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

Gideon Bornstein*

The Wharton School, University of Pennsylvania & NBER

March 2026

Abstract

Over the past four decades, the U.S. economy has seen a decline in the share of young firms alongside a rise in the profit share of GDP. This paper explores how population aging contributes to these twin trends through a demand-side channel. The core hypothesis is that younger households exhibit lower *consumer inertia*—a tendency to stick with previously chosen products—than older households. As demand shifts toward more inertial consumers, entry becomes harder, incumbents raise markups, and market share tilts toward larger firms. To quantify this mechanism, I develop and calibrate a firm dynamics model with overlapping generations of consumers who differ in their degree of inertia. Using detailed micro data, I show that younger households are significantly less inertial. The model implies that population aging accounts for 20%–30% of the observed decline in young firms and rise in profits. Reduced-form evidence across U.S. states and product categories supports the model's predictions.

*This paper is based on the first chapter of my PhD dissertation. I am indebted to Marty Eichenbaum, Guido Lorenzoni, Sergio Rebelo, Luigi Bocola, and Per Krusell for guidance and support. I am grateful to Tanvi Jindal and Paige Stevenson for superb research assistance. I thank the editor (Nir Jaimovich), five anonymous referees, Mark Aguiar, David Berger, Larry Christiano, Dean Corbae, Gaby Cugat, Pierre-Olivier Gourinchas, Sasha Indarte, Vishal Kamat, Chiara Maggi, Sara Moreira, Marti Mestieri, Abdoulaye Ndiaye, Jordan Norris, Giorgio Primiceri, Richard Rogerson, Matt Rognlie, Max Tabord-Meehan, Fabrice Tourre, Thomas Winberry, and Arlene Wong for helpful suggestions and comments. Researcher own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC, National Promotion Reports, LLC, and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. All errors are my own.
Email: gideonbo@wharton.upenn.edu.

1 Introduction

Over the past four decades, the U.S. corporate sector has become both older and more profitable. The share of young firms—defined as those five years old or younger—has fallen from 50% in the late 1980s to 30% today, while their employment share has declined from 20% to 10%.[1] Over the same period, the share of profits in GDP has risen substantially.[2] Traditional models of firm dynamics struggle to explain these twin phenomena. All else equal, higher profits should encourage more entry.

In this paper, I explore how population aging contributes to these twin phenomena through a demand-side channel: consumer inertia.[3] Consumer inertia refers to the tendency of consumers to stick with previously chosen products—that is, a reluctance to switch brands. The prevalence of consumer inertia is well documented in the industrial organization and marketing literatures.[4] I show empirically that younger households are significantly less inertial than older ones. Consequently, as the U.S. population has aged and the share of young households declined, the composition of demand has shifted toward more inertial consumers. To quantify the macroeconomic implications of this shift, I construct and calibrate a firm dynamics model with overlapping generations of households who differ in their degree of consumer inertia. Through the lens of this model, population aging accounts for 28% of the rise in the profit share and about 20% of the decline in young firms between the late 1980s and the late 2010s.

The central hypothesis is that rising consumer inertia discourages entry while leading to higher profits of large incumbent firms. I develop this argument in four steps. First, I develop a firm dynamics model with overlapping generations of households who exhibit consumer inertia. Second, I use detailed micro data to show that younger households are significantly less inertial than older ones. Third, I use the calibrated model to quantify the effects of population aging. Finally, I provide empirical support for the model's key predictions: (i) entrant brand markups are significantly lower than those of incumbents; (ii) U.S. states which experienced a larger decline in the share of young households have also experienced a larger decline in the share of young firms; and (iii) product categories with a younger customer base exhibit higher entry rates and lower markups.

[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] Papers in the literature that explore the supply-side forces of population aging include Karahan, Pugsley, and Şahin (2024), Hopenhayn, Neira, and Singhania (2018), Peters and Walsh (2019), Liang, Wang, and Lazear (2018), and Engbom (2019). The first three papers focus on the labor force growth rate, while the last two focus on the age composition of the workforce.

[4] Examples include Luco (2017) and Illanes (2016) for pension plans; Handel (2013) and Nosal (2012) for health insurance; Anderson, Kellogg, Langer, and Sallee (2015) for automobiles; Hortaçsu, Madanizadeh, and Puller (2015) for residential electricity; and Dubé, Hitsch, and Rossi (2010) and Bronnenberg, Dubé, and Gentzkow (2012) for consumer packaged goods.

Consumer inertia can arise from a range 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 the model, I capture consumer inertia parsimoniously through stochastic switching costs. Consumers face a variety of product types (e.g., phones), each containing a range of brands (e.g., iPhone, Galaxy, Nexus). Each period, households consume one brand per product type, with idiosyncratic preferences over brands. When deciding whether to switch, a household considers brand prices and preferences, but also draws a switching cost—representing the utility loss from switching. As a result, the probability of switching brands increases with the relative price of the previously chosen brand. I allow switching costs to differ between young and old households.

To study how demographics shape the distribution of firms and aggregate profits, I construct a general equilibrium firm dynamics model with overlapping generations of households who exhibit consumer inertia. Consumer inertia gives rise to life-cycle dynamics in a firm's customer base and markups. A new firm starts with no customers and builds its customer base over time. Its optimal markup reflects a balance between a harvesting motive and an investing motive.[5] The harvesting motive refers to firms' incentive to take advantage of their locked-in customer base by increasing markups. The investing motive refers to firms' incentive to increase their customer base by lowering markups. 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, the harvesting motive is muted and the investing motive dominates. As a result, entrant markups are lower than those of incumbents.

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 three firm-level state variables are their young and old customer base, and their productivity level. I assume that firms need to pay a stochastic fixed operating cost in every period, giving rise to endogenous exit.

To calibrate the degree of consumer inertia across young and old households, I use NielsenIQ's Consumer Panel dataset. The dataset contains longitudinal panel information on the purchases of roughly 160,000 U.S. households between 2004 and 2019. I merge the dataset with the GS1 U.S. dataset. This allows me to link products in NielsenIQ to the firms which produce them. NielsenIQ classifies products into 1,000 different product modules. The merged data allow me to construct an annual panel dataset of the customer base at the firm-module level.

The constructed panel dataset allows me to distinguish between a firm's sales to new versus returning customers. I calibrate the median switching cost—the key parameter governing the degree of consumer inertia—to match the share of brand sales going to new customers across young and old households. I define a household as young if the household head is under 35.

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

Among young households, 27% of brand sales are to new customers, compared to 23% for older households. This difference is statistically significant and remains stable after controlling for store, product module, and brand fixed effects. It also persists after controlling for household fixed effects, suggesting the pattern is not driven by cohort effects.

To match the lower share of new-customer sales among older households, the calibrated switching cost for old households is higher: 0.17 versus 0.15 for young households. This implies that the median old household is indifferent between keeping their current brand or switching to an otherwise similar brand that is 17% cheaper. The model's remaining structural parameters are calibrated to match key features of the U.S. economy in the late 1980s, including the firm age distribution, the employment share by firm age, and the profit share of GDP.

To assess the impact of population aging on the U.S. economy, I study an unexpected and deterministic demographic shock to both the population growth rate and the death probability of older households. The population growth rate declines gradually from 1% to 0.2%, its projected value in 2050. The death probability falls from 3% to 1.6%. The speed of these transitions is chosen to match the observed decline in the share of young households—from 43% in the 1980s to 33% in 2015–2019. I solve for the transition dynamics from the initial balanced growth path to the new equilibrium.

The demographic shift alters the distribution of firms: entry declines, and the share of older firms rises. This shift in firm demographics leads to an increase in the aggregate profit share. The rise in profits is driven primarily by higher markups, but also by a reduction in the share of operating costs and a decline in entry costs. Quantitatively, the model explains 28% of the rise in the profit share and roughly 20% of the decline in young firms between the late 1980s and late 2010s. It also predicts that these trends will continue in the coming decades as the share of young households continues to fall.

In the final part of the paper, I present three empirical analyses that support the model's key predictions. First, I merge NielsenIQ's Consumer Panel dataset with PromoData to construct monthly product-level retail markups. I find that entrant brand markups are 5–9 percentage points lower than those of incumbents. Second, I study firm formation across U.S. states over time and show that states with larger declines in the young population share also experienced larger declines in the share of young firms. This relationship remains significant after controlling for labor force growth and the share of older workers—the primary supply-side channels emphasized in the literature. Third, I examine how brand entry and markups vary across product modules with the age composition of their customer base. Product modules with younger consumers exhibit significantly higher brand entry rates and significantly lower markups. Focusing on customer age composition allows me to isolate demand-side effects of aging from potential supply-side explanations.

Related literature. This paper connects to several strands of work. First, it contributes to the recent literature on the decline in business dynamism. Several papers highlight the role of supply-side demographic forces in reducing firm formation, including Karahan et al. (2024), Hopenhayn et al. (2018), Peters and Walsh (2019), Liang et al. (2018), and Engbom (2019). Other explanations for declining dynamism include changes in the regulatory environment (Davis and Haltiwanger, 2014), skill-biased technical change (Jiang and Sohail, 2023; Kozeniauskas, 2017; Salgado, 2017), and rising entry costs (Gutierrez Gallardo et al., 2019).

Second, this paper relates to a growing literature on the rise in corporate profits and the decline in the labor share.[6] Autor, Dorn, Katz, Patterson, and Van Reenen (2020) attribute the increase in profits to the rise of *superstar* firms. In contrast, Grullon, Larkin, and Michaely (2019) argue that it reflects an inefficient outcome driven by rising concentration, a view supported by Gutierrez and Philippon (2017). My model also links the rise in profits to increased concentration, but through a demand-side mechanism: greater consumer inertia lowers entry and allows incumbents to raise markups.

Third, this paper builds on a large theoretical literature in industrial organization that studies how switching costs influence firms' pricing decisions. For a review, see Farrell and Klemperer (2007). Several papers examine how switching costs affect entry and profits (e.g., Klemperer, 1987a; Farrell and Shapiro, 1988; Gabszewicz et al., 1992), typically in duopoly settings and partial equilibrium environments. My analysis incorporates the core mechanisms emphasized in this literature but embeds them in a general equilibrium framework with a large number of firms.

Different forms of firm-level dynamic demand have also been studied in a macroeconomic context. Early examples include Winter and Phelps (1970) and Rotemberg and Woodford (1991). A common approach in this literature assumes that a firm's past production enters as a demand shifter, affecting the level of demand but not its elasticity, e.g., Ravn, Schmitt-Grohé, and Uribe (2006), Foster, Haltiwanger, and Syverson (2016), Moreira (2016), Sedláček and Sterk (2017), Gilchrist, Schoenle, Sim, and Zakrajšek (2017), and Fitzgerald, Haller, and Yedid-Levi (2024). My approach differs in three key ways. First, I explicitly model switching costs, allowing me to study how the economy responds when such costs change. Second, the model allows the demand elasticity from previous customers to differ from that of new customers, giving rise to a harvesting motive.[7] Third, the model features an extensive margin of consumers, allowing me to map it to the data.[8]

Layout. The paper proceeds as follows. Section 2 presents the model and examines how the firm's

[6]The magnitude of the rise in profits remains debated. See Karabarbounis and Neiman (2018) and Rognlie (2018) for discussions on measurement challenges. Barkai and Benzell (2018) argue the rise is robust even after addressing these concerns.

[7]The harvesting motive also arises in the "additive" version of the deep habits model (Ravn et al., 2006), which is later studied in Nakamura and Steinsson (2011).

[8]Papers with dynamic demand that include such extensive margin include Gourio and Rudanko (2014), Luttmer (2006), and Drozd and Nosal (2012), who use search models, and Perla (2019) who models consumer awareness.

markup evolves over its life cycle. Section 3 uses micro data to document how consumer inertia varies by household age and calibrates the balanced growth path equilibrium using both micro and macro moments. Section 4 quantifies the contribution of population aging to the observed trends in profitability and firm formation. I first do so using the quantitative model. Second, I present empirical evidence that supports the model's predictions. Section 5 concludes.

2 Model

In this section, I develop a firm dynamics model with overlapping generations of households who exhibit consumer inertia. The economy consists of young and old households who differ in their brand switching costs. I begin by describing the environment, defining equilibrium, and characterizing the balanced growth path. I then analyze how the optimal markup evolves over the firm's life cycle, and conclude by discussing some key modeling assumptions.

2.1 Environment

Population dynamics. The economy is populated by a continuous measure of young and old households. Let the measure of young households at time t be N_t^y and the measure of old households be N_t^o. Let $N_t \equiv N_t^y + N_t^o$ denote the total measure of households at time t.

At the start of every period, each young household has a probability q^o of becoming an old household. Each old household has a probability q_t^d of dying and exiting the economy. There is an influx of $N_t^b \equiv \left(g_t N_{t-1} + q_t^d N_{t-1}^o\right)$ of young households into the economy, so that the overall population growth rate in the economy is g_t. That is,

$$N_t^o = (1 - q_t^d) N_{t-1}^o + q^o N_{t-1}^y, \tag{1}$$

$$N_t^y = (1 - q^o) N_{t-1}^y + N_t^b. \tag{2}$$

Household problem. Households derive utility from an aggregate taste-adjusted consumption good denoted by C_t. All households supply labor inelastically, and I assume that old households' labor endowment equals L_o while that of young households is normalized to 1. The wage in the economy is normalized to 1. I further assume that all dividends in the economy are distributed equally among old households. The lifetime utility of household i that is born in period t is given by

$$U_i = \sum_{\tau=0}^{T_i} \beta^\tau \ln C_{t+\tau}^i, \tag{3}$$

where T_i is the (stochastic) age of the household before it dies.

Households consume a variety of product types, denoted by $m \in (0, 1)$. Each product type consists of an endogenous finite number of monopolistic brands, denoted by J_{mt}. In every period, a household can consume only one brand in each product type. The brand household i consumes in product type m at time t is denoted by j^{*i}_{mt}. The aggregate taste-adjusted consumption good of household i at time t is defined as follows:

$$\ln C^i_t = \int_0^1 \left[\ln c^{*i}_{mt} + \frac{1}{\sigma - 1} \epsilon^{*i}_{mt} - \ln \zeta^i_{mt} \mathbb{1}\left(\text{switch}^i_{mt}\right) \right] dm, \tag{4}$$

where c^{*i}_{mt} is the quantity consumed by household i from product type m at time t, and ϵ^{*i}_{mt} is the idiosyncratic taste of household i towards the brand it consumes. I assume that ϵ^i_{jmt} is iid across brands, consumers, and time, and discuss the distribution of these taste shocks in detail below. The parameter σ, which is assumed to be greater than 1, governs the elasticity of substitution across brands.

The third term in the integrand in equation (4) represents idiosyncratic utility cost from switching brands. The indicator $\mathbb{1}\left(\text{switch}^i_{mt}\right)$ equals zero if the household consumes the same brand as it did at time $t-1$; otherwise, it equals one. The disutility cost ζ^i_{mt} is stochastic and drawn i.i.d. from a distribution with CDF $F_i(\zeta)$. I assume that the CDF depends on the household age, taking the form of either $F_y(\cdot)$ or $F_o(\cdot)$. This difference in the distribution of switching costs generates differential consumer inertia across age groups.

The timeline of consumption decisions within a period is as follows. First, the household observes its switching-cost draws and then decides the set of product types in which to switch brands, prior to observing the realizations of taste shocks. Then, the household observes its idiosyncratic tastes towards all brands within those product types. The idiosyncratic tastes are distributed according to a Gumbel distribution with scale parameter 1 and location parameter $-\ln J_{mt}$. The location parameter ensures that preferences do not feature love-of-variety.[9] The assumption of Gumbel-distributed tastes implies that the discrete choice of brands within a product type follows a multinomial logit, allowing me to derive an analytical firm-level demand function. I further assume that the idiosyncratic tastes for brands in product types where households do not switch brands follow a standard Gumbel distribution. Finally, the household decides which brands to consume and how to allocate its expenditure across product types.[10]

To solve the household's problem within each period, I proceed by backward induction. First, I characterize the chosen brand conditional on switching brands. Next, I analyze the brand switching decision and derive the probability of switching a brand. Lastly, I show that aggregate consumption is proportional to aggregate expenditure and derive the intertemporal Euler condition that pins down the interest rate.

[9]The location parameter is chosen so that the expected taste shock of the chosen brand is independent of the number of operating brands. In particular, when there are no switching costs and all brands charge the same price, the consumer is indifferent between switching and not switching. If the location parameter were 0, the expected taste shock of the chosen brand would rise with the number of brands, mechanically increasing the probability of switching. Using $-\ln J_{mt}$ removes this mechanical force, so along the balanced growth path the switching probability does not mechanically approach one as the number of brands grows.

[10]With an arbitrarily large number of brands, the probability that a household who *decides to switch* ends up choosing the same brand as last period is negligible.

Consider a household that has decided to switch brands and is contemplating which brand to choose after observing all tastes. A key assumption I make is that households do not internalize the possibility of being *locked-in* with their chosen brand in future periods. That is, households choose brands under the belief that future switching costs will be zero ($\zeta^i_{mt+1} = 0$). In principle, households should take into account not only the current price of each brand but also their expected future prices. By assuming households' brand choice is myopic, the decision of which brand to choose depends only on current prices.[11] The lemma below characterizes the household's optimal brand choice conditional on switching.

Lemma 1. *In product types where the household switches brands, the household chooses the brand that maximizes*

$$j^{*i}_{mt} = \arg\max_{j_m} -(\sigma - 1)\ln p_{jmt} + \epsilon_{jmt}. \tag{5}$$

All proofs are relegated to the Appendix. The intuition behind Lemma 1 is straightforward. When a household chooses between two brands, it values a lower price, as it allows the household to buy a larger quantity of the good, and a higher taste shock, as it provides higher utility from each good consumed. As taste shocks are drawn from a Gumbel distribution, Lemma 1 shows that the brand choice follows a multinomial logit.

Next, I analyze the household's decision regarding whether to switch brands. The following Lemma leverages the Gumbel distributional assumption on taste shocks to characterize households' brand-switching decisions within each product type.

Lemma 2. *At the switching stage (before observing taste shocks), a household chooses to switch a brand with current price p_{jmt} if and only if*

$$\zeta^i_{mt} < \frac{p_{jmt}}{P_{mt}}, \tag{6}$$

where

$$P_{mt} = \left[\frac{1}{J_{mt}}\sum_j p^{1-\sigma}_{jmt}\right]^{\frac{1}{1-\sigma}}.$$

Recall that the location parameter of the Gumbel distribution is equal to $-\ln J_{mt}$ if the consumer switches brands and zero if the consumer remains with its previous brand. This distributional assumption implies that the incentive to switch brands depends solely on prices, not tastes. The household compares the utility cost of switching (ζ^i_{mt}) with the relative price of the brand.[12] The product type price index P_{mt} is a power mean of all brand prices within the product type. This price index is obtained by deriving the expected indirect utility from the multinomial logit brand choice, reminiscent of the results of Anderson et al. (1987).

[11] An alternative assumption that yields identical results at the macro level is that the counterpart to *switching* brands is being locked-in to a brand chosen by a random consumer of the same age in the previous period. Such *external* consumer inertia is similar to the consumption choice in Luttmer (2006) and Ravn et al. (2006) and sidesteps the myopic assumption adopted here.

[12] If the brand the consumer purchased in the previous period is no longer available, its effective price is infinite.

To study how households allocate their expenditure over time, it is useful to derive their optimal aggregate taste-adjusted consumption as a function of expenditure E_t^i. The following Lemma shows that aggregate consumption scales with overall expenditure.

Lemma 3. *The aggregate utility-adjusted consumption at time t, given total expenditure E_t^i, is*

$$\ln C_t^i = \ln E_t^i - \ln P_t^{i,t-1} + \int_0^1 F^i\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\left[\ln\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right) - \ln\bar{\zeta}\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\right]dm + \frac{\gamma}{\sigma-1}, \quad (7)$$

where j^*_{mt-1} is the brand consumer i purchased in the previous period in product type m, $\ln P_t^{i,t-1}$ is the average log-price at time t of brands consumer i purchased in the previous period, and $\ln\bar{\zeta}\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)$ is the expected log switching cost conditional on choosing to switch:

$$\ln P_t^{i,t-1} = \int_0^1 \ln p_{j^*_{mt-1}mt}dm,$$
$$\ln\bar{\zeta}\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right) = \mathbb{E}\left[\ln\zeta^i_{mt}\middle|\,\zeta^i_{mt} < \left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\right].$$

The result that aggregate consumption scales with overall expenditure implies that the problem of expenditure allocation over time can be separated from the brand choice in each product type. I assume that households can trade in annuities so that the probability of death does not affect the interest rate in the economy. Furthermore, I assume that there is a borrowing limit restricting households to non-negative asset holdings. As I show in the Appendix, the inter-temporal Euler equation of old households implies that the risk-free rate, r_t, solves:

$$\beta(1+r_t) = \frac{E^o_{t+1}}{E^o_t}. \quad (8)$$

Firm problem. Each firm in the model produces a single brand in a single product type. Firms use a linear technology, with labor as the sole input to production. The production of firm j operating in product type m is given by

$$y_{jmt} = a_{jmt}l_{jmt},$$

where a_{jmt} is the idiosyncratic productivity of the firm at time t, and l_{jmt} is the labor used for production. Productivity follows an AR(1) process in logs, given by

$$\ln a_{jmt} = \rho_a \ln a_{jmt-1} + \sigma_a\nu_{jmt},$$

where ρ_a is the persistence parameter, and ν_{jmt} is an i.i.d. productivity shock drawn from a standard normal distribution. I denote the conditional productivity distribution by $H(a_t|a_{t-1})$. For clarity, in what follows, I omit the jm subscript for the individual firm.

In each period the firm operates, it needs to pay a fixed operating cost x_t^o. The operating cost is stochastic and follows an i.i.d. 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 either to operate and pay this cost or to exit the economy.

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

A firm has three state variables: its current productivity level (a_t), its previous-period customer base among the young population (B^y_{t-1}), and its previous-period customer base among the old population (B^o_{t-1}). It discounts future profits according to the prevailing interest rate, r_t. The Bellman equation for the firm's present value, after paying the fixed cost for the current period, is given by

$$
\begin{aligned}
V_t(B^y_{t-1}, B^o_{t-1}, a_t) = \max_{\{p_t, y_t, B^y_t, B^o_t\}} \; & p_t y_t - \frac{1}{a_t} y_t + \frac{1}{1+r_t} \mathbb{E}\left[\max\left\{V_{t+1}\left(B^y_t, B^o_t, a_{t+1}\right) - x^o_{t+1}, 0\right\}\right] \\
\text{s.t.} \quad & B^y_t = \mathcal{B}^y_t\left(B^y_{t-1}, p_t\right) \ , \\
& B^o_t = \mathcal{B}^o_t\left(B^y_{t-1}, B^o_{t-1}, p_t\right) \ , \\
& y_t = \mathcal{D}_t\left(B^y_t, B^o_t, p_t\right) \ ,
\end{aligned}
$$

where $\mathcal{B}^y_t(\cdot)$ and $\mathcal{B}^o_t(\cdot)$ are the equilibrium customer accumulation equations for young and old consumers at time t, respectively, and $\mathcal{D}_t(\cdot)$ is the equilibrium demand for the firm's good at time t. I denote the pricing policy function that solves the firm's problem by $\mathcal{P}_t\left(B^y_{t-1}, B^o_{t-1}, a_t\right)$. The following proposition derives an analytic expression for the customer accumulation and demand functions.

Proposition 1. *The customer evolution function and the demand function are given by*

$$
\mathcal{B}^y_t\left(B^y_{t-1}, p_t\right) = \bar{F}_y\left(\frac{p_t}{P_{mt}}\right)(1-q^o)B^y_{t-1} + \frac{N^{sy}_{mt}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}, \tag{9}
$$

$$
\mathcal{B}^o_t\left(B^y_{t-1}, B^o_{t-1}, p_t\right) = \bar{F}_o\left(\frac{p_t}{P_{mt}}\right)\left[q^o B^y_{t-1} + (1-q^d_t)B^o_{t-1}\right] + \frac{N^{so}_{mt}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma} \tag{10}
$$

$$
\mathcal{D}_t\left(B^y_t, B^o_t, p_t\right) = \frac{E^y_t}{p_t} B^y_t + \frac{E^o_t}{p_t} B^o_t, \tag{11}
$$

where N^{sy}_{mt} and N^{so}_{mt} are the measures of young and old households who decide to switch products in product type m at time t. $\bar{F}(\cdot)$ denotes the complementary CDF, defined as $1 - F(\cdot)$.

Entrants. Potential entrants can join the economy for a fixed entry cost f_e, denoted in labor units. 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. Let

J_t^e denote the measure of potential entrants who join the economy at time t. A free entry condition implies that

$$f_e = \int \int \max \{V_t(0,0,a) - x_o, 0\} \, dG_o(x_o) dH_e(a) \,, \tag{12}$$

if the number of potential entrants is positive.[13]

2.2 Equilibrium and Balanced Growth Path

I restrict attention to a symmetric equilibrium in which all product types are identical. I assume that each product type has an arbitrarily large number of operating firms (J), ensuring that idiosyncratic firm-level shocks do not introduce aggregate uncertainty.[14]

I denote the distribution of firms across productivity levels, previous young customer base, and previous old customer base, by $\Lambda_t(B_{t-1}^y, B_{t-1}^o, a_t)$. This distribution represents the measure of firms prior to making their exit decisions. Its law of motion is governed by four components: (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. Specifically, the law of motion for the joint distribution is defined as follows. For all Borel sets $\mathbf{B}^y \times \mathbf{B}^o \times \mathbf{A} \subset \mathbb{R}^+ \times \mathbb{R}^+ \times \mathbb{R}^+$,

$$\begin{aligned} \Lambda_{t+1}\left(\mathbf{B}^y \times \mathbf{B}^o \times \mathbf{A}\right) = & \int_{x_o} \int_{\mathscr{B}_t(\mathbf{B}^y \times \mathbf{B}^o, x_o)} \int_{a_{t+1} \in \mathbf{A}} dH(a_{t+1}|a_t) d\Lambda(B_{t-1}^y, B_{t-1}^o, a_t) dG_o(x_o) \\ & + \mathbb{1}\left((0,0) \in \mathbf{B}^y \times \mathbf{B}^o\right) J_{t+1}^e \int_{a_{t+1} \in \mathbf{A}} dH_e(a_{t+1}) \,, \end{aligned} \tag{13}$$

where $\mathscr{B}_t\left(\mathbf{B}^y \times \mathbf{B}^o, x_o\right)$ indicates the set of states in which the firm chooses to continue operation and the chosen customer base is in $\mathbf{B}^y \times \mathbf{B}^o$:

$$\begin{aligned} \mathscr{B}_t\left(\mathbf{B}^y \times \mathbf{B}^o, x_o\right) = \big\{(B_{t-1}^y, B_{t-1}^o, a_t) \quad \text{s.t.} \quad & V_t(B_{t-1}^y, B_{t-1}^o, a_t) \geq x_o, \\ & \mathcal{B}_t^y\left(B_{t-1}^y, \mathcal{P}_t\left(B_{t-1}^y, B_{t-1}^o, a_t\right)\right) \in \mathbf{B}^y, \\ \text{and} \quad & \mathcal{B}_t^o\left(B_{t-1}^y, B_{t-1}^o, \mathcal{P}_t\left(B_{t-1}^y, B_{t-1}^o, a_t\right)\right) \in \mathbf{B}^o \big\}, \end{aligned}$$

Equilibrium definition. Given initial population levels of young and old households $\{N_0^y, N_0^o\}$, an initial distribution of incumbent firms across states $\Lambda_0(B_{-1}^y, B_{-1}^o, a_0)$, and a sequence of demographic transition parameters $\{g_t, q_t^d\}_{t=0}^\infty$, an equilibrium is a sequence of aggregate quantities and prices $\{E_t^o, E_t^y, C_t^o, C_t^y, \Pi_t, J_t, J_t^e, P_{mt}, r_t\}_{t=0}^\infty$, customer accumulation and demand functions $\{\mathcal{B}_t^y(\cdot), \mathcal{B}_t^o(\cdot), \mathcal{D}_t(\cdot)\}_{t=0}^\infty$, firm value and policy functions $\{V_t(\cdot), \mathcal{P}_t(\cdot)\}_{t=0}^\infty$, and distributions $\{\Lambda_t(B_{t-1}^y, B_{t-1}^o, a_t)\}_{t=1}^\infty$, such that:

[13] Because the number of firms is finite, the free-entry condition (12) need not hold exactly. Instead, profits should switch from positive to negative once an additional entrant is considered. As the number of firms grows arbitrarily large, this deviation from exact equality becomes negligible.

[14] The number of firms in the economy can be arbitrarily large by lowering the entry cost, f_e. Specifically, halving the entry cost doubles the equilibrium number of firms.

1. Allocations and consumption policy functions solve the household's problem, i.e., equations (5)–(8) are satisfied.

2. Customer accumulation and demand functions satisfy equations (9)–(11).

3. Given customer accumulation and demand functions, the pricing policy function solves the firm's problem.

4. The free entry condition (12) holds.

5. Labor market and goods market clear.

6. Given firms' value and policy functions, distributions satisfy the law of motion (13).

Balanced growth path. Consider an economy in which the population growth rate and death probability are constant over time, so $\{q_t^d, g_t\} = \{\bar{q}^d, \bar{g}\}$ for all t. The limiting behavior of the economy is then characterized by a balanced growth path (BGP). Along the BGP, the number of firms grows at the same rate as the population, $\bar{g}$, while all other (per-capita) aggregate variables remain constant over time $\{\bar{E}^o, \bar{E}^y, \bar{C}^o, \bar{C}^y, \bar{\Pi}, \bar{P}_m, \bar{r}\}$. Furthermore, the normalized distribution of firms $\Lambda_{\text{norm}}(B^y, B^o, a) \equiv \frac{\Lambda(B^y, B^o, a)}{J}$ remains invariant over time. Appendix A.3 provides details.

2.3 Optimal markup: the harvesting and investing motives

Let us now examine how the incentives that shape a firm's optimal markup vary over its life cycle. The markup is defined as price over marginal cost, $\frac{p_t}{W_t/a_t}$. To characterize the optimal markup, I focus on a specific functional form for the switching costs distribution. Specifically, I assume these brand switching costs follow a Pareto distribution with shape parameter $\eta - 1$ and median e^{θ_i}, where θ_i varies between young and old households. This distributional assumption is maintained throughout the quantitative analysis. Formally, the cumulative distribution function takes the form:

$$F_i(\zeta) = 1 - \frac{1}{2} e^{(\eta-1)\theta_i} \zeta^{1-\eta}, \quad \text{for } \zeta \in \left[2^{\frac{1}{1-\eta}} e^{\theta_i}, \infty\right). \tag{14}$$

I assume that η is greater than one and lower than σ. Under this assumption, the demand elasticity of the firm's existing customers is smaller than that of households who did not purchase the brand in the previous period. Given this distributional assumption, the optimal markup of the firm solves the following equation:

$$\mu_t = \frac{\sigma}{\sigma - 1} + \underbrace{\frac{(1-\alpha_t)(\eta-1)}{\alpha_t(\sigma-1) + (1-\alpha_t)(\eta-1)} \left(\frac{\eta}{\eta-1} - \frac{\sigma}{\sigma-1}\right)}_{\textit{harvesting motive}} - \underbrace{\sum_{\tau=1}^{\infty} \mathbb{E}_t \left[M_{t,t+\tau} \gamma_{t,t+\tau} \mathbb{1}\left[\bar{T} \geq t+\tau\right]\right]}_{\textit{investing motive}}, \tag{15}$$

where α_t denotes the share of the firm's sales coming from customers who did not purchase from it in the previous period (henceforth, *new customers*), $\bar{T}$ denotes the last period in which the firm operates before exiting the economy, and $\gamma_{t,t+\tau} \geq 0$ is proportional to the profit gains in period $t + \tau$ from acquiring more customers at time t.[15]

Equation (15) highlights the determinants of a firm's markup and how it evolves over its life cycle. The first term in the equation, $\frac{\sigma}{\sigma-1}$, represents the markup a firm would charge in the absence of consumer inertia. The second term captures the *harvesting motive*—the incentive for the firm to exploit its locked-in customer base by raising its markup. The fraction $\frac{(1-\alpha_t)(\eta-1)}{\alpha_t(\sigma-1)+(1-\alpha_t)(\eta-1)}$ lies between 0 and 1 and increases with the share of locked-in customers. When the firm has no locked-in customers ($\alpha_t = 1$), the fraction is 0; when it sells exclusively to locked-in customers ($\alpha_t = 0$), the fraction is 1. Thus, a higher share of locked-in customers strengthens the harvesting motive.

Finally, the third term in equation (15) represents the *investing motive*. Firms have an incentive to lower markups in order to attract customers. Gaining customers today allows a firm to set higher markups and increase future sales and profits. Firms enter the economy with no initial customer base, implying $\alpha_t = 1$. Thus, the harvesting motive is muted, and the firm sets a markup below $\frac{\sigma}{\sigma-1}$ due to the investing motive. As the firm accumulates a customer base, the harvesting motive becomes stronger, leading to an increase in its optimal markup.

2.4 Discussion

Before turning to the quantitative analysis, let me discuss several key model assumptions.

First, I assume that firms cannot price discriminate between their customers. If a firm could, it would charge previous customers higher prices, exploiting their switching costs. As the firm accumulates a customer base, its average markup would increase, similar to what happens in the baseline model without price discrimination. Allowing for price discrimination would result in faster growth of older firms relative to the baseline model. This is because in the baseline model, older firms charge relatively higher markups to new customers, as their harvesting motive is stronger. With price discrimination, the harvesting motive would affect only the markup charged to existing customers.[16]

Second, I assume that households are myopic in their brand choice. In particular, they do not take into account the possibility of being locked-in with the same brand in future periods. This simplifying assumption is made primarily for tractability. If a household takes into account the possibility of future lock-in, the brand choice decision depends on future prices of each brand. These future prices depend on the pricing policy function of firms together with their expected future productivity and customer base. In turn, the pricing strategy of firms depends on the brand

[15] The exact formulas for both α_t and $\gamma_{t,t+\tau}$ are relegated to Appendix A.4.

[16] For a review of how first- and second-degree price discrimination shape misallocation across heterogeneous firms, see Bornstein and Peter (2024).

choice function of households. Solving this fixed point problem involving the policy functions of both households and firms is beyond the scope of this paper.

Third, I assume that the preferences of young and old households differ only in the location parameter of the switching cost distribution. I focus on this single dimension of heterogeneity to isolate the role of consumer inertia in shaping firm pricing and consumer behavior. This implies that the demand elasticity of new and existing customers does not vary with age. However, there is evidence that demand elasticities differ across age groups. Aguiar and Hurst (2007) show that households of different ages spend different amounts of time shopping, with both younger and older households paying lower prices for identical goods than middle-aged households. Curtis et al. (2024) estimate demand elasticities across age groups and find that elasticities decline over the life cycle. While in the model, demand elasticities do not vary with age conditional on being a new or existing customer, the average elasticity of older households (i.e., the cohort's aggregate demand elasticity) is lower than that of younger households. This arises because, all else equal, a larger share of older households remain with their previously chosen brand, reducing their responsiveness to price changes.

Fourth, I assume consumers purchase a brand in each product type, every period. In the data, consumers choose to consume only a subset of product types and that subset may be interconnected.[17] One way to model this extensive margin decision is adding a reduced-form utility from choosing not to consume in a specific product type. Such an addition to the model will likely change the demand elasticities from both previous and new customers, but is unlikely to affect the qualitative predictions of the model.

Fifth, I abstract from spatial segmentation and assume all firms compete in a national market. I also assume that each firm sells a single brand in a single product type. These simplifications are not central to the mechanism, but incorporating them would likely strengthen the forces emphasized in the model. Spatial segmentation would limit consumers' exposure to alternative brands, reinforcing switching costs and the advantage of incumbents. Similarly, if firms sold multiple products, brand loyalty in one category could spill over into others, increasing consumer inertia and amplifying the markup gap between entrants and incumbents.

3 Quantitative Analysis: Balanced Growth Path

This section calibrates the model using micro data on household consumption, firm dynamics moments, as well as aggregate moments. I first describe the data and document consumer inertia across young and old households. Next, I provide a detailed discussion of the baseline calibration. Finally, I study how firms behave over their life cycle in the baseline model, focusing particularly on markups.

[17] A family with a baby, for example, is more likely to purchase goods in both the 'diapers' and 'baby formula' product types. For a model that studies consumption basket choice along these lines, see Ruiz et al. (2020).

3.1 Consumer inertia along the age distribution

To quantify consumer inertia across age groups, I use consumer panel data from NielsenIQ, which tracks household brand-level purchases over time. The panel dimension of the dataset allows me to observe repeated household choices directly and measure brand-switching behavior. While earlier studies have documented lower inertia among younger households in specific contexts—such as pension choices (Luco, 2017), health plan choices (Strombom et al., 2002), and retail banking (Tesfom and Birch, 2011)—the NielsenIQ data covers a wide range of consumer packaged goods, allowing me to study consumer inertia in a broader consumption setting.

3.1.1 Data

The dataset used to document consumer inertia is the NielsenIQ Homescan Consumer Panel Data provided by the Kilts Data Center at the University of Chicago, Booth School of Business. It includes longitudinal purchase information for approximately 160 thousand households in the U.S. from 2004 to 2019. Households receive a barcode scanner from NielsenIQ and record all consumer packaged goods purchased, covering both food and non-food items across all retail outlets nationwide.[18]

For each shopping trip, the dataset records the date, products purchased at the Universal Product Code (UPC) level, and amounts paid. A UPC-level product example is a 16 fl oz plastic bottle of Coca-Cola. NielsenIQ organizes UPC-level products into product modules, groups, and departments. Modules represent the most granular level, followed by groups and then departments. For example, a 16 oz can of "Stapleton's California Whole Prunes packed in Pear Juice" belongs to the module "canned fruit - prunes," the group "canned fruit," and the department "dry grocery." I exclude the departments of deli, packaged meats, fresh produce, and general merchandise, where branding or choice between brands may be limited. The final sample covers six departments: dry grocery, health and beauty aids, frozen foods, dairy, non-food grocery, and alcohol.

For each household, the dataset includes demographic and geographic information such as family size and ages, household income, education, race, and location. The panel composition is designed to be projectable to the U.S. population. I supplement the NielsenIQ data with the GS1 U.S. dataset, administered by GS1, a not-for-profit standards organization managing UPC barcodes in the U.S. Using GS1 data, I link UPC-level products from NielsenIQ to the firms producing them.

3.1.2 Share of sales from new customers

I decompose brand sales into purchases by previous and new customers. A brand is defined as all products (UPCs) sold by a firm within a product module. A new customer is defined as a

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

household who did not purchase the brand in the previous year. I separate customers into young and old groups, computing the share of sales to new customers within each.[19] I let α^y_{jt} and α^o_{jt} denote these shares in the young and old age groups, respectively. A household is included in the *young* age group if the age of the household head is less than 35.

Two features of the data motivate using the brand-level share of sales from new customers rather than a household-level switching indicator. Households may purchase multiple brands within a module, e.g., several cereals for different household members, so a household-level "switch" would mix normal basket variation with true brand turnover. Moreover, households sometimes stop purchasing from an entire product module for reasons unrelated to brand preferences (e.g., changes in household composition), whereas the model abstracts from this extensive margin. In contrast, the brand-level measure is well defined regardless of multi-brand purchasing, avoids non-participation issues, and corresponds directly to the model's dynamic demand component, α_t in equation (15), which governs a firm's markup and customer-base accumulation.

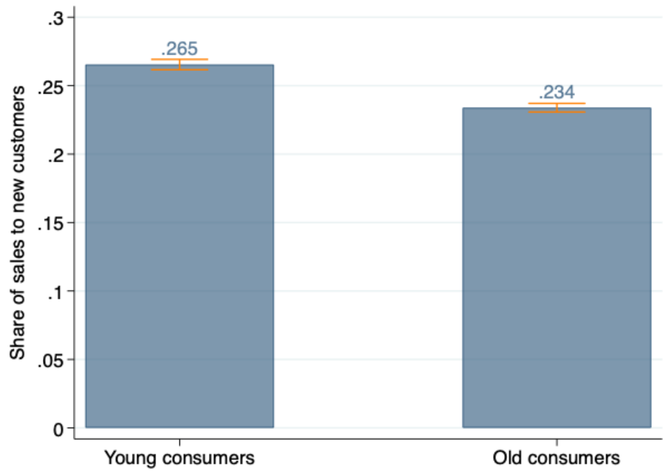
The main results are displayed in Figure 1, which shows the aggregate share of sales to new customers among young and old consumers. About 26.5% of sales to young consumers are from new customers, while the remaining 73.5% come from repeat customers who purchased the same brand in the previous year. For older consumers, new customers account for 23.4% of sales, 3.1 percentage points lower relative to young consumers. This difference is statistically significant. Table 1 shows that this difference remains stable even after controlling for store, product module, and brand fixed effects. Thus, the difference is not driven by younger and older consumers shopping at different stores or buying different products or brands.

While the model contains two age groups, I use the data to examine how consumer inertia evolves over more granular age categories. Figure 2 shows the difference in the share of sales to new customers between each age group and the 30–34 age group. The left panel reports results without additional controls, while the right panel includes household fixed effects. Consumer inertia gradually increases as consumers age, with no evidence of a discrete jump at any particular age.

One concern is that differences in consumer inertia across age groups may reflect cohort effects rather than age itself. For instance, a 60-year-old consumer might exhibit greater inertia than a 30-year-old due to different experiences growing up (e.g., no internet). Comparing the two panels in Figure 2 helps address this issue. Even after controlling for household fixed effects, thereby removing cohort-specific effects, older households remain significantly more inertial. Moreover, the estimated differences are quantitatively similar with and without household fixed effects, except

[19] For these calculations, I exclude households in their first year in the data, brands in their first year sold in a store, and outlier brands with shares equal to exactly 0 or 1. Defining a new customer as a household that has not purchased the brand in the previous year, rather than at any point in the past, avoids the mechanical correlation whereby older households are less likely to appear as new simply because they have been in the market longer. The sample is restricted to households that were actively shopping in the previous year, so differences between young and old households reflect differences in consumption behavior rather than differential observation histories.

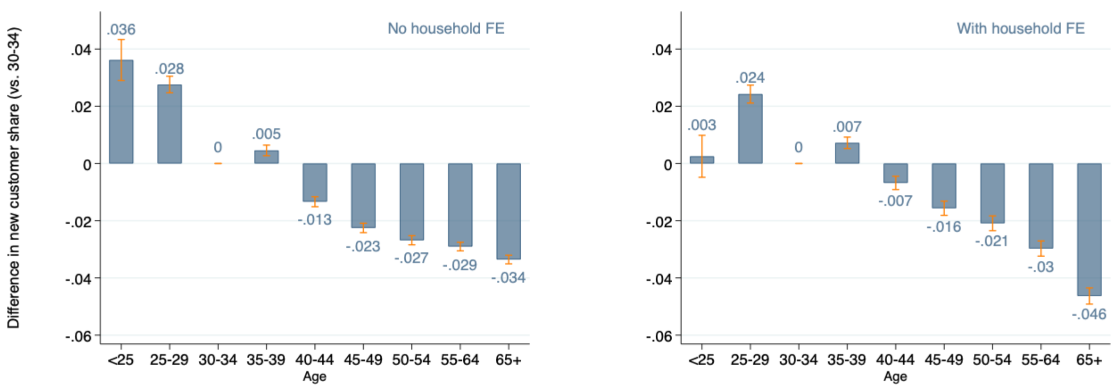
Figure 1: Share of sales to new customers for young and old customer base



Notes: This figure presents the aggregate share of brand sales that are sold to new customers. The sample is split into young (head of households younger than 35 years old) and old consumers. The remaining sales are accounted for by consumers who have purchased the brand in the previous year. The orange bars indicate 95% confidence intervals.

for households younger than 25.

Figure 2: Share of sales to new customers across granular age groups



Notes: These figures present the difference in the share of sales to new customers across age groups, where the 30–34 age group is the reference group. The left panel includes no additional controls (666K obs.), while the right panel includes household fixed effects (636K obs.). The orange bars indicate 95% confidence intervals.

Table 1: Share of sales from new customers - young vs. old

Dep. variable:	**share of sales from new customers**			
	(1)	(2)	(3)	(4)
$\mathbb{1}\,[\text{age} < 35]$	0.0314***	0.0386***	0.0363***	0.0438***
	(0.0025)	(0.0019)	(0.0010)	(0.0008)
Store f.e.	✗	✓	✓	✓
Product module f.e.	✗	✗	✓	✗
Brand f.e.	✗	✗	✗	✓

Notes: The table presents the regression results analyzing how the share of sales to new customers varies between the young and old age groups. The age indicates the age of the household head. The first column is using 644K brand-age-year observations, while the other columns use 68M brand-store-age-year observations. Standard errors in brackets. *** indicates statistical significance at 1% level.

3.1.3 Discussion

Before describing the calibration, I discuss four potential concerns regarding the use of these micro data moments to identify the degree of consumer inertia across age groups in the structural model.

First, the dataset only contains information on household consumption behavior in the retail sector. To the extent that consumer inertia varies substantially across sectors, this may introduce measurement error or bias in the calibrated aggregate degree of consumer inertia. A related study that can attenuate this concern is Einav, Klenow, Levin, and Murciano-Goroff (2021), which uses Visa debit and credit card data covering a broader set of sectors. They find that an upper bound on the share of sales to new customers across sectors is about 40%.[20]

Second, using the share of sales from new customers to measure consumer inertia could conflate *structural* state dependence, such as psychological switching costs, with *spurious* state dependence, such as auto-correlated taste shocks. Since the model interprets all state dependence as structural, this could lead to an upward bias in the calibrated level of inertia. However, using a similar NielsenIQ dataset, Dubé et al. (2010) estimate a flexible consumer choice model that differentiates structural from spurious state dependence. They find that state dependence cannot be explained away by spurious explanations, and provide support for interpreting state dependence in the data as structural.

Third, the structural model is calibrated to match the U.S. economy of the late 1980s, whereas the NielsenIQ data covers the period of 2006–2019. If consumer inertia across age groups has remained stable over time, this timing discrepancy would not affect the calibration. However, if inertia changed substantially, the micro estimates could meaningfully differ from the true levels in the late 1980s. While I cannot directly measure inertia in the earlier period, I examine whether

[20]Their estimate is an upper bound as they cannot link credit cards to customers over time; therefore, returning customers with new cards are counted as new customers.

inertia has changed over time within the available 2006–2019 sample. The annual standard deviation in the aggregate share of sales to new customers is 0.016, and the trend line slope is -0.002.[21] These patterns suggest that consumer inertia has remained relatively stable over the period, supporting the use of recent data to discipline the model's calibration.

Fourth, one may worry that consumers form preferences over a broader set of products than a single NielsenIQ module. For example, regular and low-calorie carbonated drinks are two separate product modules, even though consumers may view them as close substitutes. If consumer decisions operate at this broader level, measuring the share of sales from new customers at the module level could in principle misstate the extent of consumer inertia. To assess this concern, I recompute the new-customer-share moment at the product-group level, aggregating all modules within each NielsenIQ product group (e.g., all carbonated beverages). Under this broader definition, the average share of sales from new customers falls mechanically from 0.265 to 0.217, but the coefficient on the young-household indicator remains almost unchanged (0.030 versus 0.031). This stability indicates that the main findings do not hinge on the specific level of product aggregation. A complementary approach, in the spirit of Chintala et al. (2024), would be to construct basket-similarity measures that capture substitution across a household's wider set of related purchases; while beyond the scope of this paper, such measures offer a promising direction for future work.

3.2 Model calibration

I calibrate the model to match a balanced growth path of the U.S. economy in the late 1980s. The model has three sets of structural parameters: (i) the parameters governing population dynamics $\{g_t, q_t^d, q^o\}$, (ii) the household parameters $\{\beta, L_o, \sigma, \eta, \theta_y, \theta_o\}$, and (iii) the firm parameters $\{\rho_a, \sigma_a, \mu_o, \sigma_o, f_e\}$.

The population dynamics parameters match the demographic distribution between young and old households in the U.S. in 1987, based on World Bank population estimates. A young household is defined as an individual aged 15–34. One period in the model corresponds to one year. The aging probability (q^o) is set to 5%, and the population growth rate (g) is set to 1%. Finally, the death probability of old households (q^d) is chosen to match the share of young households (43%), resulting in a 3% annual death probability.

The discount factor is set to 0.97. The relative labor endowment of old households is calibrated to 1.2 to match the relative consumption of old households obtained from the PSID in 1989. I normalize the measure of firms in equilibrium to one and calibrate f_e to satisfy the free entry condition.[22] This leaves eight structural parameters to be determined. These parameters are calibrated to match the degree of consumer inertia observed in the micro data, as well as three features

[21] I find that also the gap between young and old consumers is relatively stable over time. Including an interaction of the young indicator ($\mathbb{1}$ [age < 35]) with a time trend yields a coefficient of 0.002.

[22] I normalize the measure of firms because scaling f_e and μ_o by a constant affects only the average firm size and total number of firms, without changing the firms' pricing, entry, exit, or other endogenous decisions.

of the U.S. business sector during 1987–1991. I select this five-year period because some calibration targets are only available from 1987 onward.

The three features of the U.S. business sector I target are: (i) the share of firms by firm age, (ii) the share of employment by firm age, and (iii) the profitability share in the economy. For the first two sets of moments, I use the Business Dynamics Statistics dataset, categorizing firms into four age groups: 0–1, 2–5, 6–10, and 11+.[23] I match the average firm and employment shares in each age category, generating six moments. Additionally, I target the profits share of GDP using data from the Bureau of Economic Analysis (BEA). The average HP-filtered aggregate profits share for that time period is 4.1%. Finally, I match the aggregate share of sales to new customers for young and old consumers. These shares help pin down the switching cost distributions governing the degree of consumer inertia across age groups. The weighting matrix I use is the identity one.

The model-implied moments and their data counterparts are displayed in Table 2.[24] Overall, the calibrated model successfully matches the targeted moments. The model closely replicates the difference in consumer inertia between young and old households, as measured by the share of sales from new customers. Table 3 presents the calibrated values of the structural parameters.

Table 2: Model Fit

Moment	Data	Model
New customer share (young)	0.27	0.27
New customer share (old)	0.23	0.23
Aggregate profits share	0.04	0.03
Firm share (age 0–1)	0.21	0.21
Firm share (age 2–5)	0.26	0.27
Firm share (age 6–10)	0.20	0.18
Employment share (age 0–1)	0.07	0.06
Employment share (age 2–5)	0.12	0.12
Employment share (age 6–10)	0.12	0.12

Notes: This table presents the data moments used for the model calibration and their model counterparts.

While the eight structural parameters are calibrated jointly, it is useful to discuss how each parameter is primarily identified. The median switching cost for young households (θ_y) is estimated to be 0.15. This implies the median young household is willing to reduce consumption by 15% rather than switch to another brand at the same price and with the same taste. This median switching cost allows the model to match the observed share of sales from new customers among

[23]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.

[24]Since the employment and firm shares each sum to one, I don't target these shares for firms older than 10 years old.

young households (26.5%). Similarly, the share of sales to new customers among old households (23%) pins down their median switching cost (θ_o), estimated at 0.17, about 13% higher than for young households.

Table 3: Calibrated Parameters

Parameter	Description	Value
θ_y	Median switching costs for young	0.15
θ_o	Median switching costs for old	0.17
η	Demand elasticity of existing customers	2.43
σ	Demand elasticity of new customers	4.66
μ_o	Average ln fixed operating costs	-3.71
σ_o	Std of ln fixed operating costs	2.37
ρ_a	Idiosyncratic productivity persistence	0.98
σ_a	Std of productivity shocks	0.04

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

The calibrated demand elasticities of existing customers (η) and new customers (σ) are equal to 2.43 and 4.66, respectively. These values are within the range of elasticities estimated in Foster, Haltiwanger, and Syverson (2008). These demand elasticities help the model match the aggregate profits share in the economy. Lower elasticities result in higher markups and higher profits. A set of moments that helps pin down the demand elasticity of new customers (σ) is the relative size of young firms.[25] A lower demand elasticity makes it harder for firms to attract customers, allowing the model to match the relatively small size of young firms.

The mean and standard deviation of fixed operating costs help match firm exit probabilities across the life cycle, which determine the firm age distribution. The average fixed operating cost governs the overall rate of exit, while its standard deviation affects how exit rates vary with age. A higher standard deviation reduces the variation of exit rates across firm ages, helping the model match the share of older firms in the economy.

Finally, the persistence and standard deviation of firm productivity shape growth and exit patterns over the firm's life cycle. The persistence parameter (ρ_a) determines the correlation between productivity and firm age. Higher productivity persistence increases the positive selection effect, meaning older firms are, on average, more productive. The survival probability increases with productivity and customer base, implying that the productivity threshold for exiting the economy declines as firms age. Without productivity shocks, all firms would have identical productivity, making selection irrelevant. A combination of high persistence ($\rho_a = 0.98$) and moderate volatility

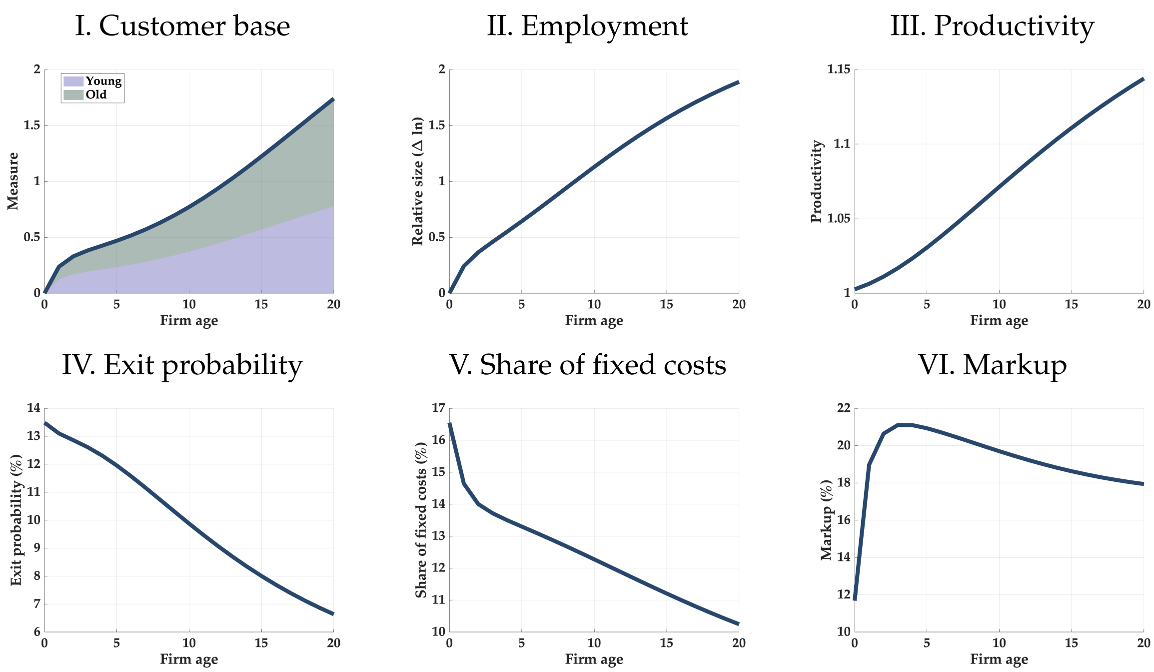
[25] Note that a change in the share of workers employed by firms of a certain age, holding constant the share of firms, is equivalent to changes in the relative size of firms of different ages.

($\sigma_a = 0.04$) generates a positive correlation between productivity and age, enabling the model to match the relative size distribution of firms by age.

3.3 Firm dynamics along the balanced growth path

Let us now explore firm behavior along the balanced growth path of the calibrated model. Figure 3 presents the life cycle of an average firm during its first 20 years. Firms enter with no initial customer base and gradually build it over time. As they age, their productivity increases due to selection, enabling them to sustain larger operating cost shocks and lowering their exit probabilities. Panel V shows that the fixed-cost share of sales is higher for younger firms. This is because young firms expect their profits to rise more rapidly in the future, relative to older firms.

Figure 3: The Life-Cycle of a Firm

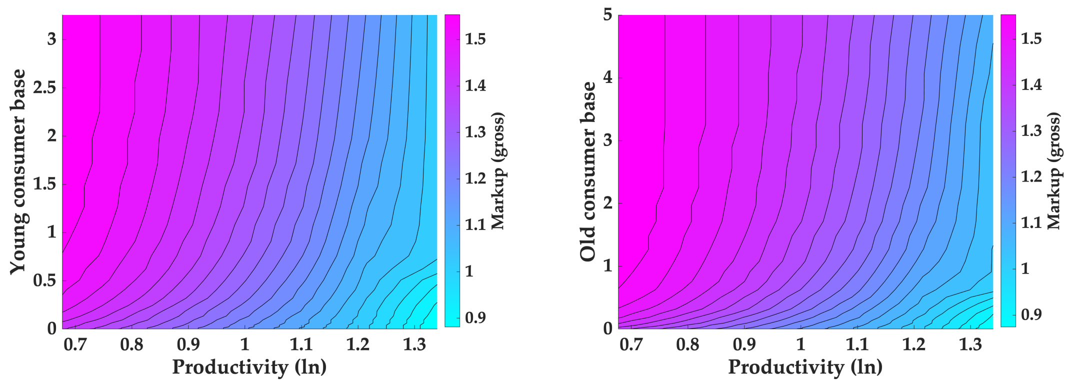


Notes: This figure presents the properties of the average firm across the first 20 years of its life. Employment is relative to the average entrant firm. Share of fixed costs is with respect to sales.

Panel VI of Figure 3 shows the markup of the average firm over its life cycle. Recall that the markup is determined by equation (15), reflecting a trade-off between the harvesting and investing motives. Entrants have no initial customer base, so the harvesting motive is muted and they charge a relatively low markup. As firms build their customer base, the harvesting motive strengthens, leading to higher markups in the early years. However, as firms age and their exit probability declines, the investing motive becomes stronger. This is because the value of acquiring new customers—an intangible asset—increases with the firm's survival probability. After year five, the average markup starts declining slightly, reaching about 18% by year 20.

To further understand firms' pricing decisions, Figure 4 shows the optimal markup as a function of productivity and customer base. The left panel presents a contour plot with productivity and the young customer base on the axes, holding the old customer base fixed at its median. The right panel shows the corresponding markup function with productivity and the old customer base on the axes, holding the young customer base at its median. In both cases, a larger customer base, other things equal, increases the firm's incentive to raise its markup due to a stronger harvesting motive. In contrast, higher productivity, holding customer base fixed, leads the firm to lower its markup. This is because more productive firms face lower exit probabilities, strengthening the investing motive: the value of acquiring new customers rises with expected firm longevity. Together, these patterns illustrate the model's central mechanism—firms with larger locked-in customer bases raise markups, while more productive firms price more aggressively to invest in future demand.

Figure 4: Markup Policy Function



Notes: This figure plots the markup policy function. The left panel presents a contour plot of the optimal markup as a function of productivity and the young customer base, for the median level of the old customer base. The right panel presents a contour plot of the optimal markup as a function of productivity and the old customer base, for the median level of the young customer base.

4 Quantitative Analysis: Entry and Profits in an Aging Economy

In this section, I study how population aging affects firm dynamics and profits in the economy. I solve for the transition dynamics of the model following a demographic shift that mimics the observed and projected changes in the U.S. between the late 1980s and 2100. The model predicts that population aging leads to lower entry rates and higher firm profits. I then present empirical evidence consistent with the model predictions.

4.1 Macro implications of the demographic transition

To study the macroeconomic effects of population aging, I consider an unexpected deterministic shock that gradually reduces the population growth rate (g_t) and death probability (q_t^d) from their initial rates to their projected values in 2050. I calibrate these terminal values using data from the World Bank's "Population Estimates and Projections" dataset. Specifically, the population growth rate declines from 1% in the baseline model to 0.2% in 2050. The death probability of old households falls from 3% to 1.6%, consistent with a decline in the share of young households from 43% to 26%. I assume that the two demographic parameters converge at a speed ρ, which is calibrated to match the share of young households in 2015–2019, 33%. After 2050, demographic parameters remain constant, and the model converges to a new balanced growth path by 2100. I solve for the full transition path, taking into account general equilibrium.[26] I focus on how population aging affects firm formation and the aggregate profit share.

Table 4 compares the aggregate profit share and the share of young firms between the initial balanced growth path (corresponding to the late 1980s) and the period 2015–2019. The model predicts an increase in the profit share of 79 basis points, which accounts for 28% of the observed rise in the data. This increase can be decomposed into three components. About half of the rise (47%) is driven by an increase in average markups. The remainder reflects a decline in the share of fixed operating costs and a reduction in entry costs, due to fewer firms entering. Recall from Figure 3 that the fixed-cost share declines with firm age, so the aging of the firm population reduces the aggregate share of fixed costs. The rise in average markups can itself be decomposed further: 22% stems from a shift in the distribution of firms toward older incumbents, while the remaining 78% reflects changes in the markup policy function. As the customer base becomes more inertial, incumbent firms face more locked-in customers, face lower effective demand elasticities, and respond by raising markups.

Table 4: The Aggregate Implications of Population Aging

	1987–1991 to 2015–2019		
	Model	Data	Contribution
Aggregate profits share	+0.79	+2.78	28%
Firm share of young firms	-2.88	-11.68	25%
Emp. share of young firms	-1.41	-8.81	16%

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

While aggregate profits have risen, firm formation has declined. The bottom two rows of Table 4 compare the decline in the share of young firms in the model to the decline observed in the data.

[26] The numerical algorithm is detailed in Appendix B.

In the model, the share of firms aged five or younger falls by 2.88 percentage points, from 48% to 45%, between the late 1980s and 2015–2019. The employment share of these firms declines by 1.41 percentage points, from 18% to 16.6%. These changes account for 25% of the decline in the firm share and 16% of the decline in the employment share of young firms observed in the data.

Looking ahead, the model predicts that the twin trends of rising profits and declining firm entry will continue as the population continues to age. The profit share is projected to increase by an additional 30 basis points, further widening the gap between the late 1980s and late 2010s. The share of young firms is expected to fall by another 2 percentage points, reaching 43%, while their employment share declines by an additional 60 basis points to 15.9%.

4.2 Supporting empirical evidence

This section presents three empirical findings that provide support for the model's central mechanisms. First, entrant brands charge lower markups than incumbents, consistent with the model's prediction that firms with small customer bases set low markups due to the investing motive. Second, U.S. states that experienced larger declines in their share of young households also experienced larger declines in the share of young firms, providing reduced-form evidence for the model's demographic channel. Third, product categories with younger customer bases exhibit both higher entry rates and lower markups, paralleling the model's implications across product types. Together, these results provide empirical support for the two key forces emphasized by the model: the life-cycle pattern of markups and the sensitivity of firm entry to changes in consumer inertia.

4.2.1 The relative markup of entrant brands

To study the behavior of entrant brand markups, I merge the NielsenIQ Homescan Consumer Panel Data with PromoData. PromoData contains monthly wholesale cost information at the Universal Product Code (UPC) level for the years 2006–2012. By combining these datasets, I can construct the *retail markup* for each product as the ratio of the retail price to the modal wholesale price in a given month.[27]

The NielsenIQ panel begins in 2004, which allows me to identify entrant brands in the merged dataset with PromoData. I define a brand as an entrant during the first 12 months after its introduction. I estimate regressions of the following form:

$$\mu_{jt} = \beta \mathbb{1}\left\{j \text{ is an entrant at } t\right\} + \gamma_{m(j)t} + \epsilon_{jt}, \tag{16}$$

where μ_{jt} is the retail markup of brand j at time t, $m(j)$ is the product module in which brand j operates, and $\gamma_{m(j)t}$ denotes a set of fixed effects. Depending on the specification, $\gamma_{m(j)t}$ includes

[27] This approach is closest to Stroebel and Vavra (2019) and Sangani (2022). Other studies that use the same or similar datasets to construct retail markups include Eichenbaum, Jaimovich, and Rebelo (2011), Gopinath, Gourinchas, Hsieh, and Li (2011), Nakamura and Zerom (2010), Anderson, Rebelo, and Wong (2018), and Afrouzi, Drenik, and Kim (2020).

product-module fixed effects, time fixed effects, or module-by-time fixed effects. Table 5 reports how the markups of entrant brands differ from those of incumbents. The first three columns show regressions weighted by total brand costs; the last three are unweighted.

Table 5: Retail Markups of Entrant Brands

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ [entrant brand]	-0.047**	-0.048**	-0.046*	-0.087***	-0.092***	-0.080**
	(0.023)	(0.023)	(0.025)	(0.030)	(0.030)	(0.035)
Module f.e.	✓	✓	✗	✓	✓	✗
Time f.e.	✗	✓	✗	✗	✓	✗
Module-time f.e.	✗	✗	✓	✗	✗	✓
Weighted	✓	✓	✓	✗	✗	✗
Obs.	121K	121K	114K	121K	121K	114K

Notes: The table presents the regressions studying the markup behavior of entrant brands. The dependent variable is the brand markup at a monthly frequency. The markup is defined as the ratio between the retail price and the modal wholesale price. Standard errors in brackets. If weighted, then weights are equal to the total wholesale costs of the brand. *** (**) {*} - 99% (95%) {90%} confidence interval does not include zero.

Across all specifications, the markup of entrant brands is significantly lower than that of incumbents. The cost weighted regressions suggest the markup of entrant brands is about 4.7 percentage points lower than that of older brands. The unweighted regressions suggest the difference is even larger—about 8 percentage points in the specification with product module by time fixed effects. Notably, the quantitative model delivers similar differences: the cost-weighted entrant markup is 4.2 percentage points lower than that of incumbents, and the unweighted difference is 7.8 percentage points. These are untargeted moments.[28]

4.2.2 Cross-state analysis

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. Formally, I estimate regressions of the following form:

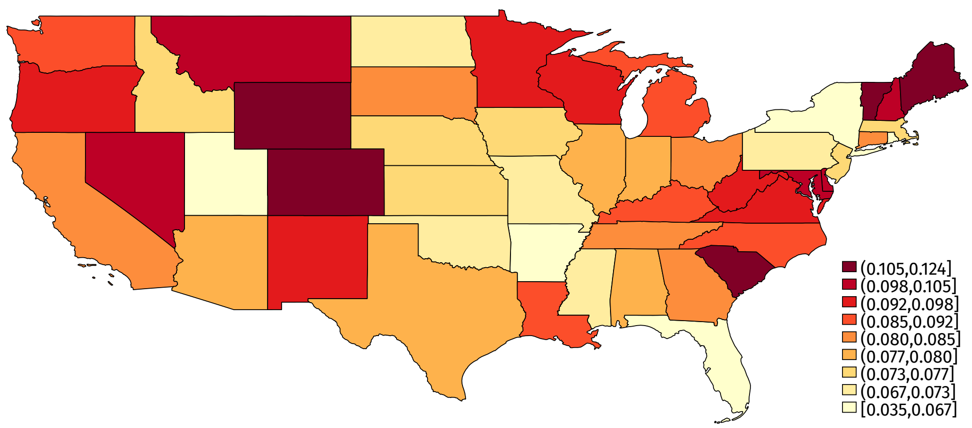
$$Y_{skt} = \beta \, \text{ShareYoung}_{st} + X_{st}'\delta + \gamma_s + \delta_{kt} + \varepsilon_{skt}, \tag{17}$$

[28] Adam, Renkin, and Züllig (2025) study the behavior of markups across the firm life cycle using Danish data on manufacturing firms. They also find that the markup of entrant firms is significantly lower than that of incumbents. Moreover, their non-parametric estimates show a similar life cycle markup pattern to the one I find in the model—a sharp rise over the first few years of a firm followed by a slow decline.

where Y_{skt} denotes either (i) the share of workers employed by young firms (5 years or younger) or (ii) the share of young firms in state s, sector k (2-digit NAICS), in year t. I choose these indicators as they are less affected by business cycle fluctuations.[29] The key explanatory variable ShareYoung_{st} is the share of young adults (ages 15–34) in the state's adult population. All specifications include state fixed effects as well as sector-by-year fixed effects.

Figure 5 shows the decline in the share of young adults across U.S. states from 1980 to 2019.[30] All states experienced population aging—a decline in the share of young adults—but the magnitude of this change varies widely. Florida, which already had a relatively small young population in 1980, saw only a modest decline. In contrast, Wyoming's share fell from 39% in 1980 to 26% in 2019. The median decline across states over this period is 8.3 percentage points.

Figure 5: State-Level Decline in Share of Young Population (1980–2019)



Notes: This figure shows the change in the share of young adults (ages 15–34) across U.S. states between 1980 and 2019. The change is measured in percentage points. All states experienced a decline in the share of young adults over this period, though the magnitude of the decline varies substantially across states.

Before turning to the results, I discuss a potential concern in interpreting β as capturing the demand-side effect of aging on firm formation. The share of young population can influence firm formation not only through consumer inertia but also through supply-side channels. To mitigate this omitted-variable concern, I include two demographic controls emphasized in the literature: the growth rate of the labor force and the share of older workers in the workforce. Slower labor-force growth has been shown to reduce firm formation (Karahan et al., 2024; Hopenhayn et al., 2018), and an aging workforce may also hinder entry (Liang et al., 2018; Engbom, 2019). These controls help isolate the demand-side channel highlighted by the model. In addition, to address

[29]The data source is the Business Dynamics Statistics.

[30]The state-level population by age dataset is from the National Cancer Institute (NCI), DCCPS, Surveillance Research Program.

potential endogeneity in ShareYoung_{st} arising from migration, I instrument for it using the state's age composition ten years earlier, following Shimer (2001), Karahan et al. (2024), and Engbom (2019).

Table 6 reports the regression results. Columns (1)–(3) present OLS estimates; columns (4)–(6) present IV estimates. The OLS results reveal a strong positive association: a one percentage point decline in the share of young adults is associated with a 0.36 percentage point decline in the employment share of young firms and a 0.83 percentage point decline in the firm share. The IV estimates yield similar conclusions: the implied effects are 0.39 and 0.93 percentage points, respectively.

Table 6: Population Aging and Firm Formation Across States

	Dependent variable: share of workers employed by young firms					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of young population	0.36***	0.36***	0.34**	0.39**	0.39**	0.38**
	(0.12)	(0.12)	(0.13)	(0.15)	(0.15)	(0.18)
Labor-force growth rate		0.021***	0.020***		0.020***	0.020***
		(0.01)	(0.01)		(0.01)	(0.01)
Share of older workers			−0.017			−0.008
			(0.03)			(0.04)
Instrumented	✗	✗	✗	✓	✓	✓
	Dependent variable: share of young firms					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of young population	0.83***	0.82***	0.83***	0.93***	0.92***	0.95***
	(0.16)	(0.16)	(0.17)	(0.20)	(0.20)	(0.23)
Labor-force growth rate		0.042***	0.043***		0.040***	0.041***
		(0.01)	(0.01)		(0.01)	(0.01)
Share of older workers			0.008			0.034
			(0.03)			(0.05)
Instrumented	✗	✗	✗	✓	✓	✓

Notes: The table presents the regressions studying how the share of young population affects firm formation. 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. All specifications include sector-by-time as well as state fixed effects. Standard errors in parenthesis. Standard errors are clustered at the state level. *** (**) - 99% (95%) confidence interval does not include zero.

A back-of-the-envelope calculation suggests that the observed decline in the share of young households between 1987–1991 and 2015–2019 accounts for 44% of the decline in the employment share of young firms (3.9pp of an 8.8pp decline). For the firm share, the corresponding figure is

79% (9.3pp of an 11.7pp decline), indicating that population aging plays a quantitatively important role.

Finally, let me discuss a tension between the cross-state analysis and the model environment I study. In the model, firms compete nationally, and there is no geographical location choice. In contrast, the empirical analysis presented here effectively treats each state as an independent economy. This abstraction ignores inter-state spillovers: firms may prefer to locate in states with a higher share of young households, where market penetration is easier. Such geographic reallocations of firm formation represent a zero-sum game at the national level. Consequently, the cross-state estimates likely represent an upper bound on the aggregate impact of consumer inertia on firm formation.

4.2.3 Cross-product-type analysis

This subsection examines how consumer age composition shapes firm entry and markups across product modules in the NielsenIQ dataset. The main advantage of the cross-product-type analysis relative to the cross-state one is that the share of young customers does not conflate the demand-side channels of the age structure with supply-side forces. In particular, variation in the age composition of consumers across product modules reflects differences in who buys what, not differences in labor supply or migration patterns. Formally, I estimate regressions of the following form:

$$Y_{mt} = \beta \, \text{ShareYoungCust}_{mt} + \gamma_{d(m)} + \delta_t + \varepsilon_{mt}, \tag{18}$$

Table 7 presents the regression results. Columns (1)–(2) examine the relationship between the share of young customers and entry rates, using weights based on total sales or on the number of firms in each module. Both specifications yield positive and statistically significant coefficients: modules with a larger share of young customers experience higher entry. Quantitatively, a 10 percentage point decline in the share of young customers is associated with a 40–50 basis point decline in the entry rate. Given that entry rates fell by roughly 3 percentage points between the late 1980s and the late 2010s, the decline in young customers accounts for 12–16% of the aggregate trend.

One caveat is that firms often offer products across multiple modules. As a result, variation in the age composition across modules may generate weaker variation in entry than aggregate demographic changes. For example, a dairy brand may sell across the milk, yogurt, and cream modules; differences in the share of young customers across these modules would not necessarily translate into differences in entry rates.

Columns (3)–(4) show that modules with a larger share of young customers also exhibit lower markups. A 10 percentage point decline in the share of young customers is associated with a 13–15 percentage point increase in average markups, consistent with the model's prediction that greater consumer inertia raises markups by strengthening the harvesting motive. The estimated

Table 7: Cross-Product-Type Regressions

Dep. variable:	**Entry rate**		**Retail markup**	
	(1)	(2)	(3)	(4)
Share of young customers	0.048***	0.037***	-1.532***	-1.326***
	(0.015)	(0.009)	(0.543)	(0.217)
Weighting	Sales	Firms	Sales	Firms
Obs.	6K	6K	2K	2K

Notes: The table presents the cross-product-type regressions. The dependent variable in the first two columns is the entry rate at the product-module level. The dependent variable in columns (3)–(4) is the average markup at the product-module level. All regressions include department and year fixed effects. Standard errors in brackets. The two types of weights considered are the number of operating firms in a product module or the total amount of sales in a product module. *** (**) {*} - 99% (95%) {90%} confidence interval does not include zero.

magnitude is larger than what the model predicts. One possible explanation is that the model assumes the demand elasticity of unattached consumers is constant across age groups, whereas in the data younger consumers may be more price elastic; a higher elasticity among younger households would generate lower markups.

5 Conclusion

This paper studies how population aging contributes to the twin trends of declining business dynamism and rising corporate profits through a demand-side mechanism: consumer inertia. Using micro data on household purchasing behavior, I show that younger households are significantly less inertial than older ones. As the population has aged, the composition of demand has shifted toward more inertial consumers, raising the cost of customer acquisition for new firms and increasing the pricing power of incumbents. Empirical evidence from both cross-state variation and cross-product-category variation supports this mechanism, documenting that firm formation is lower in markets with a less dynamic customer base.

I develop a model of entry, exit, and firm dynamics in the presence of consumer inertia. I calibrate the model using both micro and macro moments so that the balanced growth path equilibrium corresponds to the U.S. economy in the late 1980s. I then simulate the observed and projected demographic shift in the U.S. between the late 1980s and 2050 and study its macroeconomic implications. The model implies that population aging accounts for about 20% of the declining share of young firms and about 30% of the rising share of aggregate profits since the late 1980s.

While the model highlights how population aging can shift the distribution of firms and raise markups, several important questions remain open. First, what are the welfare implications of increased inertia and the associated rise in market power? Assessing welfare requires taking a stand on the origins of inertia. If switching costs reflect behavioral biases or informational frictions, high-markup firms are potentially under-producing. But if switching costs are contractual or pecuniary in nature, the social planner may prefer a less productive firm with a relatively high markup to cease operation, instead of reallocating production resources toward that firm.

Second, what are the growth implications of a declining share of young firms in a market where customer accumulation is slow? While young firms account for a small share of employment, their potential contribution to innovation or creative destruction may be understated when inertia slows their expansion. In such a setting, employment shares are a poor proxy for long-run economic contribution.

A third avenue for future research is to endogenize firm investments in demand accumulation. In this paper, consumer inertia is exogenous and firms face it passively. But in many industries, firms invest heavily in marketing and advertising to overcome switching costs and build customer loyalty. Introducing an advertising margin—where firms can spend to increase consumer awareness or reduce switching costs—could deepen our understanding of how firms respond strategically to a rise in consumer inertia.

References

ADAM, K., T. RENKIN, AND G. ZÜLLIG (2025): "Markups and Marginal Costs Over the Firm Life: Implications for the Optimal Inflation Target," Tech. rep., University of Bonn and University of Mannheim, Germany.

AFROUZI, H., A. DRENIK, AND R. KIM (2020): "Growing by the masses-revisiting the link between firm size and market power," .

AGUIAR, M. AND E. HURST (2007): "Life-cycle prices and production," *American Economic Review*, 97, 1533–1559.

ANDERSON, E., S. REBELO, AND A. WONG (2018): "Markups across space and time," Tech. rep., National Bureau of Economic Research.

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

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

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

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 S. G. BENZELL (2018): "70 Years of US Corporate Profits," *Stigler Center for the Study of the Economy and the State New Working Paper Series*.

BORNSTEIN, G. AND A. PETER (2024): "Nonlinear pricing and misallocation," Tech. rep., National Bureau of Economic Research.

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

CHINTALA, S. C., J. LIAUKONYTĖ, AND N. YANG (2024): "Browsing the aisles or browsing the app? How online grocery shopping is changing what we buy," *Marketing Science*, 43, 506–522.

CURTIS, C., J. GARIN, AND R. LESTER (2024): "Does the Phillips Curve Lie Down as we Age?" Tech. rep.

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

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

——— (2014b): "The secular decline in business dynamism in the US," *Unpublished draft, University of Maryland*.

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

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

EICHENBAUM, M., N. JAIMOVICH, AND S. REBELO (2011): "Reference prices, costs, and nominal rigidities," *American Economic Review*, 101, 234–262.

EINAV, L., P. J. KLENOW, J. D. LEVIN, AND R. MURCIANO-GOROFF (2021): "Customers and retail growth," Tech. rep., National Bureau of Economic Research.

EINAV, L., E. LEIBTAG, AND A. NEVO (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 P. KLEMPERER (2007): “Coordination and lock-in: Competition with switching costs and network effects,” *Handbook of industrial organization*, 3, 1967–2072.

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

FITZGERALD, D., S. HALLER, AND Y. YEDID-LEVI (2024): “How exporters grow,” *Review of Economic Studies*, 91, 2276–2306.

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

——— (2016): “The slow growth of new plants: Learning about demand?” *Economica*, 83, 91–129.

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

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

GOPINATH, G., P.-O. GOURINCHAS, C.-T. HSIEH, AND N. LI (2011): “International prices, costs, and markup differences,” *American Economic Review*, 101, 2450–2486.

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

GRULLON, G., Y. LARKIN, AND R. MICHAELY (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 T. PHILIPPON (2017): “Declining Competition and Investment in the US,” Tech. rep., National Bureau of Economic Research.

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

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

HATHAWAY, I. AND R. LITAN (2014): “The other aging of America: the increasing dominance of older firms,” *Brookings Institution*.

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

HORTAÇSU, A., S. A. MADANIZADEH, AND S. L. PULLER (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 F. SOHAIL (2023): "Skill-Biased Entrepreneurial Decline," *Review of Economic Dynamics*, 48, 18–44.

KARABARBOUNIS, L. AND B. NEIMAN (2018): "Accounting for Factorless Income," in *NBER Macroeconomics Annual 2018, volume 33*, University of Chicago Press.

KARAHAN, F., B. PUGSLEY, AND A. ŞAHIN (2024): "Demographic Origins of the Start-up Deficit," *American Economic Review*, 114, 1986–2023.

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

——— (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., H. WANG, AND E. P. LAZEAR (2018): "Demographics and Entrepreneurship," *Journal of Political Economy*, 126, S140–S196.

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., S. MALIAR, AND F. VALLI (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," Tech. rep., Northwestern University.

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

Nakamura, E. and D. Zerom (2010): "Accounting for incomplete pass-through," *The review of economic studies*, 77, 1192–1230.

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 C. Walsh (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 A. Şahin (2015): "Grown-up business cycles," *The Review of Financial Studies*.

Ravn, M., S. Schmitt-Grohé, and M. Uribe (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 M. Woodford (1991): "Markups and the business cycle," *NBER macroeconomics annual*, 6, 63–129.

Rouwenhorst, K. G. (1995): "Asset pricing implications of equilibrium business cycle models," *Frontiers of business cycle research*, 1, 294–330.

Ruiz, F. J., S. Athey, and D. M. Blei (2020): "Shopper," *The Annals of Applied Statistics*, 14, 1–27.

Salgado, S. (2017): "Technical Change and Entrepreneurship," .

Sangani, K. (2022): "Markups across the income distribution: Measurement and implications," *Available at SSRN 4092068*.

Sedláček, P. and V. Sterk (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.

Stroebel, J. and J. Vavra (2019): "House prices, local demand, and retail prices," *Journal of Political Economy*, 127, 1391–1436.

Strombom, B. A., T. C. Buchmueller, and P. J. Feldstein (2002): "Switching costs, price sensitivity and health plan choice," *Journal of Health economics*, 21, 89–116.

TESFOM, G. AND N. J. BIRCH (2011): "Do switching barriers in the retail banking industry influence bank customers in different age groups differently?" *Journal of Services Marketing*, 25, 371–380.

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

A Model Appendix

A.1 Proofs

Proof of Lemma 1.

Proof. Fix a product type m in which the household has decided to switch. For a given expenditure level E_{mt}, the household chooses the brand that maximizes taste-adjusted consumption:

$$\max_j \quad \ln c_{jmt} + \frac{1}{\sigma - 1}\,\epsilon_{jmt},$$
$$\text{s.t.} \quad p_{jmt}c_{jmt} = E_{mt}.$$

Substituting the constraint yields

$$\max_j \; \ln E_{mt} - \ln p_{jmt} + \frac{1}{\sigma - 1}\,\epsilon_{jmt}.$$

Since $\ln E_{mt}$ is independent of j, the optimal brand is independent of the expenditure level. Multiplying by $(\sigma - 1) > 0$ gives

$$j^*_{mt} \;=\; \arg\max_j \; \big\{ - (\sigma - 1)\ln p_{jmt} + \epsilon_{jmt} \big\}.$$

□

Proof of Lemma 2.

Proof. When deciding whether to switch brands or not, the consumer compares the taste-adjusted consumption of its previous brand to the expected taste-adjusted consumption from switching. This is because the switching decision takes place before taste-shocks are realized. Let us first derive the expected taste-adjusted consumption conditional on switching,

$$\mathbb{E}\left[\max_j \left\{ -\ln p_{jmt} + \frac{1}{\sigma - 1}\epsilon_{jmt} \right\}\right]. \tag{19}$$

To derive the expression for this expectation term, I proceed in two steps:

1. I show that the probability that brand j is chosen is equal to

$$Pr(j^*_{mt} = j) = \frac{1}{J_{mt}} \left(\frac{p_{jmt}}{P_{mt}}\right)^{1-\sigma}, \tag{20}$$

   where

$$P_{mt} = \left(\frac{1}{J_{mt}} \sum_{j'} p_{j'mt}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

2. I show that the expected taste shock conditional on a firm with price p_{jmt} being chosen is equal to
$$\mathbb{E}\left[\frac{1}{\sigma-1}\epsilon_{j*mt}\middle| p_{jmt}, j^*_{mt}=j\right] = -\ln P_{mt} + \ln p_{jmt} + \frac{\gamma}{\sigma-1}. \tag{21}$$
where γ is the Euler–Mascheroni constant. Using the expression above, the law of iterated expectations implies that
$$\mathbb{E}\left[\max_j\left\{-\ln p_{jmt} + \frac{1}{\sigma-1}\epsilon_{jmt}\right\}\right] = -\ln P_{mt} + \frac{\gamma}{\sigma-1}. \tag{22}$$

Probability of a brand being chosen. The probability that firm j is chosen conditional on its taste shock being equal to ϵ_j is given by
$$\begin{aligned}
P\left(j^*_{mt}=j|\epsilon_j\right) &= \prod_{k\neq j} P\left(\frac{1}{\sigma-1}\epsilon_j - \ln p_j \geq \frac{1}{\sigma-1}\epsilon_k - \ln p_k\right)\\
&= \prod_{k\neq j} P\left(\epsilon_k < (\sigma-1)\left(\ln p_k - \ln p_j\right) + \epsilon_j\right)\\
&= \prod_{k\neq j} e^{-e^{-\left[(\sigma-1)\left(\ln p_k - \ln p_j\right)+\epsilon_j+\ln J_m\right]}}\\
&= \left(\prod_{k} e^{-e^{-\left[(\sigma-1)\left(\ln p_k - \ln p_j\right)+\epsilon_j+\ln J_m\right]}}\right) e^{e^{-\epsilon_j-\ln J_m}}\\
&= \left(e^{-e^{-\epsilon_j}\frac{1}{J_m}\sum_k e^{-(\sigma-1)\left(\ln p_k - \ln p_j\right)}}\right) e^{e^{-\epsilon_j-\ln J_m}}\\
&= \left(e^{-Qe^{-\epsilon_j}}\right) e^{e^{-\epsilon_j-\ln J_m}},
\end{aligned}$$
where $Q \equiv \frac{1}{J_m}\sum_k e^{-(\sigma-1)(\ln p_k - \ln p_j)}$. To obtain the probability that firm j is chosen, we now use the pdf of ϵ_j.
$$\begin{aligned}
P\left(j^*_{mt}=j\right) &= \int_{-\infty}^{\infty}\left(e^{-Qe^{-\epsilon_j}}\right) e^{e^{-\epsilon_j-\ln J_m}} e^{-e^{-\epsilon_j-\ln J_m}} e^{-\epsilon_j-\ln J_m} d\epsilon & (23)\\
&= \frac{1}{J_m}\int_{-\infty}^{\infty}\left(e^{-Qe^{-\epsilon_j}}\right) e^{-\epsilon_j} d\epsilon & (24)\\
&= \frac{1}{J_m}\int_{0}^{\infty}\left(e^{-Qx}\right) dx & (25)\\
&= \frac{1}{J_m}\frac{1}{Q} & (26)
\end{aligned}$$
where the second-to-last equality uses integration by substitution with $x = e^{-\epsilon}$, and the last equality uses $\int e^{-Qx}dx = -e^{-Qx}/Q$. Using the definition of Q, we obtain (adding back the full notation)
$$P\left(j^*_{mt}=j\right) = \frac{1}{\sum_k e^{-(\sigma-1)(\ln p_{kmt} - \ln p_{jmt})}} = \frac{1}{J_{mt}}\left(\frac{p_{jmt}}{P_{mt}}\right)^{1-\sigma}, \tag{27}$$
where
$$P_{mt} = \left[\frac{1}{J_{mt}}\sum_k p_{kmt}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}.$$

Expected taste of chosen brand. We start by deriving the pdf of ϵ_j conditional on firm j being chosen, $f_\epsilon\left(\epsilon_j | j^*_{mt} = j\right)$. To do so, we will use Bayes rule twice:

$$\begin{aligned}
f_\epsilon\left(\epsilon_j | j^*_{mt} = j\right) &= \frac{f_{\epsilon,\text{chosen}}\left(\epsilon_j, j^*_{mt} = j\right)}{P(j^*_{mt} = j)} \\
&= \frac{P\left(j^*_{mt} = j | \epsilon_j\right)}{P(j^*_{mt} = j)} e^{-e^{-\epsilon_j - \ln J_{mt}}} e^{-\epsilon_j - \ln J_{mt}} \\
&= \left(e^{-Qe^{-\epsilon_j}}\right) e^{e^{-\epsilon_j - \ln J_{mt}}} J_{mt} Q e^{-e^{-\epsilon_j - \ln J_{mt}}} e^{-\epsilon_j - \ln J_{mt}} \\
&= J_{mt} Q \left(e^{-Qe^{-\epsilon_j}}\right) e^{-\epsilon_j - \ln J_{mt}}.
\end{aligned}$$

Given the pdf, we can now compute

$$\mathbb{E}\left[\frac{1}{\sigma - 1}\epsilon_j \middle| j^*_{mt} = j\right] = \int \frac{1}{\sigma - 1}\epsilon_j J_m Q \left(e^{-Qe^{-\epsilon_j}}\right) e^{-\epsilon_j - \ln J_m} d\epsilon_j \tag{28}$$

$$= \frac{Q}{\sigma - 1} \int \epsilon_j \left(e^{-Qe^{-\epsilon_j}}\right) e^{-\epsilon_j} d\epsilon_j \tag{29}$$

Using a change of variables $x = Qe^{-\epsilon}$, so that $\epsilon = \ln Q - \ln x$ and $\frac{\partial \epsilon}{\partial x} = -\frac{1}{x}$

$$\begin{aligned}
\mathbb{E}\left[\frac{1}{\sigma - 1}\epsilon_j \middle| j^*_{mt} = j\right] &= \frac{Q}{\sigma - 1}\left[\ln Q \int_0^\infty e^{-x}\frac{1}{Q}dx - \int_0^\infty \ln x e^{-x}\frac{1}{Q}dx\right], \\
&= \frac{1}{\sigma - 1}\left[\ln Q - \frac{d}{d\alpha}\int_0^\infty x^\alpha e^{-x} dx\bigg|_{\alpha=0}\right] \\
&= \frac{1}{\sigma - 1}\left[\ln Q - \frac{d}{d\alpha}\left.\Gamma(\alpha + 1)\right|_{\alpha=0}\right] \\
&= \frac{1}{\sigma - 1}\left(\ln Q + \gamma\right) \\
&= \frac{1}{\sigma - 1}\ln\left(\frac{p_{jmt}}{P_{mt}}\right)^{\sigma - 1} + \frac{\gamma}{\sigma - 1} \\
&= \ln p_{jmt} - \ln P_{mt} + \frac{\gamma}{\sigma - 1}
\end{aligned}$$

where γ is the Euler–Mascheroni constant.

Computing the expected taste-adjust consumption shifter conditional on switching. We can use the law of iterated expectations to obtain

$$\begin{aligned}
\mathbb{E}\left[\max_j\left\{-\ln p_{jmt} + \frac{1}{\sigma - 1}\epsilon_{jmt}\right\}\right] &= \sum_j P(j^*_{mt} = j)\mathbb{E}\left[\left\{-\ln p_{jmt} + \frac{1}{\sigma - 1}\epsilon_{jmt}\right\}\middle| j^*_{mt} = j\right] \\
&= \sum_j P(j^*_{mt} = j)\left[-\ln P_{mt} + \frac{\gamma}{\sigma - 1}\right] \\
&= -\ln P_{mt} + \frac{\gamma}{\sigma - 1}.
\end{aligned}$$

The decision whether to switch brands. The customer chooses to switch brands from brand j when

$$-\ln p_{jmt} + \frac{\gamma}{\sigma-1} + \ln \zeta_{mt} < \mathbb{E}\left[\max_{j}\left\{-\ln p_{jmt} + \frac{1}{\sigma-1}\epsilon_{jmt}\right\}\right].$$

Using the previous derivation of the RHS term, we obtain the result of the Lemma that a customer switches brand when

$$\ln \zeta_{mt} < \ln p_{jmt} - \ln P_{mt}. \tag{30}$$

□

Proof of Lemma 3.

Proof. Recall that the definition of aggregate consumption is given by

$$\ln C_t^i = \int_0^1 \left[\ln c_{mt}^{*i} + \frac{1}{\sigma-1}\epsilon_{mt}^{*i} - \ln \zeta_{mt}^i \mathbb{1}\left(\text{switch}_{mt}^i\right)\right] dm, \tag{31}$$

We proceed in two steps. First, conditional on brand choices, how does the household allocate expenditure across products:

$$\max_{E_{mt}^i} \int_0^1 \left[\ln E_{mt}^i - \ln p_{j^*mt} + \frac{1}{\sigma-1}\epsilon_{j^*mt} - \ln \zeta_{mt}^i \mathbb{1}\left(\text{switch}_{mt}^i\right)\right] dm,$$
$$\text{s.t.} \quad \int_0^1 E_{mt}^i dm = E_t^i.$$

Solving the first order condition, we get the standard results that these Cobb-Douglas preferences imply that the households allocate expenditure equally across all product types regardless of their prices,

$$E_{mt}^i = E_t^i, \quad \forall m. \tag{32}$$

This implies

$$\ln C_t^i = \ln E_t^i + \int_0^1 \left[-\ln p_{j^*mt}^i + \frac{1}{\sigma-1}\epsilon_{j^*mt}^i - \ln \zeta_{mt}^i \mathbb{1}\left(\text{switch}_{mt}^i\right)\right] dm, \tag{33}$$

In Lemma 2 we showed that conditional on switching, $\mathbb{E}\left[-\ln p_{j^*mt} + \frac{1}{\sigma-1}\epsilon_{j^*mt}\right] = \frac{\gamma}{\sigma-1} - \ln P_{mt}$ and that switching happens when $\zeta_{mt} < \frac{p_{jmt}}{P_{mt}}$. The iid assumption on switching costs then implies that

$$\begin{aligned}\ln C_t^i =& \ln E_t^i + \frac{\gamma}{\sigma-1} - \int_0^1 F^i\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\left[\ln P_{mt} + \ln \bar{\zeta}\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\right] dm \\ &- \int_0^1 \left(1 - F^i\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\right) \ln p_{j^*_{mt-1}mt} dm,\end{aligned}$$

where $\ln \bar{\zeta}\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right) \equiv \mathbb{E}\left[\ln \zeta \middle| \zeta < \left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\right]$ is the expected switching cost conditional on switching. The equation above uses the assumption that $\mathbb{E}\epsilon_{jmt} = \gamma$ for brands which the consumer does not switch. Rearranging we prove the result:

$$\ln C_t^i = \ln E_t^i - \ln P_{t-1}^i + \int_0^1 F^i\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\left[\ln\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right) - \ln \bar{\zeta}\left(\frac{p_{j^*_{mt-1}mt}}{P_{mt}}\right)\right] dm + \frac{\gamma}{\sigma-1}, \tag{34}$$

where

$$\ln P^i_{t-1} = \int_0^1 \ln p_{j^*_{mt-1}mt} dm.$$

□

Proof of Proposition 1.

Proof. Start with the customer base evolution equation for young households. From Lemma 2, we know that a previous customer will continue purchasing the brand if and only if $\zeta_{mt} \geq \frac{p_{jmt}}{P_{mt}}$. Thus, a fraction $\bar{F}_y\left(\frac{p_{jmt}}{P_{mt}}\right)$ of the previous young customer base will continue purchasing the brand. Due to aging, the measure of young customers who have purchased the brand in the previous period is given by $(1-q^o)B^y_t$.

In the first part of the proof of Lemma 2, we have proven that the probability of an unattached customer purchasing a brand is given by $\frac{1}{J_{mt}}\left(\frac{p_{jmt}}{P_{mt}}\right)^{1-\sigma}$. Multiplying by the measure of unattached young customers, N^{sy}_{mt}, we get the measure of new customers. Together, we obtain the desired expression:

$$\mathcal{B}^y_t\left(B^y_{t-1}, p_t\right) = \bar{F}_y\left(\frac{p_t}{P_{mt}}\right)(1-q^o)B^y_{t-1} + \frac{N^{sy}_{mt}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}.$$

The customer base evolution equation for old customers is derived in a similar way. The main difference is that the measure of old customers who have purchased the brand in the previous period include both young customers who have aged and the old customers who haven't passed away $(q^o B^y_{t-1} + (1-q^d_t)B^o_{t-1})$. We obtain:

$$\mathcal{B}^o_t\left(B^y_{t-1}, B^o_{t-1}, p_t\right) = \bar{F}_o\left(\frac{p_t}{P_{mt}}\right)\left[q^o B^y_{t-1} + (1-q^d_t)B^o_{t-1}\right] + \frac{N^{so}_{mt}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}.$$

Finally, in Lemma 3, we have shown that households allocate their expenditure equally across all brands they consume. This immediately implies the expression for the demand function:

$$\mathcal{D}_t\left(B^y_t, B^o_t, p_t\right) = \frac{E^y_t}{p_t}B^y_t + \frac{E^o_t}{p_t}B^o_t.$$

□

A.2 Households' Recursive Problem

The problem of allocating expenditure over time can be written recursively as follows. First, consider the problem of a young household:

$$W^y_t(A) = \max_{E,A'} \quad \ln E + (1-q^o)\beta W^y_{t+1}(A') + q^o\beta W^o_{t+1}(A'),$$
$$\text{s.t.} \quad E + \frac{1}{1+r_t}A' = 1 + A,$$
$$A' \geq 0,$$

where $W_t^y(A)$ is the value function at time t for a young households with asset level A. The value function for old households is defined as follows

$$
\begin{aligned}
W_t^o(A) = \max_{E,A'} \quad & \ln E + \beta(1-q_{t+1}^d)W_{t+1}^o(A'), \\
\text{s.t.} \quad & E + \frac{1-q_{t+1}^d}{1+r_t}A' = I_t^o + A, \\
& A' \geq 0,
\end{aligned}
$$

where $I_t^o \equiv L_o + \Pi_t/N_t^o$ is the income of old households at time t. Note that I assume there are annuity markets, so that the return an old person receives conditional on surviving is $\frac{1+r_t}{1-q_t^d}$. In equilibrium, net supply of assets is equal to zero, so the borrowing constraint implies that $A=0$ for both young and old households. The equilibrium interest rate will therefore be pinned down by the age group for which the borrowing constraint is not binding. Assuming that the income of older households is higher, an assumption that will hold in the calibrated model, the equilibrium interest rate can be backed out from the old households Euler equation:

$$
\beta(1+r_t) = \frac{E_{t+1}^o}{E_t^o}. \tag{35}
$$

A.3 Balanced Growth Path

Consider an economy in which $q_t^d = \bar{q}^d$ and $g_t = \bar{g}$ for all t. Let us first derive the limiting share of young households ($s_t^y \equiv \frac{N_t^y}{N_t}$) and old households ($s_t^o \equiv \frac{N_t^o}{N_t}$). Using the population laws of motions we have

$$
\begin{aligned}
N_t &= (1+\bar{g})N_{t-1}, \\
N_t^o &= q^o N_{t-1}^y + (1-q_t^d)N_{t-1}^o.
\end{aligned}
$$

Dividing the two equations in the limiting economy we obtain

$$
(1+\bar{g})s_o = q^o(1-s_o) + (1-\bar{q}^d)s_o,
$$

so that

$$
s_o = \frac{q_o}{q_o + \bar{q}^d + \bar{g}}, \tag{36}
$$

where $\bar{s}^o$ is the share of old households in the economy in the limiting economy. That is, the share of old population is increasing in the aging probability q^o, and decreasing in the death probability ($\bar{q}^d$) and population growth rate ($\bar{g}$).

Conjecture that in the limiting economy, the measure of firms grows at the same rate of population, $\bar{g}$. We conjecture that the product-type price index is constant over time $\bar{P}_m$, as well as the fraction of households who decide to remain with their previous brand. The latter implies that the share of unattached customers also grows at rate $\bar{g}$. We will show that conditional on their state variables, all firm outcomes remain unchanged over time, thus proving the conjecture. First, let us consider the customer base evolution equation for young customers:

$$\mathcal{B}_t^y\left(B_{t-1}^y, p_t\right) = \bar{F}_y\left(\frac{p_t}{P_{mt}}\right)(1-q^o)B_{t-1}^y + \frac{N_{mt}^{sy}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}.$$

Denote by $\bar{n}_m^{sy}$ the ratio between the measure of young customers switching brands relative to the number of firms N_{mt}^{sy}/J_{mt}. This share is constant in the limiting economy as we conjectured both the numerator and denominator grow at the same rate. Then, in the limiting economy, the customer base evolution equation for young households becomes:

$$\mathcal{B}^y\left(B_{t-1}^y, p_t\right) = \bar{F}_y\left(\frac{p_t}{\bar{P}_m}\right)(1-q^o)B_{t-1}^y + \bar{n}_m^{sy}\left(\frac{p_t}{\bar{P}_m}\right)^{1-\sigma}.$$

Similarly, we obtain

$$\mathcal{B}^o\left(B_{t-1}^y, B_{t-1}^o, p_t\right) = \bar{F}_o\left(\frac{p_t}{\bar{P}_m}\right)\left[q^o B_{t-1}^y + (1-\bar{q}^d)B_{t-1}^o\right] + \bar{n}_m^{so}\left(\frac{p_t}{\bar{P}_m}\right)^{1-\sigma},$$

where $\bar{n}_m^{so}$ is the ratio between the measure of old customers switching brands relative to the number of firms N_{mt}^{so}/J_{mt}. The demand function is given by

$$\mathcal{D}\left(B_t^y, B_t^o, p_t\right) \qquad = \frac{\bar{E}^y}{p_t}B_t^y + \frac{\bar{E}^o}{p_t}B_t^o.$$

The recursive problem of the firm in the limiting economy then becomes:

$$\begin{aligned} V(B_{t-1}^y, B_{t-1}^o, a_t) = \max_{\{p_t, y_t, B_t^y, B_t^o\}} & \; p_t y_t - \frac{\bar{W}}{a_t}y_t + \frac{1}{1+\bar{r}}\mathbb{E}\left[\max\left\{V\left(B_t^y, B_t^o, a_{t+1}\right) - x_{t+1}^o\bar{W}, 0\right\}\right] \\ \text{s.t.} \quad & B_t^y = \mathcal{B}^y\left(B_{t-1}^y, p_t\right), \\ & B_t^o = \mathcal{B}^o\left(B_{t-1}^y, B_{t-1}^o, p_t\right), \\ & y_t = \mathcal{D}\left(B_t^y, B_t^o, p_t\right). \end{aligned}$$

As the problem of the firm consists of no varying aggregate variable, its optimal controls will not vary over time conditional on its state variables. Let $\bar{\Pi}$ denote the average flow profits of operating firms in the economy. As we conjectured that the measure of firms will grow at rate $\bar{g}$, so will the measure of entrants J_t^e. As a result, the net profits per household in the economy will not vary over time in the limiting economy. This is because flow profits, entry costs, and the measure of households, all grow at the same rate. This completes the argument that a balanced growth path exists in which the measure of firms grows at the same rate as population growth, and all individual policy functions do not vary over time.

A.4 The optimal markup

Recall the firm's problem is

$$V_t(B^y_{t-1}, B^o_{t-1}, a_t) = \max_{\{p_t, y_t, B^y_t, B^o_t\}} p_t y_t - \frac{W_t}{a_t} y_t + \frac{1}{1+r_t}\mathbb{E}\left[\max\left\{V_{t+1}\left(B^y_t, B^o_t, a_{t+1}\right) - x^o_{t+1}W_{t+1}, 0\right\}\right]$$

$$\text{s.t.} \quad B^y_t = \mathcal{B}^y_t\left(B^y_{t-1}, p_t\right), \qquad [\lambda^y_t]$$

$$B^o_t = \mathcal{B}^o_t\left(B^y_{t-1}, B^o_{t-1}, p_t\right), \qquad [\lambda^o_t]$$

$$y_t = \mathcal{D}_t\left(B^y_t, B^o_t, p_t\right), \qquad [\nu_t]$$

Taking first order conditions we obtain

$$[y_t]: \quad p_t - \frac{W_t}{a_t} = \nu_t,$$

$$[p_t]: \quad y_t = -\frac{\partial \mathcal{B}^y_t}{\partial p_t}\lambda^y_t - \frac{\partial \mathcal{B}^o_t}{\partial p_t}\lambda^o_t - \frac{\partial \mathcal{D}_t}{\partial p_t}\nu_t,$$

$$[B^y_t]: \quad \nu_t \frac{\partial \mathcal{D}_t}{\partial B^y_t} + \frac{1}{1+r_t}\mathbb{E}\left[\frac{\partial V_{t+1}}{\partial B^y_t}\mathbb{1}\left[V_{t+1} \geq x^o_{t+1}W_{t+1}\right]\right] = \lambda^y_t,$$

$$[B^o_t]: \quad \nu_t \frac{\partial \mathcal{D}_t}{\partial B^o_t} + \frac{1}{1+r_t}\mathbb{E}\left[\frac{\partial V_{t+1}}{\partial B^o_t}\mathbb{1}\left[V_{t+1} \geq x^o_{t+1}W_{t+1}\right]\right] = \lambda^o_t,$$

where the envelope conditions are

$$\frac{\partial V_t}{\partial B^y_{t-1}} = \lambda^y_t \frac{\partial \mathcal{B}^y_t}{\partial B^y_{t-1}} + \lambda^o_t \frac{\partial \mathcal{B}^o_t}{\partial B^y_{t-1}},$$

$$\frac{\partial V_t}{\partial B^o_{t-1}} = \lambda^o_t \frac{\partial \mathcal{B}^o_t}{\partial B^o_{t-1}}.$$

Combining the first order conditions, we obtain

$$y_t = -\left(p_t - \frac{W_t}{a_t}\right)\left(\frac{\partial \mathcal{D}_t}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B^y_t}\frac{\partial \mathcal{B}^y_t}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B^o_t}\frac{\partial \mathcal{B}^o_t}{\partial p_t}\right)$$
$$- \frac{1}{1+r_t}\mathbb{E}_t\left[\left(\frac{\partial V_{t+1}}{\partial B^y_t}\frac{\partial \mathcal{B}^y_t}{\partial p_t} + \frac{\partial V_{t+1}}{\partial B^o_t}\frac{\partial \mathcal{B}^o_t}{\partial p_t}\right)\mathbb{1}\left[V_{t+1} \geq x^o_{t+1}W_{t+1}\right]\right] \quad (37)$$

In Proposition 1, we have shown that

$$\mathcal{B}^y_t\left(B^y_{t-1}, p_t\right) = \bar{F}_y\left(\frac{p_t}{P_{mt}}\right)(1-p_o)B^y_{t-1} + \frac{N^{sy}_{mt}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma},$$

$$\mathcal{B}^o_t\left(B^y_{t-1}, B^o_{t-1}, p_t\right) = \bar{F}_o\left(\frac{p_t}{P_{mt}}\right)\left[p_o B^y_{t-1} + (1-p_d)B^o_{t-1}\right] + \frac{N^{so}_{mt}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}$$

$$\mathcal{D}_t\left(B^y_t, B^o_t, p_t\right) = \frac{E^y_t}{p_t}B^y_t + \frac{E^o_t}{p_t}B^o_t,$$

Using these expressions together with the Pareto distribution of brand switching, we have

$$
\begin{aligned}
\frac{\partial \mathcal{D}_t}{\partial p_t} &= -\frac{1}{p_t} y_t, \\
\frac{\partial \mathcal{D}_t}{\partial B_t^y} &= \frac{E_t^y}{p_t}, \\
\frac{\partial \mathcal{D}_t}{\partial B_t^o} &= \frac{E_t^o}{p_t}, \\
\frac{\partial \mathcal{B}_t^y}{\partial p_t} &= \frac{B_t^y}{p_t}\left[(1-\eta)(1-\alpha_t^y) + (1-\sigma)\alpha_t^y\right], \\
\frac{\partial \mathcal{B}_t^o}{\partial p_t} &= \frac{B_t^o}{p_t}\left[(1-\eta)(1-\alpha_t^o) + (1-\sigma)\alpha_t^o\right], \\
\frac{\partial \mathcal{B}_t^y}{\partial B_{t-1}^y} &= \frac{1}{B_{t-1}^y}(1-\alpha_t^y) B_t^y, \\
\frac{\partial \mathcal{B}_t^o}{\partial B_{t-1}^y} &= \frac{1}{B_{t-1}^y}\frac{p_o B_{t-1}^y}{p_o B_{t-1}^y + (1-p_d) B_{t-1}^o}(1-\alpha_t^o) B_t^o, \\
\frac{\partial \mathcal{B}_t^o}{\partial B_{t-1}^o} &= \frac{1}{B_{t-1}^o}\frac{(1-p_d) B_{t-1}^o}{p_o B_{t-1}^y + (1-p_d) B_{t-1}^o}(1-\alpha_t^o) B_t^o,
\end{aligned}
$$

where α_t^y and α_t^o denote the share of purchases of a firm from customers who did not purchase that brand in the previous period (henceforth, *new customers*):

$$
\begin{aligned}
\alpha_t^y &= \frac{\frac{N_{mt}^{sy}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}}{\frac{N_{mt}^{sy}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma} + (1-p_o) B_{t-1}^y \frac{1}{2} e^{(\eta-1)\theta_y}\left(\frac{p_t}{P_{mt}}\right)^{1-\eta}}, \\
\alpha_t^o &= \frac{\frac{N_{mt}^{so}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma}}{\frac{N_{mt}^{so}}{J_{mt}}\left(\frac{p_t}{P_{mt}}\right)^{1-\sigma} + \left(p_o B_{t-1}^y + (1-p_d) B_{t-1}^o\right) \frac{1}{2} e^{(\eta-1)\theta_o}\left(\frac{p_t}{P_{mt}}\right)^{1-\eta}}.
\end{aligned}
$$

Using these expressions we have

$$
\frac{\partial \mathcal{D}_t}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B_t^y}\frac{\partial \mathcal{B}_t^y}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B_t^o}\frac{\partial \mathcal{B}_t^o}{\partial p_t} = -\frac{y_t}{p_t} - \frac{E_t^y}{p_t}\frac{B_t^y}{p_t}\left[(\eta-1)(1-\alpha_t^y) + (\sigma-1)\alpha_t^y\right] - \frac{E_t^o}{p_t}\frac{B_t^o}{p_t}\left[(\eta-1)(1-\alpha_t^o) + (\sigma-1)\alpha_t^o\right]
$$

using the expression for y_t from the demand function we have

$$
\frac{\partial \mathcal{D}_t}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B_t^y}\frac{\partial \mathcal{B}_t^y}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B_t^o}\frac{\partial \mathcal{B}_t^o}{\partial p_t} = -\frac{1}{p_t^2}\left[E_t^y B_t^y\big(\eta(1-\alpha_t^y) + \sigma\alpha_t^y\big) + E_t^o B_t^o\big(\eta(1-\alpha_t^o) + \sigma\alpha_t^o\big)\right].
$$

This can be further simplified to

$$
\frac{\partial \mathcal{D}_t}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B_t^y}\frac{\partial \mathcal{B}_t^y}{\partial p_t} + \frac{\partial \mathcal{D}_t}{\partial B_t^o}\frac{\partial \mathcal{B}_t^o}{\partial p_t} = -\frac{y_t}{p_t}\left[\sigma - (\sigma-\eta)(1-\alpha_t)\right], \tag{38}
$$

where α_t is the share of purchases of the firm from new customers:

$$
\alpha_t = \frac{E_t^y B_t^y}{p_t y_t}\alpha_t^y + \frac{E_t^o B_t^o}{p_t y_t}\alpha_t^o.
$$

Using the envelope condition, we obtain

$$\frac{\partial V_{t+1}}{\partial B_t^o} = \left(p_{t+1} - \frac{W_{t+1}}{a_{t+1}}\right) \frac{\partial \mathcal{D}_{t+1}}{\partial B_{t+1}^o} \frac{\partial \mathcal{B}_{t+1}^o}{\partial B_t^o} + \frac{1}{1+r_{t+1}} \mathbb{E}\left[\frac{\partial V_{t+2}}{\partial B_{t+1}^o} \frac{\partial \mathcal{B}_{t+1}^o}{\partial B_t^o} \mathbb{1}\left[V_{t+2} \geq x_{t+2}^o W_{t+2}\right]\right]$$

Iterating forward and substituting the expression for $\frac{\partial \mathcal{D}_{t+1}}{\partial B_{t+1}^o}$, we obtain

$$\frac{\partial V_{t+1}}{\partial B_t^o} = \mathbb{E}_{t+1} \sum_{\tau=1}^{\infty} M_{t+1,t+\tau} \mathbb{1}\left[\bar{T} \geq t+\tau\right] \left(1 - \frac{1}{\mu_{t+\tau}}\right) E_{t+\tau}^o \frac{\partial \mathcal{B}_{t+\tau}^o}{\partial B_t^o},$$

where $M_{t+1,t+\tau}$ is the stochastic discount factor between periods $t+1$ and $t+\tau$,

$$M_{t+1,t+\tau} = \prod_{z=2}^{\tau} \left(\frac{1}{1+r_{t+z}}\right),$$

$\bar{T}$ indicates the last period of operation of the firm, so that for all $t \leq \bar{T}$, we have $V_t \geq x_t^o W_t$, and $V_{\bar{T}+1} < x_{\bar{T}+1}^o W_{\bar{T}+1}$. And $\frac{\partial \mathcal{B}_{t+1+\tau}^o}{\partial B_t^o}$ is defined as follows,

$$\frac{\partial \mathcal{B}_{t+1+\tau}^o}{\partial B_t^o} = \prod_{z=1}^{\tau} \frac{\partial \mathcal{B}_{t+z}^o}{\partial B_{t+z-1}^o}.$$

Similarly, we get that

$$\frac{\partial V_{t+1}}{\partial B_t^y} = \mathbb{E}_{t+1} \sum_{\tau=1}^{\infty} M_{t+1,t+\tau} \mathbb{1}\left[\bar{T} \geq t+\tau\right] \left(1 - \frac{1}{\mu_{t+\tau}}\right) \left[E_{t+\tau}^y \frac{\partial \mathcal{B}_{t+\tau}^y}{\partial B_t^y} + E_{t+\tau}^o \frac{\partial \mathcal{B}_{t+\tau}^o}{\partial B_t^y}\right],$$

where

$$\frac{\partial \mathcal{B}_{t+\tau}^y}{\partial B_t^y} = \prod_{z=1}^{\tau} \frac{\partial \mathcal{B}_{t+z}^y}{\partial B_{t+z-1}^y},$$

and $\frac{\partial \mathcal{B}_{t+\tau}^o}{\partial B_t^y}$ is defined recursively as

$$\frac{\partial \mathcal{B}_{t+\tau}^o}{\partial B_t^y} = \frac{\partial \mathcal{B}_{t+\tau}^o}{\partial B_{t+\tau-1}^y} \frac{\partial \mathcal{B}_{t+\tau-1}^y}{\partial B_t^y} + \frac{\partial \mathcal{B}_{t+\tau}^o}{\partial B_{t+\tau-1}^o} \frac{\partial \mathcal{B}_{t+\tau-1}^o}{\partial B_t^y}.$$

Plugging into the optimality condition (37) with the expressions for $\frac{\partial \mathcal{B}_t^y}{\partial p_t}$ and $\frac{\partial \mathcal{B}_t^o}{\partial p_t}$, we obtain

$$\begin{aligned} 1 = &\left(1 - \frac{1}{\mu_t}\right) \left[\sigma - (\sigma - \eta)(1 - \alpha_t)\right] \\ &+ \mathbb{E}_t \sum_{\tau=1}^{\infty} M_{t,t+\tau} \mathbb{1}\left[\bar{T} \geq t+\tau\right] \left(1 - \frac{1}{\mu_{t+\tau}}\right) \left[\left(E_{t+\tau}^y \frac{\partial B_{t+\tau}^y}{\partial B_t^y} + E_{t+\tau}^o \frac{\partial B_{t+\tau}^o}{\partial B_t^y}\right) \frac{B_t^y}{p_t y_t} \left(\sigma - (\sigma - \eta)(1 - \alpha_t^y) - 1\right) \right. \\ &\left. + E_{t+\tau}^o \frac{\partial B_{t+\tau}^o}{\partial B_t^o} \frac{B_t^o}{p_t y_t} \left(\sigma - (\sigma - \eta)(1 - \alpha_t^o) - 1\right)\right] \end{aligned}$$

Multiplying by μ_t and rearranging

$$\mu_t = \frac{\sigma - (\sigma - \eta)(1 - \alpha_t)}{\sigma - 1 - (\sigma - \eta)(1 - \alpha_t)} - \mathbb{E}_t \sum_{\tau=1}^{\infty} M_{t,t+\tau} \mathbb{1}\left[\bar{T} \geq t+\tau\right] \gamma_{t,t+\tau},$$

where

$$\gamma_{t,t+\tau} = (\mu_{t+\tau} - 1)\,\frac{\mu_{t+\tau}}{\mu_t}\left[\left(\frac{E^y_{t+\tau}}{E^y_t}\frac{\partial B^y_{t+\tau}}{\partial B^y_t} + \frac{E^o_{t+\tau}}{E^y_t}\frac{\partial B^o_{t+\tau}}{\partial B^y_t}\right)\frac{B^y_t E^y_t}{p_t y_t}\frac{\sigma - 1 - (\sigma-\eta)(1-\alpha^y_t)}{\sigma - 1 - (\sigma-\eta)(1-\alpha_t)} \right.$$
$$\left. + \frac{E^o_{t+\tau}}{E^o_t}\frac{\partial B^o_{t+\tau}}{\partial B^o_t}\frac{B^o_t E^o_t}{p_t y_t}\frac{\sigma - 1 - (\sigma-\eta)(1-\alpha^o_t)}{\sigma - 1 - (\sigma-\eta)(1-\alpha_t)}\right]$$

Rearranging the first term on the RHS we obtain the desired expression,

$$\mu_t = \frac{\sigma}{\sigma-1} + \frac{(1-\alpha_t)(\eta-1)}{(1-\alpha_t)(\eta-1)+\alpha_t(\sigma-1)}\left(\frac{\eta}{\eta-1} - \frac{\sigma}{\sigma-1}\right) - \mathbb{E}_t\sum_{\tau=1}^{\infty} M_{t,t+\tau}\mathbb{1}\left[\bar{T} \geq t+\tau\right]\gamma_{t,t+\tau}.$$

B Numerical Appendix

B.1 Algorithm for Balanced Growth Path Equilibrium

I use a value function iteration procedure to compute the balanced growth path 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 distribution of firms D, the price index, P_m, the measure of profits in the economy, Π, and the normalized measure of young and old households that switch brands, n_m^{sy} and n_m^{so}.[31]

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, Π, n_m^{sy}, and n_m^{so}. Check distance between value function, distribution function, and aggregate variables from previous guess. If the difference is not sufficiently small, repeat from step (1).

Grid. I use a three-dimensional grid to represent the state variables of the firm: their young and old customer base and their productivity. I construct the productivity using the Rouwenhorst (1995) 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

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

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 31, B_{max} to 5, and κ to 3. The high maximal level of customer base ensures that for different parameter specifications, which I consider when estimating the model, 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.

[31] For the initial stationary equilibrium, I normalize the ratio between the measure of households and number 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, I also solve for that ratio to match a value for entrants that is equal to f_e.

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 $N_a \times N_B \times N_B$ matrix. The value function is given by

$$V(B_y, B_o, a) = \max_{\{p,y,B'\}} py - \frac{w}{a}y + \frac{1}{1+r}\mathbb{E}\left[\max\left\{V\left(B', a'\right) - x_o' w, 0\right\}\right]$$

$$\text{s.t.} \quad B_y' = \frac{1}{2}e^{(\eta-1)\theta_y}(1-q_o)B_y\left(\frac{p}{P_m}\right)^{1-\eta} + n_m^{sy}\left(\frac{p}{P_m}\right)^{1-\sigma},$$

$$B_o' = \frac{1}{2}e^{(\eta-1)\theta_o}\left[q_o B_y + (1-q^d)B_o\right]\left(\frac{p}{P_m}\right)^{1-\eta} + n_m^{so}\left(\frac{p}{P_m}\right)^{1-\sigma},$$

$$y = \frac{E_y}{p}B_y' + \frac{E_o}{p}B_o',$$

where $\frac{1}{1+r} = \beta$ in the stationary equilibrium, and w is normalized to 1 without loss of generality. 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 value on the grid by choice of a markup on a grid of markup that starts below 1 and ends at $\frac{\eta}{\eta-1}$. The resulting maximization procedure yields the present value for each point on the grid, as well as the policy choices over the grid $B_y'(B_y, B_o, a)$, $B_o'(B_y, B_o, a)$, $p(B_y, B_o, a)$, and $y(B_y, B_o, a)$. With the present value at hand, I derive the survival probability of each firm which I denote by $s(B_y, B_o, a)$. $s(B_y, B_o, a)$ 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 $N_a N_B^2$ states, and I denote the ergodic distribution by a vector Λ of that size. $\Lambda(B_y, B_o, a)$ denotes the measure of firms that have an initial customer base $\{B_y, B_o\}$ and productivity a.

The transition matrix, denoted by Π_T, is of size $N_a N_B^2 \times N_a N_B^2$. The law of motion for the distribution is given by

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

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. In every update of the value function, I update the ergodic distribution one time (i.e., not until full convergence).

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

B.2 Algorithm for Transition Dynamics

The initial stationary equilibrium is calibrated to match features of the U.S. economy in the late 1980s. I then consider an unexpected and deterministic change to the demographic parameters q_t^d and g_t that move them gradually over time until reaching their terminal values in 2050. I assume that after 2050 these parameters remain unchanged. I further assume that the model converges to the new balanced growth path equilibrium by 2100. I denote the period 2100 by T.

Following the algorithm described in the previous section, I start by computing the terminal balanced growth path 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, $\{P_{mt}, n_{mt}^{sy}, n_{mt}^{so}, J_t, \Pi_t\}_{t=1}^{T}$. Use the implied E_t^o to compute the equilibrium path of interest rate r_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 balanced growth path 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.