,\text{unattached}} \exp\left(\frac{\eta-1}{\sigma-1}\epsilon_j^i\right) di\right]\left(\frac{p_j}{P}\right)^{-\eta} C\ .$$

Rewriting this in terms of expectations we have

$$y_j = \left\{(1-\theta)B\mathbb{E}\left[e^{\frac{\eta-1}{\sigma-1}\epsilon_j^i}\middle| j_m^i = j, \text{lock-in}\right] + (B'-(1-\theta)B)\mathbb{E}\left[e^{\frac{\eta-1}{\sigma-1}\epsilon_j^i}\middle| j_m^i = j, \text{unattached}\right]\right\}\left(\tfrac{p_j}{P}\right)^{-\eta} C\ ,$$

where we have used that the measure of inertial customers is equal to $(1-\theta)B$ and the measure of unattached customers equals $B' - (1-\theta)B$.

For inertial households the taste shock is assumed to satisfy $e^{\frac{\eta-1}{\sigma-1}\epsilon_j^i} = \Gamma\left(1 - \frac{\eta-1}{\sigma-1}\right)$. Using Lemma 4 we have that for active households $e^{\frac{\eta-1}{\sigma-1}\epsilon_j^i} = \left(\frac{p}{P_m}\right)^{\eta-1}\Gamma\left(1-\frac{\eta-1}{\sigma-1}\right)$. So we can write the demand for firm j as follows,

$$y_j = \left[(1-\theta)B\Gamma\left(1-\frac{\eta-1}{\sigma-1}\right) + (B'-(1-\theta)B)\left(\frac{p}{P_m}\right)^{\eta-1}\Gamma\left(1-\frac{\eta-1}{\sigma-1}\right)\right]\left(\frac{p_j}{P}\right)^{-\eta} C\ .$$

Using equation (13) we can rewrite the equation above as follows,

$$y_j = \left[(1-\theta)B + \frac{\theta}{M}\left(\frac{p_j}{P_m}\right)^{\eta-\sigma}\right]\Gamma\left(1-\frac{\eta-1}{\sigma-1}\right)\left(\frac{p_j}{P}\right)^{-\eta} C\ .$$

Finally, using the expression for the aggregate price level P and that $C = w/P$, the Γ function cancels out and we have:

$$y_j = \left[(1-\theta)Bp_j^{-\eta} + \frac{\theta}{M}{P_m}^{\sigma-\eta}p_j^{-\sigma}\right]\frac{1}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}w\ .$$

□

Proof of Proposition 7

Proposition 7. *The markup of a firm with customer base B and productivity a is implicitly defined by the following equation,*

$$\mu = \frac{\sigma}{\sigma-1} + \underbrace{\alpha\left(\frac{\eta}{\eta-1} - \frac{\sigma}{\sigma-1}\right)}_{\text{harvesting motive}} \underbrace{- (1-\alpha)\sum_{\tau=1}^{\infty}\left(\beta(1-\theta)\right)^{\tau}\mathbb{E}\left[\mathbb{1}\left(\overline{T} > \tau\right)\gamma_{+\tau}\right]}_{\text{investing motive}}, \tag{17}$$

where $\overline{T}$ is the stopping time indicating that the firm exits the economy in $\overline{T}$ periods. $\mathbb{1}\left(\overline{T} > \tau\right)$ is an indicator that takes the value 1 if the firm still operates τ periods ahead. The variables α and γ_{τ} are given by

$$\alpha = \frac{(\eta-1)(1-\theta)B}{(\eta-1)(1-\theta)B + (\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{\eta-\sigma}}, \qquad \gamma_{+\tau} = \frac{w_{+\tau}}{a_{+\tau}}\frac{a}{w}\left(\frac{p_{+\tau}}{P_{+\tau}}\right)^{-\eta}\left(\frac{p}{P}\right)^{\eta}\left(\mu_{+\tau}-1\right),$$

where a variable with subscript $+\tau$ corresponds to the variable τ periods ahead.

Proof. The firm's problem is given by

$$\begin{aligned} V(B,a) = \max_{\{p,y,B'\}} \; & py - \frac{w}{e^{a}}y + \frac{1}{1+r}\mathbb{E}\left[\max\left\{V\left(B',a'\right) - x_o w, 0\right\}\right] \\ \text{s.t.} \quad & B' = (1-\theta)B + \frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma}, \\ & y = \left[(1-\theta)Bp^{-\eta} + \frac{\theta}{J}{P_m}^{\sigma-\eta}p^{-\sigma}\right]\frac{1}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}\left(w+\Pi\right). \end{aligned}$$

Denote the Lagrange multiplier on the first constraint by λ_B and on the second by λ_y. Taking first order and envelope conditions, I have

$$[y]: \qquad \lambda_y = p - \frac{w}{e^{a}}, \tag{31}$$

$$[p]: \qquad py = \frac{\eta(1-\theta)Bp^{-\eta} + \sigma\frac{\theta}{J}{P_m}^{\sigma-\eta}p^{-\sigma}}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}\left(w+\Pi\right)\lambda_y + (\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma}\lambda_B, \tag{32}$$

$$[B']: \qquad \lambda_B = \frac{1}{1+r}\mathbb{E}\left[V_B(B',a')\mathbb{1}\left(V(B',a') > x_o'w'\right)\right], \tag{33}$$

$$[B]: \qquad V_B(B,a) = (1-\theta)\lambda_B + \frac{(1-\theta)p^{-\eta}}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}\left(w+\Pi\right)\lambda_y \tag{34}$$

Iterating equations (33) and (34) and using $\frac{1}{1+r} = \beta\frac{w+\Pi}{w'+\Pi'}\frac{P'}{P}$, I get

$$\lambda_B = \frac{w+\Pi}{\left(\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}\right)^{\frac{1}{1-\eta}}}\sum_{\tau=1}^{\infty}\beta^{\tau}(1-\theta)^{\tau}\mathbb{E}\left[\mathbb{1}\left(T \geq \tau\right)\left(\frac{p_{+\tau}}{\tilde{P}_{+\tau}}\right)^{-\eta}\left(p_{+\tau} - e^{-a_{+\tau}}w_{+\tau}\right)\right], \tag{35}$$

where $\mathbb{1}(T > \tau)$ is an indicator that takes the value 1 if the firm is still operating τ periods in the future. The $+\tau$ subscript corresponds to variables τ periods ahead. $\tilde{P} \equiv \left(\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}\right)^{\frac{1}{1-\eta}}$. Combining equations (31) and (32) together with the demand function and rearranging, I obtain

$$\mu = \frac{\eta(1-\theta)B \quad + \quad \sigma\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{\eta-\sigma}}{(\eta-1)(1-\theta)B + (\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{\eta-\sigma}} - \frac{(\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma}p^{\eta}}{(\eta-1)(1-\theta)B + (\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{\eta-\sigma}}\frac{e^{a}}{w}\frac{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}{(w+\Pi)}\lambda_B, \tag{36}$$

where $\mu = \frac{p}{w/e^a}$ is the firm's markup. Using the expression for λ_B from equations (33) and (35), I obtain

$$\mu = \tfrac{\sigma}{\sigma-1} + \alpha \left(\tfrac{\eta}{\eta-1} - \tfrac{\sigma}{\sigma-1} \right) - (1-\alpha) \textstyle\sum_{\tau=1}^{\infty} \beta^{\tau} (1-\theta)^{\tau} \mathbb{E} \left[\mathbb{1} \left(\overline{T} > \tau \right) \gamma{+\tau} \right] \ , \tag{37}$$

where

$$\alpha = \frac{(\eta-1)(1-\theta)B}{(\eta-1)(1-\theta)B + (\sigma-1)\frac{\theta}{J}\left(\frac{p}{P_m}\right)^{\eta-\sigma}} \ ,$$

and

$$\gamma_{+\tau} = \frac{w_{+\tau}}{w} \frac{e^a}{e^{a_{+\tau}}} \left(\frac{p_{+\tau}}{\tilde{P}_{+\tau}} \right)^{-\eta} \left(\frac{p}{\tilde{P}} \right)^{\eta} (\mu_{+\tau} - 1) \ .$$

$\square$

B Other Results

B.1 Comparison to Other Structural Models of Consumer Inertia

In this section, I highlight the advantages of the structural model of consumer inertia proposed in this paper relative to other prominent structural models of consumer inertia. I focus on three examples: a model of switching costs, a model with additive deep habits, and a model with multiplicative deep habits.

The common way of modeling consumer inertia in the industrial organization and marketing literatures is by introducing switching costs. Such switching costs stand for learning costs, transaction costs, psychological and emotional costs, incomplete information, or contractual costs imposed by firms. While switching costs can be introduced in a variety of ways, the approach the literature often takes is assuming a multinomial logit discrete choice problem of the following form. The indirect utility of household i from choosing product j when its price is p_j is given by,

$$U_{ij} = -(\sigma - 1)\ln p_j + (1-\theta)\mathbb{1}\left[j_i^0 = j\right] + \epsilon_j^i \ , \tag{38}$$

where j_i^0 is the previous consumption choice of household i. $\mathbb{1}\left[j_i^0 = j\right]$ takes the value one if the product is the same as the one consumed in the previous period, and zero otherwise. I choose the notation above so that the interpretation of parameters is similar to the stylized model. The term $(1-\theta) > 0$ governs the size of switching costs in the market. Note that, for simplicity, I assumed that products only differ by their price, and not along other characteristics.

The multinomial logit switching costs specification is not suitable to study the behavior of firms in general equilibrium for two reasons. First, as I show below, if firms are atomistic, this specification implies that the switching costs, regardless of their size, do not alter the firm's problem. In particular, the firm's problem does not depend on its initial customer base. Second, this specification implies that the price elasticity of demand of previous customers is the same as the demand elasticity of new customers. I discuss the implications of assuming an equal elasticity of demand for new and past customers in the final part of this section, when presenting the multiplicative deep habits model.

Suppose there is a finite number of firms operating in the market, and denote their number by J. Let the previous customers of firm j relative to the average customer base of a firm be denoted by B_j^0. Without loss of generality, I assume that the measure of consumers in the market is equal to one so that the average customer base of a firm is $\frac{1}{J}$. So the customer base of firm j is given by $\frac{1}{J}B_j^0$. Using the multinomial logit assumption that the distribution of the ϵ term follows a standard Gumbel distribution, I obtain the following law of motion for the customer base of the firm:

$$B_j = \sum_{j'} B_{j'}^0 \frac{e^{\mathbb{1}_{j=j'}(1-\theta)} p_j^{1-\sigma}}{e^{1-\theta} p_{j'}^{1-\sigma} + \sum_{z \neq j'} p_z^{1-\sigma}} \ . \tag{39}$$

We can rewrite the expression above as follows,

$$B_j = \left(\frac{p_j}{P_j}\right)^{1-\sigma} + \frac{B_0^j}{J}\left(\frac{p_j}{\tilde{P}_j}\right)^{1-\sigma} , \tag{40}$$

where

$$P_j = \left[\sum_{j' \neq j} \frac{B_{j'}^0}{J} \frac{1}{\frac{1}{J}\sum_{z \neq j'} p_z^{1-\sigma} + \frac{1}{J} e^{1-\theta} p_{j'}}\right]^{-\frac{1}{1-\sigma}} ,$$

and

$$\tilde{P}_j = \left[\frac{1}{\frac{1}{J}\sum_{z \neq j} p_z^{1-\sigma} + \frac{1}{J} e^{1-\theta} p_j}\right]^{-\frac{1}{1-\sigma}} .$$

Taking the number of firms to infinity, $J \to \infty$, I have that

$$B_j = \left(\frac{p_j}{P}\right)^{1-\sigma} , \tag{41}$$

where

$$P = \left[\frac{1}{J}\sum_{j'} p_{j'}^{1-\sigma} dj'\right]^{\frac{1}{1-\sigma}} .$$

Therefore, when the number of firms goes to infinity and firms are atomistic, the switching costs do not affect the firm's problem. This is because, relative to the measure of customers who look for a product, the measure of customers who previously bought from the firm are negligible. For this reason, the multinomial logit discrete choice problem with switching costs is not suitable to study the behavior of firms in equilibrium if firms are atomistic.

The second structural model of consumer inertia I consider is the additive deep habits model, which was introduced by Ravn et al. (2006). The utility function of the household in that model is given by

$$U = \left[\int_i \left(c_i - (1-\theta)c_i^0\right)^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} , \tag{42}$$

where c_i is the consumption of product i, and c_i^0 is the consumption of that product in the previous period. The parameter $(1-\theta) \in (0,1)$ governs the degree of consumer inertia. The resulting demand function of the firm is

$$y_j = (1-\theta)y_j^0 + \left(\frac{p_j}{P}\right)^{-\sigma} \tilde{C} , \tag{43}$$

where y_j^0 is the production of the firm in the previous period, P is the aggregate price index, and $\tilde{C}$ is an aggregate quantity that governs the level of demand. Compare the demand function (43) to the demand function in the static mode:

$$y_j = (1-\theta)B_j w p_j^{-1} + \left(\frac{p_j}{P}\right)^{-\sigma} \tilde{C} . \tag{44}$$

We see that the two models deliver a similar demand function. Indeed, the implications of my model are very similar to the additive deep habits model. Similar to my quantitative model, the additive deep habits model includes both the harvesting and investment motives. Firms have incentive to push up prices and exploit their customer base, as well as an incentive to reduce markups in order to attract customers and increase the demand for their products in future periods.

The key difference is that the demand elasticity coming from previous production is equal to 0 in the deep habits model, and is equal to 1 in my static model.[36] The fully inelastic term in equation (43) implies that the firm has an incentive to set the markup to infinity and make infinite profits. This is in contrast to my model, where the optimal markup of the firm is finite. Schmitt-Grohé and Uribe (2007) show numerically that if households can drop varieties out of their consumption basket, then firms have no incentive to deviate from the finite price that solves the first order condition of the problem.

Since the markup that maximizes the unconstrained problem of the firm in the deep habits model is equal to infinity, one cannot use a value function iteration to solve for the optimal behavior of firms. As a result, the quantitative firm dynamics literature has adopted variants of the multiplicative deep habits model, instead. Some examples include Foster et al. (2016), Moreira (2016), and Gilchrist et al. (2017).

In its simplest form, the multiplicative deep habits model, which was also introduced in Ravn et al. (2006), assumes the following utility function,

$$U = \left[\int_i \left(\frac{1}{\left(c_i^0\right)^{1-\theta}} c_i \right)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}} .$$

The resulting demand function is given by

$$y_j = \left(y_j^0\right)^{1-\theta} \left(\frac{p_j}{P}\right)^{-\sigma} \tilde{C} , \tag{45}$$

so the firm's past production, y_j^0, acts as a demand shifter. A key implication of the multiplicative deep habits model is that the elasticity of demand faced by the firm is independent of the initial customer base of the firm, or of its past production. This implies that the harvesting motive is muted by assumption. That is, the firm has no direct incentive to increase markups due to a larger customer base. In a static version of the multiplicative deep habits model, firms would set the same markup independent of the degree of consumer inertia, $1-\theta$. In a dynamic version of the model, the investment motive is present. Firms have an incentive to reduce their markups in order to increase production, and, as a result, increase the demand for their products in future periods.

The lower is the previous production of the firm, the stronger is the investment motive. This is because lowering markups reduces profits by more, if current demand is higher. Therefore, as

[36] In my quantitative model, the demand elasticity coming from locked-in customers is equal to $\eta \in (1, \sigma)$.

in my model, the markup set by firms is increasing in their past production. In my model, as well as in the additive deep habits model, this is both because the harvesting motive is increasing in past production and because the investment motive is decreasing in past production. In the multiplicative deep habits model, this is only because of the investment motive. While this distinction may not be essential when the degree of consumer inertia is constant over time, it is crucial when considering a change in consumer inertia. In the multiplicative deep habits model, an increase in consumer inertia leads to a decline in the markups set by all firms, as it strengthens the investment motive. The decline in markups is simply a result of the muted harvesting motive in the multiplicative deep habits model.

B.2 The Sophisticated Consumer and the Simple Consumer: An Equivalence Result

In this subsection, I compare the consumption behavior of a sophisticated consumer and a simple consumer in a dynamic version of the static model. The simple consumer does not internalize it can get locked into the product it chooses, while the sophisticated consumer does. The sophisticated consumer uses a log-linear approximation for the firm's pricing decision.

I find that the consumption behavior of the sophisticated consumer is identical to that of a simple consumer with a different elasticity of substitution. I derive the explicit formula for the elasticity of substitution of the simple consumer that makes the consumption decisions of the two consumers isomorphic. If the persistent coefficient in the firm's law of motion is non-negative, then the elasticity of substitution of the simple consumer is higher than that of the sophisticated consumer.

I assume the household's utility is given by

$$\sum_{t=0}^{\infty} \beta^t \ln\left(e^{\frac{1}{\sigma-1}\epsilon_{jt}} c_{jt}\right) \ ,$$

where c_{jt} is the consumption of the household at time t, and ϵ_{jt} is the idiosyncratic taste of the household towards the good consumed. As in the static model, I assume the household spends its income w on the chosen product. I assume that the wage is time-invariant so that the consumption of the chosen product is given by

$$c_{jt} = \frac{w}{p_{jt}} \ .$$

The consumption decision of the simple consumer is the same as in Section 2. The chosen product of the simple household at time 0 is given by,

$$j = \arg\max_{j'} -(\sigma-1)\ln p_{j'0} + \epsilon_{j'0} \ . \tag{46}$$

The sophisticated household, on the other hand, needs to take into account not only the current price of the good but also the expected relative price of the good in future periods. I assume that firms exit the economy with exogenous probability δ, and that the probability of re-optimization is θ. So, with probability $(1-\delta)(1-\theta)$ the household is locked into the product it purchased in the preceding period, and it can re-optimize its product choice otherwise. Since this probability is the same across all products, when choosing what product to consume, the household only needs to consider its utility given that it is locked into the product in the future. In particular, the sophisticated household is maximizing

$$j = \arg\max_{j'} \sum_{t=0}^{\infty} \beta^t (1-\delta)^t (1-\theta)^t \ln\left(e^{\frac{1}{\sigma-1}\epsilon_{j't}} \frac{w}{p_{j't}}\right) .$$

Rewriting this problem, I obtain

$$j = \arg\max_{j'} \sum_{t=0}^{\infty} \beta^t (1-\delta)^t (1-\theta)^t \left[\epsilon_{j't} + (\sigma-1)\ln(w) - (\sigma-1)\ln p_{j't}\right] .$$

And since w is independent of the chosen product, the product chosen by the sophisticated household solves

$$j = \arg\max_{j'} \sum_{t=0}^{\infty} \beta^t (1-\delta)^t (1-\theta)^t \left[\epsilon_{j't} - (\sigma-1)\ln p_{j't}\right] .$$

I assume that the taste shock for a product to which the household is locked into is constant and independent of past tastes toward that product. This assumption implies that the chosen product satisfies

$$j = \arg\max_{j'} -(\sigma-1) \sum_{t=0}^{\infty} \beta^t (1-\delta)^t (1-\theta)^t \ln p_{j't} + \epsilon_{j'0} .$$

Suppose the sophisticated household uses a log-linear rule to forecast a firm's price, so that

$$\ln p^e_{jt+1} = \rho \ln p_{jt} + (1-\rho)\ln \bar{p} ,$$

where ρ is the persistence on the relative price of the firm, and $\bar{p}$ is the price to which a firm eventually converges as it ages. Substituting into the expression that pins down the chose product, I obtain

$$j = \arg\max_{j'} -(\sigma-1) \sum_{t=0}^{\infty} \beta^t (1-\delta)^t (1-\theta)^t \left[\rho^t \ln p_{j'0} + (1-\rho^r)\ln \bar{p}\right] + \epsilon_{j'0} .$$

Removing the constant and simplifying the sum, I get the following expression which pins down the chosen product:

$$j = \arg\max_{j'} -\frac{\sigma-1}{1-\beta\rho(1-\delta)(1-\theta)} \ln p_{j'0} + \epsilon_{j'0} . \quad (47)$$

We see that the only difference in the consumption decision of the sophisticated consumer (47) relative to the simple consumer (46) is in the coefficient multiplying the price. Therefore, if the parameter σ of the simple consumer satisfies

$$\sigma_{\text{simple}} = 1 + \frac{\sigma_{\text{sophisticated}} - 1}{1-\beta\rho(1-\delta)(1-\theta)} ,$$

then the consumption choice of the simple consumer is identical to the consumption choice of the sophisticated consumer. Consequently, if we estimate the parameter σ to match data moments, the two models are isomorphic. The only difference is in the interpretation of the estimated coefficient.

C Estimation of Consumer Inertia Across Age Groups

Table 7: Consumer Inertia Across Age Groups – Dry Groceries Department

Product Category		**Age Group**			
		20–34	**35–49**	**50–64**	**65+**
Baby food	$\hat{\theta}$	0.66	0.34	0.45	0.67
(*obs. = 31,412*)	(s.e.)	(0.0082)	(0.0068)	(0.0078)	(0.0102)
Baking mixes	$\hat{\theta}$	0.57	0.42	0.36	0.38
(*obs. = 168,075*)	(s.e.)	(0.0048)	(0.0030)	(0.0026)	(0.0029)
Baking supplies	$\hat{\theta}$	0.57	0.26	0.23	0.28
(*obs. = 278,671*)	(s.e.)	(0.0036)	(0.0020)	(0.0018)	(0.0021)
Bread and baked goods	$\hat{\theta}$	0.49	0.32	0.28	0.29
(*obs. = 495,220*)	(s.e.)	(0.0026)	(0.0018)	(0.0015)	(0.0016)
Breakfast food	$\hat{\theta}$	0.66	0.02	0.06	0.08
(*obs. = 92,400*)	(s.e.)	(0.0067)	(0.0015)	(0.0016)	(0.0025)
Candy	$\hat{\theta}$	0.77	0.47	0.52	0.59
(*obs. = 515,836*)	(s.e.)	(0.0031)	(0.0020)	(0.0018)	(0.0021)
Canned fruit	$\hat{\theta}$	0.58	0.40	0.39	0.34
(*obs. = 223,378*)	(s.e.)	(0.0045)	(0.0028)	(0.0023)	(0.0023)
Canned seafood	$\hat{\theta}$	0.62	0.54	0.45	0.44
(*obs. = 98,473*)	(s.e.)	(0.0071)	(0.0046)	(0.0037)	(0.0038)
Canned vegetables	$\hat{\theta}$	0.60	0.38	0.32	0.35
(*obs. = 625,430*)	(s.e.)	(0.0024)	(0.0016)	(0.0013)	(0.0015)
Carbonated beverages	$\hat{\theta}$	0.21	0.05	0.03	0.04
(*obs. = 127,472*)	(s.e.)	(0.0037)	(0.0012)	(0.0009)	(0.0014)
Cereal	$\hat{\theta}$	0.62	0.27	0.35	0.26
(*obs. = 137,691*)	(s.e.)	(0.0046)	(0.0028)	(0.0030)	(0.0029)
Coffee	$\hat{\theta}$	0.62	0.42	0.47	0.42
(*obs. = 107,867*)	(s.e.)	(0.0061)	(0.0038)	(0.0034)	(0.0037)
Condiments	$\hat{\theta}$	0.59	0.33	0.27	0.36
(*obs. = 643,965*)	(s.e.)	(0.0025)	(0.0015)	(0.0012)	(0.0016)
Cookies	$\hat{\theta}$	0.57	0.27	0.22	0.29
(*obs. = 193,370*)	(s.e.)	(0.0047)	(0.0027)	(0.0022)	(0.0027)
Crackers	$\hat{\theta}$	0.58	0.42	0.40	0.43
(*obs. = 182,948*)	(s.e.)	(0.0048)	(0.0030)	(0.0027)	(0.0031)
Desserts	$\hat{\theta}$	0.55	0.44	0.39	0.33
(*obs. = 132,067*)	(s.e.)	(0.0053)	(0.0037)	(0.0033)	(0.0032)
Dressings and mayo	$\hat{\theta}$	0.39	0.21	0.15	0.19
(*obs. = 153,828*)	(s.e.)	(0.0048)	(0.0025)	(0.0019)	(0.0024)
Dried fruit	$\hat{\theta}$	0.68	0.66	0.57	0.39
(*obs. = 104,280*)	(s.e.)	(0.0060)	(0.0047)	(0.0042)	(0.0042)
Dried grains	$\hat{\theta}$	0.55	0.30	0.22	0.22
(*obs. = 99,596*)	(s.e.)	(0.0060)	(0.0032)	(0.0027)	(0.0031)

Product Category		**Age Group**			
		20–34	**35–49**	**50–64**	**65+**
Dry mixes	$\hat{\theta}$	0.37	0.20	0.19	0.37
(*obs. = 216,138*)	(s.e.)	(0.0034)	(0.0020)	(0.0019)	(0.0029)
Flour	$\hat{\theta}$	0.56	0.34	0.23	0.32
(*obs. = 63,240*)	(s.e.)	(0.0068)	(0.0048)	(0.0038)	(0.0046)
Gum	$\hat{\theta}$	0.56	0.33	0.41	0.60
(*obs. = 36,791*)	(s.e.)	(0.0104)	(0.0059)	(0.0069)	(0.0091)
Jams and spreads	$\hat{\theta}$	0.59	0.33	0.34	0.31
(*obs. = 171,556*)	(s.e.)	(0.0050)	(0.0029)	(0.0026)	(0.0027)
Juice	$\hat{\theta}$	0.59	0.42	0.39	0.40
(*obs. = 393,583*)	(s.e.)	(0.0030)	(0.0021)	(0.0019)	(0.0022)
Non-carbonated drinks	$\hat{\theta}$	0.63	0.57	0.56	0.56
(*obs. = 158,783*)	(s.e.)	(0.0049)	(0.0035)	(0.0031)	(0.0037)
Nuts	$\hat{\theta}$	0.53	0.28	0.18	0.27
(*obs. = 151,698*)	(s.e.)	(0.0055)	(0.0030)	(0.0023)	(0.0029)
Oil	$\hat{\theta}$	0.53	0.17	0.17	0.19
(*obs. = 138,749*)	(s.e.)	(0.0056)	(0.0025)	(0.0020)	(0.0024)
Packaged milk	$\hat{\theta}$	0.64	0.53	0.51	0.50
(*obs. = 111,840*)	(s.e.)	(0.0061)	(0.0042)	(0.0037)	(0.0041)
Pasta	$\hat{\theta}$	0.45	0.19	0.12	0.15
(*obs. = 166,704*)	(s.e.)	(0.0045)	(0.0024)	(0.0017)	(0.0023)
Pet food	$\hat{\theta}$	0.73	0.29	0.20	0.31
(*obs. = 314,393*)	(s.e.)	(0.0041)	(0.0021)	(0.0016)	(0.0022)
Pickles and olives	$\hat{\theta}$	0.51	0.22	0.16	0.27
(*obs. = 199,839*)	(s.e.)	(0.0043)	(0.0023)	(0.0018)	(0.0025)
Ready-to-serve food	$\hat{\theta}$	0.53	0.30	0.30	0.37
(*obs. = 284,810*)	(s.e.)	(0.0037)	(0.0020)	(0.0019)	(0.0023)
Snacks	$\hat{\theta}$	0.60	0.33	0.25	0.35
(*obs. = 561,320*)	(s.e.)	(0.0027)	(0.0016)	(0.0013)	(0.0017)
Soup	$\hat{\theta}$	0.45	0.08	0.13	0.13
(*obs. = 144,893*)	(s.e.)	(0.0050)	(0.0019)	(0.0021)	(0.0022)
Spices	$\hat{\theta}$	0.57	0.45	0.32	0.35
(*obs. = 286,235*)	(s.e.)	(0.0039)	(0.0024)	(0.0019)	(0.0023)
Sugar and sweeteners	$\hat{\theta}$	0.42	0.25	0.22	0.23
(*obs. = 109,345*)	(s.e.)	(0.0049)	(0.0031)	(0.0027)	(0.0030)
Table syrups	$\hat{\theta}$	0.50	0.37	0.28	0.34
(*obs. = 61,412*)	(s.e.)	(0.0066)	(0.0050)	(0.0044)	(0.0047)
Tea	$\hat{\theta}$	0.63	0.50	0.45	0.47
(*obs. = 135,188*)	(s.e.)	(0.0059)	(0.0038)	(0.0034)	(0.0039)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'dry groceries' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

Table 8: Consumer Inertia Across Age Groups: Frozen Food Department

Product Category		20–34	35–49	50–64	65+
Baked goods	$\hat{\theta}$	0.54	0.35	0.32	0.35
(*obs.* = *114,392*)	(s.e.)	(0.0053)	(0.0034)	(0.0031)	(0.0036)
Breakfast foods	$\hat{\theta}$	0.51	0.25	0.14	0.22
(*obs.* = *76,175*)	(s.e.)	(0.0064)	(0.0039)	(0.0030)	(0.0040)
Desserts	$\hat{\theta}$	0.49	0.28	0.26	0.32
(*obs.* = *65,733*)	(s.e.)	(0.0070)	(0.0043)	(0.0038)	(0.0043)
Frozen juice	$\hat{\theta}$	0.62	0.46	0.44	0.48
(*obs.* = *48,707*)	(s.e.)	(0.0080)	(0.0060)	(0.0055)	(0.0061)
Ice cream	$\hat{\theta}$	0.45	0.34	0.25	0.30
(*obs.* = *151,657*)	(s.e.)	(0.0038)	(0.0029)	(0.0026)	(0.0029)

Product Category		20–34	35–49	50–64	65+
Pizza and snacks	$\hat{\theta}$	0.54	0.36	0.38	0.40
(*obs.* = *118,502*)	(s.e.)	(0.0058)	(0.0033)	(0.0033)	(0.0040)
Prepared foods	$\hat{\theta}$	0.57	0.35	0.34	0.43
(*obs.* = *462,361*)	(s.e.)	(0.0028)	(0.0018)	(0.0017)	(0.0020)
Unprepared meat	$\hat{\theta}$	0.53	0.42	0.41	0.42
(*obs.* = *166,662*)	(s.e.)	(0.0050)	(0.0032)	(0.0028)	(0.0032)
Vegetables	$\hat{\theta}$	0.54	0.31	0.29	0.35
(*obs.* = *279,791*)	(s.e.)	(0.0034)	(0.0022)	(0.0020)	(0.0023)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'frozen food' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

Table 9: Consumer Inertia Across Age Groups: Dairy Department

Product Category		20–34	35–49	50–64	65+
Butter and margarine	$\hat{\theta}$	0.21	0.07	0.04	0.06
(*obs.* = *72,954*)	(s.e.)	(0.0052)	(0.0025)	(0.0019)	(0.0023)
Cheese	$\hat{\theta}$	0.45	0.27	0.29	0.32
(*obs.* = *466,350*)	(s.e.)	(0.0026)	(0.0016)	(0.0015)	(0.0018)
Cottage and sour cream	$\hat{\theta}$	0.36	0.21	0.20	0.23
(*obs.* = *123,050*)	(s.e.)	(0.0043)	(0.0028)	(0.0024)	(0.0028)
Dough products	$\hat{\theta}$	0.15	0.06	0.05	0.08
(*obs.* = *71,358*)	(s.e.)	(0.0038)	(0.0019)	(0.0016)	(0.0024)
Eggs	$\hat{\theta}$	0.18	0.07	0.06	0.07
(*obs.* = *57,092*)	(s.e.)	(0.0048)	(0.0028)	(0.0024)	(0.0025)

Product Category		20–34	35–49	50–64	65+
Milk	$\hat{\theta}$	0.42	0.20	0.14	0.18
(*obs.* = *168,301*)	(s.e.)	(0.0036)	(0.0022)	(0.0018)	(0.0021)
Pudding	$\hat{\theta}$	0.61	0.09	0.06	0.09
(*obs.* = *11,948*)	(s.e.)	(0.0172)	(0.0066)	(0.0050)	(0.0068)
Spreads and dips	$\hat{\theta}$	0.55	0.39	0.36	0.43
(*obs.* = *89,988*)	(s.e.)	(0.0065)	(0.0040)	(0.0036)	(0.0044)
Yogurt	$\hat{\theta}$	0.37	0.19	0.24	0.38
(*obs.* = *62,270*)	(s.e.)	(0.0062)	(0.0038)	(0.0042)	(0.0053)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'dairy' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

Table 10: Consumer Inertia Across Age Groups: Alcoholic Beverages Department

Product Category		20–34	35–49	50–64	65+
Beer	$\hat{\theta}$	0.64	0.43	0.44	0.41
(*obs.* = *85,242*)	(s.e.)	(0.0067)	(0.0039)	(0.0037)	(0.0048)
Liquor	$\hat{\theta}$	0.72	0.55	0.50	0.54
(*obs.* = *131,577*)	(s.e.)	(0.0058)	(0.0037)	(0.0032)	(0.0035)
Wine	$\hat{\theta}$	0.60	0.41	0.34	0.36
(*obs.* = *177,075*)	(s.e.)	(0.0054)	(0.0028)	(0.0023)	(0.0028)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'alcoholic beverages' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

Table 11: Consumer Inertia Across Age Groups: Non-Food Groceries Department

Product Category		Age Group			
		20–34	35–49	50–64	65+
Charcoal and logs	$\hat{\theta}$	0.78	0.54	0.54	0.63
(*obs. = 35,046*)	(s.e.)	(0.0135)	(0.0074)	(0.0066)	(0.0076)
Detergents	$\hat{\theta}$	0.53	0.14	0.06	0.09
(*obs. = 103,983*)	(s.e.)	(0.0062)	(0.0026)	(0.0016)	(0.0021)
Disposable diapers	$\hat{\theta}$	0.72	0.10	0.68	0.84
(*obs. = 16,905*)	(s.e.)	(0.0139)	(0.0056)	(0.0137)	(0.0161)
Fresheners	$\hat{\theta}$	0.62	0.38	0.29	0.47
(*obs. = 106,070*)	(s.e.)	(0.0071)	(0.0040)	(0.0031)	(0.0045)
Household cleaners	$\hat{\theta}$	0.71	0.62	0.59	0.60
(*obs. = 290,877*)	(s.e.)	(0.0042)	(0.0028)	(0.0025)	(0.0027)
Household supplies	$\hat{\theta}$	0.69	0.54	0.59	0.53
(*obs. = 329,787*)	(s.e.)	(0.0042)	(0.0025)	(0.0023)	(0.0025)

Product Category		Age Group			
		20–34	35–49	50–64	65+
Laundry supplies	$\hat{\theta}$	0.53	0.34	0.33	0.33
(*obs. = 212,973*)	(s.e.)	(0.0042)	(0.0026)	(0.0024)	(0.0026)
Paper products	$\hat{\theta}$	0.62	0.28	0.40	0.40
(*obs. = 384,252*)	(s.e.)	(0.0033)	(0.0020)	(0.0020)	(0.0023)
Personal soap	$\hat{\theta}$	0.77	0.65	0.64	0.61
(*obs. = 172,386*)	(s.e.)	(0.0053)	(0.0037)	(0.0033)	(0.0038)
Pet care	$\hat{\theta}$	0.78	0.42	0.38	0.51
(*obs. = 294,597*)	(s.e.)	(0.0042)	(0.0024)	(0.0020)	(0.0027)
Tobacco	$\hat{\theta}$	0.70	0.62	0.54	0.57
(*obs. = 64,436*)	(s.e.)	(0.0093)	(0.0056)	(0.0045)	(0.0056)
Wrapping materials	$\hat{\theta}$	0.64	0.39	0.38	0.49
(*obs. = 261,765*)	(s.e.)	(0.0041)	(0.0026)	(0.0024)	(0.0027)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'dry groceries' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

Table 12: Consumer Inertia Across Age Groups: Health and Beauty Care Department

Product Category		Age Group			
		20–34	35–49	50–64	65+
Baby needs	$\hat{\theta}$	0.72	0.64	0.68	0.73
(*obs. = 100,264*)	(s.e.)	(0.0057)	(0.0047)	(0.0044)	(0.0055)
Cosmetics	$\hat{\theta}$	0.80	0.65	0.69	0.68
(*obs. = 238,877*)	(s.e.)	(0.0042)	(0.0029)	(0.0028)	(0.0031)
Cough remedies	$\hat{\theta}$	0.72	0.63	0.58	0.64
(*obs. = 192,933*)	(s.e.)	(0.0045)	(0.0035)	(0.0031)	(0.0035)
Deodorant	$\hat{\theta}$	0.41	0.53	0.75	0.67
(*obs. = 39,932*)	(s.e.)	(0.0081)	(0.0070)	(0.0078)	(0.0084)
Diet aids	$\hat{\theta}$	0.73	0.64	0.65	0.69
(*obs. = 15,188*)	(s.e.)	(0.0165)	(0.0115)	(0.0103)	(0.0126)
Ethnic haba	$\hat{\theta}$	0.88	0.63	0.70	0.77
(*obs. = 15,989*)	(s.e.)	(0.0170)	(0.0115)	(0.0104)	(0.0118)
Feminine hygiene	$\hat{\theta}$	0.60	0.52	0.48	0.52
(*obs. = 33,984*)	(s.e.)	(0.0103)	(0.0073)	(0.0065)	(0.0077)
First aid	$\hat{\theta}$	0.71	0.55	0.66	0.57
(*obs. = 207,669*)	(s.e.)	(0.0046)	(0.0032)	(0.0030)	(0.0033)
Fragrances (women)	$\hat{\theta}$	0.76	0.74	0.71	0.62
(*obs. = 51,924*)	(s.e.)	(0.0099)	(0.0062)	(0.0052)	(0.0062)

Product Category		Age Group			
		20–34	35–49	50–64	65+
Grooming aids	$\hat{\theta}$	0.74	0.75	0.74	0.75
(*obs. = 112,097*)	(s.e.)	(0.0069)	(0.0045)	(0.0040)	(0.0047)
Hair care	$\hat{\theta}$	0.74	0.60	0.57	0.53
(*obs. = 265,245*)	(s.e.)	(0.0042)	(0.0026)	(0.0024)	(0.0030)
Medications	$\hat{\theta}$	0.76	0.64	0.64	0.61
(*obs. = 608,664*)	(s.e.)	(0.0028)	(0.0019)	(0.0017)	(0.0018)
Men toiletries	$\hat{\theta}$	0.73	0.63	0.57	0.59
(*obs. = 31,070*)	(s.e.)	(0.0144)	(0.0086)	(0.0068)	(0.0080)
Oral hygiene	$\hat{\theta}$	0.76	0.68	0.60	0.61
(*obs. = 174,046*)	(s.e.)	(0.0051)	(0.0037)	(0.0032)	(0.0035)
Sanitary protection	$\hat{\theta}$	0.55	0.09	0.15	0.52
(*obs. = 41,113*)	(s.e.)	(0.0100)	(0.0032)	(0.0044)	(0.0084)
Shaving needs	$\hat{\theta}$	0.57	0.20	0.21	0.63
(*obs. = 70,608*)	(s.e.)	(0.0076)	(0.0038)	(0.0035)	(0.0061)
Skin care	$\hat{\theta}$	0.70	0.75	0.73	0.66
(*obs. = 186,762*)	(s.e.)	(0.0047)	(0.0036)	(0.0030)	(0.0035)
Vitamins	$\hat{\theta}$	0.74	0.58	0.65	0.60
(*obs. = 282,778*)	(s.e.)	(0.0043)	(0.0029)	(0.0025)	(0.0027)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'health and beauty care' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

Table 13: Consumer Inertia Across Age Groups: General Merchandise Department

Product Category		20–34	35–49	50–64	65+
Appliances	$\hat{\theta}$	0.78	0.75	0.77	0.75
(*obs. = 215,371*)	(s.e.)	(0.0052)	(0.0033)	(0.0028)	(0.0031)
Automotive	$\hat{\theta}$	0.72	0.59	0.59	0.58
(*obs. = 112,032*)	(s.e.)	(0.0078)	(0.0044)	(0.0038)	(0.0041)
Batteries	$\hat{\theta}$	0.77	0.52	0.62	0.58
(*obs. = 67,145*)	(s.e.)	(0.0094)	(0.0061)	(0.0054)	(0.0058)
Cookware	$\hat{\theta}$	0.51	0.39	0.44	0.59
(*obs. = 26,965*)	(s.e.)	(0.0142)	(0.0080)	(0.0057)	(0.0091)
Electric goods	$\hat{\theta}$	0.71	0.54	0.58	0.60
(*obs. = 94,698*)	(s.e.)	(0.0077)	(0.0048)	(0.0045)	(0.0050)
Gardening	$\hat{\theta}$	0.82	0.57	0.61	0.47
(*obs. = 44,976*)	(s.e.)	(0.0114)	(0.0079)	(0.0066)	(0.0066)
Kitchen gadgets	$\hat{\theta}$	0.77	0.70	0.65	0.72
(*obs. = 275,187*)	(s.e.)	(0.0045)	(0.0030)	(0.0026)	(0.0032)
Magazines	$\hat{\theta}$	0.84	0.76	0.69	0.74
(*obs. = 17,141*)	(s.e.)	(0.0200)	(0.0150)	(0.0123)	(0.0128)
Pesticides	$\hat{\theta}$	0.77	0.56	0.50	0.52
(*obs. = 116,456*)	(s.e.)	(0.0072)	(0.0042)	(0.0034)	(0.0037)
Photo supplies	$\hat{\theta}$	0.70	0.64	0.75	0.68
(*obs. = 16,202*)	(s.e.)	(0.0215)	(0.0129)	(0.0124)	(0.0136)
Records and tapes	$\hat{\theta}$	0.58	0.48	0.63	0.52
(*obs. = 95,621*)	(s.e.)	(0.0070)	(0.0049)	(0.0049)	(0.0052)
School supplies	$\hat{\theta}$	0.73	0.58	0.57	0.63
(*obs. = 584,250*)	(s.e.)	(0.0031)	(0.0020)	(0.0018)	(0.0022)
Tableware	$\hat{\theta}$	0.79	0.69	0.67	0.63
(*obs. = 112,248*)	(s.e.)	(0.0068)	(0.0048)	(0.0043)	(0.0051)
Tools	$\hat{\theta}$	0.74	0.70	0.66	0.80
(*obs. = 99,523*)	(s.e.)	(0.0071)	(0.0048)	(0.0043)	(0.0052)

Notes: This table presents regression coefficients of equation (20) for different product categories in the 'dry groceries' department. Note that in almost all product categories young households are significantly less inertia. i.e., the estimated θ is significantly higher than any of the other groups.

D Additional Regressions Results

Table 14: Consumer Inertia and Entry Rates – State Analysis

	Dependent variable: firm entry rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer inertia index	-1.44^{***}	-1.41^{***}	-1.47^{***}	-1.53^{***}	-1.51^{***}	-1.58^{***}
	(0.29)	(0.29)	(0.29)	(0.53)	(0.52)	(0.60)
Labor-force growth rate		0.04^{***}	0.04^{***}		0.04^{***}	0.04^{***}
		(0.01)	(0.01)		(0.01)	(0.01)
Share of older workers			0.01			0.016
			(0.012)			(0.024)
State and time f.e.	✓	✓	✓	✓	✓	✓
Instrumented	✗	✗	✗	✓	✓	✓
	Dependent variable: share of workers employed by entrants					
	(1)	(2)	(3)	(4)	(5)	(6)
Consumer inertia index	-0.45^{***}	-0.44^{***}	-0.51^{***}	-0.64^{**}	-0.63^{**}	-0.73^{**}
	(0.15)	(0.16)	(0.18)	(0.29)	(0.29)	(0.34)
Labor-force growth rate		0.012^{***}	0.012^{***}		0.011^{***}	0.012^{***}
		(0.003)	(0.003)		(0.003)	(0.003)
Share of older workers			0.014			0.025
			(0.01)			(0.02)
State and time f.e.	✓	✓	✓	✓	✓	✓
Instrumented	✗	✗	✗	✓	✓	✓

Notes: This table presents the regression results of (22). The sample period is 1980–2019. In the top panel, the dependent variable is the share entrants out of all firms. The dependent variable in the bottom panel is the share workers employed by entrants. 95% confidence intervals in brackets. Inference was done using a bootstrap procedure, clustered at the state level. *** (**) - 99% (95%) confidence interval does not include zero.

E Numerical Appendix

E.1 Algorithm for Stationary Equilibrium

I use a value function iteration procedure to compute the stationary equilibrium of the economy. The algorithm consists of the following two steps. I describe the steps in more details below.

0) Start with a guess for the present value of the firm on the grid points, V, the two price indices, P_m and P_B, and the measure of profits in the economy, Π.[37]

1) Solve the optimal pricing decision of firms given a guess for the value function in the following period, and aggregate endogenous variables. Obtain an updated guess for V, together with policy functions of firms.

2) Compute the ergodic distribution of firms across the two dimensions of heterogeneity. Obtain an updated guess for the endogenous aggregate variables P_m, P_b, and Π. Check distance between value function and aggregate variables from previous guess. If the difference is not sufficiently small, repeat from step (1).

Grid. I use a two-dimensional grid to represent the state variables of the firm: their customer base and their productivity. I construct the productivity using the Tauchen and Hussey (1991) approach. The grid points are denoted by a_i, where $i = 1, ..., N_a$. I set N_a to 15. I denote the resulting Markov transition matrix by Π_a, which is a 15×15 matrix whose columns sum to one.

The customer base grid is constructed in a similar way to the capital grid in Maliar et al. (2010), so that the grid is denser for lower values of customer base. In particular, the customer base grid points are given by

$$B_j = \left(\frac{j}{N_B}\right)^{\kappa} B_{max}, \quad \text{for } j = 1, \dots, N_B \, ,$$

where N_B is the number of customer grid points, B_{max} is the largest measure of customer base considered, and κ governs the degree of the polynomial grid. I set N_B to 500, B_{max} to 5, and κ to 2. The high maximal level of customer base ensures that for different parameter specifications, which I consider when estimating via GMM, the ergodic distribution of firms contains no firms at the upper bound of customer base. The polynomial grid ensures that despite having a high upper bound for customer base, most of the grid points are in the region where the majority of firms in equilibrium lie.

Step 1 - Solving the Firm's Problem. The present value of a firm, gross of paying the fixed operating costs, is defined over the grid points. I denote it by V, an $N_a \times N_B$ matrix. The value

[37] For the initial stationary equilibrium, I normalize the measure of firms to 1 and calibrate f_e to match the present value of entrants in equilibrium. For the final stationary equilibrium, where f_e is taken as given,

function is given by

$$
\begin{aligned}
V(B,a) = \max_{\{p,y,B'\}} & \; py - \frac{w}{a}y + \frac{1}{1+r}\mathbb{E}\left[\max\left\{V\left(B',a'\right) - x_o'w, 0\right\}\right] \\
\text{s.t.} \quad & B' = (1-\theta)B + \frac{\theta}{J}\left(\frac{p}{P_m}\right)^{1-\sigma} , \\
& y = \left[(1-\theta)Bp^{-\eta} + \frac{\theta}{J}{P_m}^{\sigma-\eta}p^{-\sigma}\right]\frac{1}{\theta P_m^{1-\eta} + (1-\theta)P_B^{1-\eta}}(w+\Pi) ,
\end{aligned}
$$

where $\frac{1}{1+r} = \beta$ in the stationary equilibrium, and w is normalized to 1 without loss of generality. We can substitute the constraints to arrive at the following firm's problem

$$
V(B,a) = \max_{B'} \pi(B,a,B') + \frac{1}{1+r}\mathbb{E}\max\left\{V\left(B',a'\right) - x_o', 0\right\} ,
$$

where $\pi(B,a,B')$ is the periodic profits of a firm with initial customer base B, productivity a, which chooses to sell to a measure B' of customers. The current guess for the value function allows me to construct the expected discounted future profits of the firm, net of operating costs. I then maximize the firm's present profits on the grid of customer base levels. The resulting maximization procedure yields the present value for each point on the grid, as well as the policy choices over the grid $B'(B,a)$, $p(B,a)$, and $y(B,a)$. With the present value at hand, I derive the survival probability of each firm which I denote by $s(B,a)$. $s(B,a)$ corresponds to the probability that its present value of profits net of paying the fixed operating costs is greater than zero.

Step 2 - Computing the Ergodic Distribution. With the policy functions at hand, I construct the transition matrix. There are N_aN_B states, and I denote the ergodic distribution by a vector Λ of that size. $\Lambda(B,a)$ denotes the measure of firms that have an initial customer base B, productivity a. 3.2, where the distribution is defined prior to the exit decision.

The transition matrix, denoted by Π_T, is of size $N_aN_B \times N_aN_B$. The law of motion for the distribution is given by

$$
\Lambda(B',a') = \sum_B \sum_a \Lambda(B,a)s(B,a)\mathbb{1}\left(B'(B,a) = B'\right)\Pi_a(a',a) + \mathbb{1}(B'=0)\Pi_e(a) ,
$$

where $\Pi_a(a',a)$ is the exogenous probability of drawing the productivity a' given past productivity a. $Pi_e(a)$ is the probability of an entrant drawing productivity a. Note that by writing the law of motion in this way, I assume that the measure of entrants is equal to one. I start from a guess for Λ and iterate until convergence. Once I obtain the resulting Λ, I divide it by a constant that ensures that the measure of operating firms is equal to 1.

After obtaining Λ, I can compute the implied endogenous aggregate variables $\{P_m, P_B, \Pi\}$. If the maximal difference between the implied aggregate difference and their initial guess is sufficiently small, and the maximal difference between the implied present value of a firm on each grid point is sufficiently close to the initial guess, I have found the stationary equilibrium. Otherwise, I update the guess. For the new guess, I use a convex combination between the initial guess and the implied one.

E.2 Algorithm for Transition Dynamics

The initial stationary equilibrium is calibrated to match features of the U.S. economy in the late 1980s. I denote the probability of re-optimization in the initial stationary equilibrium by θ_0. I then consider an unexpected and deterministic shock to that probability that according to observed and predicted demographic shifts in the U.S. population. In particular, I consider a vector of θ of length 51, corresponding to the period between the early 1990s and 2050. I assume that after 2050 the age composition does not change so that the re-optimization probability is kept constant at its 2050 level. I further assume that the model converges to the new stationary equilibrium by 2100. I denote the period 2100 by T.

Similar to the previous section, I start by computing the terminal stationary equilibrium. The only difference is that when computing the terminal equilibrium, the measure of firms J is not normalized to 1 but is instead endogenous. It is set so that the expected zero-profits condition in equilibrium holds. So instead of iterating over 4 aggregate endogenous variables, I iterate over 5 aggregate endogenous variables.

Solving the transition dynamics of the economy consists of two main steps:

0) Start with an initial guess for the aggregate endogenous variables along the transition path, $\{P_{mt}, P_{Bt}, J_t, \Pi_t\}_{t=1}^{T}$.

1) Solve backwards the present value of firms, and obtain the policy rules in each period. The terminal present value of firms is that of the terminal stationary equilibrium.

2) Iterate forward to compute the distribution of firms in every period. Using the distribution of firms and the policy rules, compute the implied aggregate endogenous variables. If the difference between the guess and implied variables is not close enough, update the guess and repeat from step (1). The initial distribution of firms is the ergodic distribution of firms in the initial stationary distribution.

References

ANDERSON, S. P., DEPALMA, A. and THISSE, J.-F. (1987). The ces is a discrete choice model. *Economics Letters*, **24** 139.

ANDERSON, S. T., KELLOGG, R., LANGER, A. and SALLEE, J. M. (2015). The intergenerational transmission of automobile brand preferences. *The Journal of Industrial Economics*, **63** 763–793.

ANDREWS, I., GENTZKOW, M. and SHAPIRO, J. M. (2017). Measuring the sensitivity of parameter estimates to estimation moments. *The Quarterly Journal of Economics*, **132** 1553–1592.

ARKOLAKIS, C. (2010). Market penetration costs and the new consumers margin in international trade. *Journal of political economy*, **118** 1151–1199.

AUTOR, D., DORN, D., KATZ, L. F., PATTERSON, C. and VAN REENEN, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, **135** 645–709.

BAI, J. (2009). Panel data models with interactive fixed effects. *Econometrica*, **77** 1229–1279.

BAQAEE, D. R. and FARHI, E. (2020). Productivity and misallocation in general equilibrium. *The Quarterly Journal of Economics*, **135** 105–163.

BARKAI, S. (2016). Declining labor and capital shares. *Stigler Center for the Study of the Economy and the State New Working Paper Series*, **2**.

BARKAI, S. and BENZELL, S. G. (2018). 70 years of us corporate profits. *Stigler Center for the Study of the Economy and the State New Working Paper Series*.

BRONNENBERG, B. J., DUBÉ, J.-P. H. and GENTZKOW, M. (2012). The evolution of brand preferences: Evidence from consumer migration. *American Economic Review*, **102** 2472–2508.

DAVIS, S. J. and HALTIWANGER, J. (2014). Labor market fluidity and economic performance. Tech. rep., National Bureau of Economic Research.

DE LOECKER, J., EECKHOUT, J. and UNGER, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, **135** 561–644.

DECKER, R., HALTIWANGER, J., JARMIN, R. and MIRANDA, J. (2014a). The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives*, **28** 3–24.

DECKER, R., HALTIWANGER, J., JARMIN, R. and MIRANDA, J. (2014b). The secular decline in business dynamism in the us. *Unpublished draft, University of Maryland*.

DELLAVIGNA, S. and GENTZKOW, M. (2019). Uniform pricing in us retail chains. *The Quarterly Journal of Economics*, **134** 2011–2084.

DROZD, L. A. and NOSAL, J. B. (2012). Understanding international prices: Customers as capital. *American Economic Review*, **102** 364–95.

DUBÉ, J.-P., HITSCH, G. J. and ROSSI, P. E. (2010). State dependence and alternative explanations for consumer inertia. *The RAND Journal of Economics*, **41** 417–445.

EINAV, L., LEIBTAG, E. and NEVO, A. (2010). Recording discrepancies in nielsen homescan data: Are they present and do they matter? *QME*, **8** 207–239.

ENGBOM, N. (2019). Firm and worker dynamics in an aging labor market. Tech. rep., Federal Reserve Bank of Minneapolis.

FARRELL, J. and KLEMPERER, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. *Handbook of industrial organization*, **3** 1967–2072.

FARRELL, J. and SHAPIRO, C. (1988). Dynamic competition with switching costs. *The RAND Journal of Economics* 123–137.

FOSTER, L., HALTIWANGER, J. and SYVERSON, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, **98** 394–425.

FOSTER, L., HALTIWANGER, J. and SYVERSON, C. (2016). The slow growth of new plants: Learning about demand? *Economica*, **83** 91–129.

GABSZEWICZ, J., PEPALL, L. and THISSE, J.-F. (1992). Sequential entry with brand loyalty caused by consumer learning-by-using. *The Journal of Industrial Economics* 397–416.

GARCIA-MACIA, D., HSIEH, C.-T. and KLENOW, P. J. (2016). How destructive is innovation? Tech. rep., National Bureau of Economic Research.

GILCHRIST, S., SCHOENLE, R., SIM, J. and ZAKRAJŠEK, E. (2017). Inflation dynamics during the financial crisis. *American Economic Review*, **107** 785–823.

GOURIO, F. and RUDANKO, L. (2014). Customer capital. *Review of Economic Studies*, **81** 1102–1136.

GRULLON, G., LARKIN, Y. and MICHAELY, R. (2019). Are us industries becoming more concentrated? *Review of Finance*, **23** 697–743.

GUTIERREZ, G. (2017). Investigating global labor and profit shares. *Unpublished Working Paper, SSRN*.

GUTIERREZ, G. and PHILIPPON, T. (2017). Declining competition and investment in the us. Tech. rep., National Bureau of Economic Research.

GUTIERREZ GALLARDO, G., JONES, C. and PHILIPPON, T. (2019). Entry costs and the macroeconomy. *NBER Working Paper*.

HALL, R. E. (2018). New evidence on the markup of prices over marginal costs and the role of mega-firms in the us economy. Tech. rep., National Bureau of Economic Research.

HANDEL, B. R. (2013). Adverse selection and inertia in health insurance markets: When nudging hurts. *American Economic Review*, **103** 2643–82.

HATHAWAY, I. and LITAN, R. (2014). The other aging of america: the increasing dominance of older firms. *Brookings Institution*.

HOPENHAYN, H., NEIRA, J. and SINGHANIA, R. (2018). From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share. Tech. rep., National Bureau of Economic Research.

HOPENHAYN, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society* 1127–1150.

HORTAÇSU, A., MADANIZADEH, S. A. and PULLER, S. L. (2015). Power to choose? an analysis of consumer inertia in the residential electricity market. Tech. rep., National Bureau of Economic Research.

ILLANES, G. (2016). Switching costs in pension plan choice. *Unpublished manuscript*.

JIANG, H. and SOHAIL, F. (2017). Skill biased entrepreneurial decline. Tech. rep., Mimeo, Washington University in St. Louis.

KARABARBOUNIS, L. and NEIMAN, B. (2018). Accounting for factorless income. In *NBER Macroeconomics Annual 2018, volume 33*. University of Chicago Press.

KARAHAN, F., PUGSLEY, B. and ŞAHIN, A. (2019). Demographic origins of the startup deficit. Tech. rep., National Bureau of Economic Research.

KEHRIG, M. and VINCENT, N. (2021). The micro-level anatomy of the labor share decline. *The Quarterly Journal of Economics*, **136** 1031–1087.

KLEMPERER, P. (1987a). Entry deterrence in markets with consumer switching costs. *The Economic Journal*, **97** 99–117.

KLEMPERER, P. (1987b). Markets with consumer switching costs. *The quarterly journal of economics*, **102** 375–394.

KOZENIAUSKAS, N. (2017). What's driving the decline in entrepreneurship. *manuscript, New York University*.

LIANG, J., WANG, H. and LAZEAR, E. P. (2014). Demographics and entrepreneurship. Tech. rep., National Bureau of Economic Research.

LUCO, F. (2017). Switching costs and competition in retirement investment.

LUTTMER, E. (2006). Consumer search and firm growth. Tech. rep., Federal Reserve Bank of Minneapolis.

MALIAR, L., MALIAR, S. and VALLI, F. (2010). Solving the incomplete markets model with aggregate uncertainty using the krusell–smith algorithm. *Journal of Economic Dynamics and Control*, **34** 42–49.

MOREIRA, S. (2016). Firm dynamics, persistent effects of entry conditions, and business cycles.

NAKAMURA, E. and STEINSSON, J. (2011). Price setting in forward-looking customer markets. *Journal of Monetary Economics*, **58** 220–233.

NEVO, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, **69** 307–342.

NOSAL, K. (2012). Estimating switching costs for medicare advantage plans. *Unpublished manuscript, University of Mannheim*.

PERLA, J. (2019). A model of product awareness and industry life cycles. *Unpublished Paper, University of British Columbia*.

PETERS, M. and WALSH, C. (2019). Declining dynamism, increasing markups and missing growth: The role of the labor force. *Increasing Markups and Missing Growth: The Role of the Labor Force (November 6, 2019)*.

PUGSLEY, B. W. and ŞAHIN, A. (2015). Grown-up business cycles. *The Review of Financial Studies*.

RAVN, M., SCHMITT-GROHÉ, S. and URIBE, M. (2006). Deep habits. *The Review of Economic Studies*, **73** 195–218.

ROGNLIE, M. (2018). Comment on "accounting for factorless income"(karabarbounis and neiman, nber macro annual 2018).

ROTEMBERG, J. J. and WOODFORD, M. (1991). Markups and the business cycle. *NBER macroeconomics annual*, **6** 63–129.

SALGADO, S. (2017). Technical change and entrepreneurship.

SCHMITT-GROHÉ, S. and URIBE, M. (2007). Why the monopolist does not deviate from the symmetric equilibrium in a model with good-specific subsistence points. *Note, Duke University*.

SEDLÁČEK, P. and STERK, V. (2017). The growth potential of startups over the business cycle. *American Economic Review*, **107** 3182–3210.

SHIMER, R. (2001). The impact of young workers on the aggregate labor market. *The Quarterly Journal of Economics*, **116** 969–1007.

TAUCHEN, G. and HUSSEY, R. (1991). Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models. *Econometrica: Journal of the Econometric Society* 371–396.

WINTER, S. and PHELPS, E. (1970). Optimal price policy under atomistic competition. *Microeconomic Foundations of Employment and Inflation Theory* 309–337.