How do Firms Grow? The Life Cycle of Products Matters*

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March 2018

Abstract

We exploit detailed product- and firm-level data to study the size of firms and products over their life cycles. We build a dataset that contains information on the product portfolio of each firm in the consumer goods sector over the period 2006–2015. We document that, with the exception of the first few quarters, sales of products decline at a steady pace throughout most of their life cycle. These dynamics are robust across very heterogenous types of products, and contrast with the profile of firms, which grow throughout most of their life cycle. Motivated by these results, we create a statistical framework of firm growth as a function of the vintages of products. Using this decomposition we quantify, for young and mature firms, the importance of new product introduction (both the intensive and extensive margins) and the impact of decreasing sales of older vintages. We find that firms must grow by continuously adding products that generate sufficiently large revenue in order to compensate the reduction in revenue accruing from previous vintages of products. We structurally estimate a model of heterogeneous multiproduct firms and decompose sales over the life cycle of the product to understand the mechanisms behind their decline. Our results indicate that demand-side factors are behind the decline in sales of products and are consistent with preferences for newer vintages of products.

JEL Classification Numbers: L1, L2, O3.
Keywords: Product Life Cycle; Firm Dynamics; Multi-Product Firms.

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*We are grateful to Fernando Alvarez, Jonathan Eaton, Erik Hurst, Robert Shimer, Joseph Vavra and seminar participants at UC San Diego. We would like to thank Arthur Middlebrooks at the Kilts Center for Marketing for helpful comments and Olga Denislamova for excellent research assistance. Empirical results are calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

It is a well established that new firms start small, in terms of revenue and employment, and grow over time as they age. Several authors have suggested mechanisms to explain these patterns, such as the accumulation of organizational capital or the ability to overcome financial constraints. In addition, recent work has explored empirically the relationship between product entry and exit and the innovation activities of the firm. This research has validated several predictions of Schumpeterian growth models, namely, that the degree of reallocation of products within firms is closely linked to their ability to grow both in terms of revenue and productivity. Less is known, however, about the product life cycle and how it impacts the growth of firms. What is the contribution of the product life cycle to firm growth? Do firms grow because they are able to launch more products, better products, or products that survive longer in the market? Are more experienced firms better able to introduce newer and better varieties?

In order to address these questions, this paper examines the relationship between the life cycle of the firm and the life cycle of the product. To do so we use detailed firm- and product-level data in the consumer goods sector at the quarterly level over the period 2006–2015. Our data allow us to measure products at its finest level of aggregation – barcodes consisting of a 12-digit number called the Universal Product Code (UPC) – and link those barcodes to firms. We use the longitudinal structure of the data set to identify both when a firm enters/exits the market and when a new product is introduced/discontinued. As a result, we are able to study the dynamics of each firm's unique portfolio of products as a function of their age. In particular, we estimate the revenue profile of products and firms, and use information on the price and the quantity sold of each of the products to tease out the potential underlying mechanisms explaining firm growth.

We begin by characterizing the life cycle of a product. In our data, the life cycle of the product is short. The median product lasts between 3 and 4 years, which is two years shorter than the median duration of firms. But, in contrast to what is known about the firm life cycle, the probability of exit conditional on survival is fairly constant. We find that short lasting products generate little sales at entry, implying that revenue at entry is an important determinant for the survival of products.

Importantly, with the exception of the first few quarters, the sales of products decline at fast pace throughout most of their life cycle. This finding is important because it challenges the standard view of the product life cycle, which assumes that the stage of market growth lasts longer than that of market decline (Levitt, 1965). Taking advantage of the fact that we observe prices and quantities at the product level, we decompose the contribution of both to the decline in revenue. Both quantities and prices decline throughout the life cycle of the product, but the evolution of sales results mostly from the evolution of quantities. We estimate the life cycle profile using econometric specifications that decomposes longitudinal outcomes into age-period-cohort effects, while accounting for heterogeneity in the consumer goods sector. This methodology is well suited to measure the age patterns while accounting for cohort specific effects and aggregate factors affecting sales.

The life cycle of the products differs greatly from the life cycle of the firm. In our data, the revenue of the firms increases over most of their life cycle. The firms that survive longer are larger both in revenue and in the number of products they produce (this holds even conditional on age). Most of the firms' products are introduced at the beginning of their life cycle. As a result, the likelihood of introducing new products declines with age and the rate at which they discontinue products is constant over their life cycle. As firms grow older, they are more likely to introduce *incremental innovations* – products within existing product lines - rather than *extensions* – products outside the main business line of the firm. Previous studies have only been able to study the dynamics of firms' product lines due to data availability issues. Our findings suggest that most of the activity of larger firms, in terms of product reallocation occur within existing product lines.

In order to conciliate the decline in sales over the product life cycle with an increasing path of firms' growth, we conduct a growth decomposition over the life cycle of the firm and divide it into that attributable to new products and that traceable to older products vintages. In our data, firms' sales grow on average 6% a year. But, given that the average revenue and the survival probability of a product declines as it ages, the contribution of prior cohorts of products to firm growth declines over time. In fact, almost all revenue growth of the firms in our data can be attributed to the introduction of new products whose contribution to revenue growth is approximately 11% a year. As a result, in order to grow, firms must either introduce new products or introduce more successful products (products with higher initial average revenue). We estimate that firms offset the product life cycle effect by adding products to their portfolio at a rate of 25% a year, and the products that they generate account for half of the average revenue of existing products.

Our main finding is that, if firms stop adding new products to their portfolio, they will on average experience negative growth rates. This is more relevant as firms age since the product life cycle effect pushes their rate of growth downward. Furthermore, adding new products is not a sufficient condition for growth. We find that, even if firms add a sufficiently large number of products, these products need to be able to generate enough revenue to compensate the reduction in revenue of previous vintages.

In order to uncover the mechanisms behind the decline of sales over the product life cycle, the last part of the paper estimates the model of heterogenous multiproduct firms of Hottman, Redding and Weinstein (2016) since their framework requires only price and expenditure data. After estimating the elasticities of substitution within and between firms within a product group, we obtain the values for product appeal and product costs up to a normalization. We show that the life cycle patterns of quantities follow closely those of product appeal and the life cycle patterns of prices follow those of costs. We then use the model to decompose the growth of product sales into that attributable to costs, product appeal, scope, and markups. We find that product appeal explains around 90% of the variability of sales relative to the level of sales at introduction. Cost, on the other hand, plays a very minor role. Our findings suggests that demand factors, such as preferences for more up-to-date varieties, are behind the life cycle patterns we document at the product level.

Our paper contributes to several active research areas. Recent papers have examined the determinants of firm heterogeneity and have characterized the contribution of several margins such as productivity, appeal, markups, and product scope (e.g., Melitz (2003); Manova and Zhang (2012); Feenstra and Romalis (2014)). In particular, Hottman, Redding and Weinstein (2016) decompose the firm-size distribution into the relative contributions of each component. They find that differences in firm appeal are the principal reason some firms are large and others are not. Differences in firm appeal can account for 50-75% of the variance in firm size. We build on their work to study the life cycle patterns of products. We find that product appeal varies systematically over time and declines as the product ages. Relative to their findings, the contribution of the average marginal cost in the variability of sales is even smaller at the product level than it is at the firm level indicating that, at the product level, appeal falls much faster than marginal costs.

The paper is also related to the growing body of work that emphasizes the firms' endogenous determination of the number of products. Examples of this work can be seen in the business cycle literature (Bilbiie, Ghironi and Melitz, 2012; Minniti and Turino, 2013) or in international trade (Arkolakis and Muendler, 2010; Mayer, Melitz and Ottaviano, 2014; Timoshenko, 2015). Most of this literature has assumed, however, that firms are homogeneous – there are no differences in the amount of products they produce or in the rate at which they introduce them to the market. An exception is the price-setting literature, which allows for differences in productivity across products within the same firm (Midrigan, 2011; Bhattarai and Schoenle, 2014; Alvarez and Lippi, 2014). Our empirical results emphasize the importance of allowing for this margin to understand the growth of firms. As a result, our conceptual framework complements this literature by introducing product entry decisions in the context of multiproduct firms with heterogeneous products.

The literature studying the firm life cycle is vast both in international trade and macroeconomics. Recently the work by Hsieh and Klenow (2014) highlighted the importance of this margin to explain productivity differences across countries. Recently, Eslava and Haltiwanger (2017) decomposed the variance of life cycle growth into fundamentals vs. distortions and find that fundamentals explain around 75% of the variability of output relative to birth level. Atkeson and Kehoe (2005) suggest that firms' life cycle is driven by the accumulation of plant-specific organization capital. In this interpretation, establishments grow with age as they invest in new technologies, develop new markets, and produce a wider array of higher quality products. Foster, Haltiwanger and Syverson (2016) show that even in commodity-like markets, establishment growth is largely driven by rising demand for a plant's products as it becomes older. Our paper complements this work by decomposing firm growth into the part attributable to new products and the contribution of older vintages. The importance of product entry on firm growth emphasized by our growth decomposition is also useful to reconcile the growing literature on product reallocation (Broda and Weinstein, 2010; Argente, Lee and Moreira, 2018) with the parallel literature on innovation (Klette and Kortum, 2004; Lentz and Mortensen, 2008; Akcigit and Kerr, 2010; Acemoglu, Akcigit, Alp, Bloom and Kerr, 2017; Garcia-Macia, Hsieh and Klenow, 2016).

Fewer papers study empirically the life cycle of the product. Due to data limitations, most of the literature has focused on specific examples where products can be traced from entry. Examples studying durables goods can be found in Copeland and Shapiro (2016), Gowrisankaran and Rysman (2012) and Abe, Ito, Munakata, Ohyama and Shinozaki (2016). Argente and Yeh (2017) study the life cycle of different pricing moments at the product level. We contribute to this literature by examining a wider set of goods that include non-durable items and by studying not only prices but also the life cycle of quantities and the survival probability of products as a function of the age of the firm. To the best of our knowledge, our paper is the first to examine the life cycle of the firm and the life cycle of the prices and quantities of products jointly.

The rest of the paper is organized as follows. Section 2 presents the data and describes our procedure to identify manufactures for each products. In section 3, we show the evolution of revenue, prices, quantities over the life cycle of products, as well as the survival patterns. Product life cycle refers to the product's age, i.e. the time since a product first appeared on the market. In section 4 we develop a statistical model of firm growth as a function of products vintage. Section 5 presents a structural model to understand mechanisms behind empirical findings. Section 6 concludes.

2 Data and Measurement

2.1 Definition of Products and Life Cycle

In this paper we show that the outcomes of products vary over their life cycle in a systematic way. Our unit of analysis is a barcode at different points in time. A barcode is a 12-digit Universal Product Code (UPC), a code consisting of 12 numerical digits that is uniquely assigned to each specific product and represents the finest level of disaggregation at the product level. UPCs were originally created to allow retail outlets to easily scan products. Defining products as barcodes has some important advantages. First, barcodes are by design unique to every product. It is rare for an observable change in product attributes to occur without the introduction of a new barcode. By using barcodes, we eliminate the possibility that differences in outcomes of products over time come from quality differences.[1] The most common alternative is to define goods by industry classifications, which will aggregate potentially very heterogeneous barcodes.[2] Changes in industry-level outcomes can result from changes in the composition of barcodes within those industries.

Second, barcodes are so widespread that our data is likely to cover all products in the Consumer Packaged Goods sector that are produced by firms (Basker and Simcoe, 2017). Producers have a strong incentive to purchase barcodes for all products that have more than a trivial amount of sales because the codes are inexpensive and allow sellers to access to stores with scanners as well as internet sales.

Finally, because firms and products are included in the sample provided that a sale occurs, we observe a wide range of products, and we can explore heterogeneity in a very rich way. Given these features, a barcode is likely to correspond closely to the level at which product choice decisions are made by firms and consumers.

Nevertheless, using a barcode as unit of analysis also has limitations. New barcodes can represent anything from a minor change in a characteristic of an existing product to a major product innovation. Similarly, some barcodes may correspond to relatively minor and unsuccessful products, while other barcodes may belong to superstar products. Even though it is not trivial to identify major versus minor changes in a systematic way across the broad set of goods, our dataset has an extraordinary array of barcode information such as sizes, packaging, colors, scents, flavors, brands, among others. This information allows us to study

[1] Firms have strong incentives not to reuse barcodes. Assigning more than one product to a single barcode can interfere with a store's inventory system and pricing policy. Moreover, it is reasonable to assume that all goods with different UPCs differ in some way that might cause consumers to pay a different price for them and that it is rare for a meaningful quality change to occur that does not result in a change of UPC.

[2] Our data reveal that large firms typically sell hundreds of different products within even a narrowly defined sector.

the outcomes of products over their life cycle after accounting for a rich set of characteristics and to aggregate products based on their characteristics.

We identify the state of the life cycle of a product by using information on its age, i.e. the time since a product first appeared on the market. The scanner datasets do not directly measure age of a product. We infer product age by observing the timing of the initial transaction of the product in the dataset. It is, therefore, key to cover a sufficiently large number of product transactions to identify the entry moment with little delay. Moreover, it is also important to cover a long period. Finally, we caveat that we cannot determine product age for products that have transactions in the first periods of the dataset.

Our analysis focused on the sales, prices, quantities and duration of barcodes. For each product, we calculate quarterly total sales, average price and total quantity at the national level by aggregating weekly information from all stores in the data. Unless a product is not left-censored i.e. the product has been available before the data period, we can document how sales, price and quantity change over product's life cycle. We further discuss this censoring issue in the following section.

2.2 Data Description and Summary Statistics

We rely primarily on the Nielsen Retail Measurement Services (RMS) scanner data set that is provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. The data is generated by point-of-sale systems in retail stores. Each individual store reports weekly sales and quantities of every UPC code that had any sales volume during that week.

The main advantage of this dataset is its size and coverage. Overall, the RMS consists of more than 100 billion unique observations at the week $\times$ store $\times$ UPC level. Our sample period covers the period 2006-2015. Per year, the data set comprises around 12 billion transactions per year worth, on average, \$220 billion of dollars. Over our sample period the total sales across all retail establishments are worth approximately \$2 trillion and represent 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores. A key distinctive feature of this database is that the data collection points are a large number of stores, and thus will give us good coverage of the universe of products and of the full portfolio of firms in this sector. In comparison to other scanner data sets collected at the store level, the RMS covers a much wider range of products and stores. In comparison to scanner data sets collected at the household level, the RMS also has a wider range of products because it reflects the universe of transactions for the categories it covers as opposed to the purchases of a sample of households.[3]

The original data consist of approximately 1.64 million distinct products identified by UPC. The data is organized into 1,070 detailed product modules that are aggregated into 114 product groups that are then grouped into 10 major departments.[4] For example, a 31-ounce bag of Tide Pods has UPC 037000930389, is produced by Procter & Gamble, and is mapped to product module "Detergent-Packaged" in product group "Detergent", which belongs to the "Non-Food Grocery" department.

Our data set combines all sales at the national and quarterly level, although we also conduct some exercises at the store quarterly level when studying staggered entry. For each product j in quarter t, we define revenue r_{jt} as the total sales across all stores and weeks in the quarter. Likewise, quantity q_{jt} is defined as total quantities sold across all stores and weeks in the quarter. Price p_{jt} is defined by the ratio of revenue to quantity, which is equivalent to the quantity weighted average price.[5]

A critical part of our analysis is the identification of entries and exits. For each product we use the panel structure to identify the entry and exit periods. We define entry as the first quarter of sales of a product and exit as the quarter after we last observe a product being sold. We cannot determine entry and exit for some products. For products that are already active in the first two quarters of the sample (2006Q1 and 2006Q2), we classify them as left censored. Those can include products created just before 2006 or very established products. Likewise, products that have transactions in last two quarters of the sample (2015Q3 and 2015Q4), we classify them as right censored. For those, we cannot determine exit and thus cannot measure duration.

In order to minimize concerns of potential measurement error in the calculation of a product's entry and exit, our baseline sample excludes private label products, considers products with at least one transaction per quarter after entering, and excludes products in the Alcohol and General Merchandise departments.[6] We exclude private label goods because, in order to protect the identity of the retailer, Nielsen alters the UPCs associated with private

[3]Our dataset contains approximately 40,000 distinct stores from around 90 retail chains, across 371 MSAs and 2,500 counties. Table A.I in Appendix shows that in comparison to the IRI Symphony data set, a similar data set widely used in the academic literature, the RMS covers 14 times more products in a given year. In terms of revenue the RMS represents roughly 2 percent of total household consumption whereas the IRI Symphony is 30 times smaller. The Nielsen Homescan, for example, that contains information on the purchases of 40,000-60,000 US households covers less than 60% of the products the RMS covers in a given year.

[4]The ten major departments are: Health and Beauty aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery, Alcohol, and General Merchandise).

[5]We use the weight and the volume of the product to compute unit values.

[6]In addition, given that our estimates of products' entries and exits might be affected by the entries and exits of stores in the sample, we consider only a balanced sample of stores during our sample period.

label goods. As a result, multiple private label items are mapped to a single UPC that makes it difficult to interpret the entry and exit patterns of these items since it is not possible to determine the producer of these goods. We consider products without missing quarters to rule out the possibility that our results are driven by seasonal products, promotional items, or products with very small revenue. And, finally, we exclude the two departments for which the coverage in our data is smaller and less likely to be representative.

In our baseline sample we have 617,046 products. Table 3 describes the characteristics of products in terms of their censoring. We divide products into four categories: (i) uncensored, (ii) left-censored, (iii) right-censored and (iv) both left- and right-censored. We observe product entry and exit within the data when the product is uncensored. To investigate product's life cycle for certain periods after the entry, we will mainly use uncensored and right censored products. For 2/3 of products we can identify entry and thus we can measure age. Among those, for more than 50% we can also identify exit, and thus we are able to measure both age and duration. The remaining 1/3 of products were already active in the first periods of our dataset, and thus we cannot measure age. Among those, we can identify exit for 60% of the products.[7] If we account for the average sales that the different products generate, the products for which we can determine age account for close to 60% of sales and both age and duration account for 10% of the revenue. This is expected because more successful products are likely to last longer and thus will be censored. Some of the best-selling products had been available before 2006 and did not exit the market until 2015.

We study the implications of the life cycle of products to firm growth. In order to do that, we link firms and products with information obtained from GS1 US, the single official source of UPCs. This allow us to perform the analysis at the parent company level, as opposed to at the level of the manufacturing firm.[8] Given that the GS1 US data contains all of the company prefixes generated in the US, we combine these prefixes with the UPC codes in the RMS.[9] The link between firms and products allow us to characterize their portfolio. With

[7]On average there are 248,965 products are active per quarter. Every quarter, uncensored products represent 21.9% of total products, and right censored represent 26.2% of total products.

[8]Argente, Lee and Moreira (2018) provide more details on this data. In order to obtain a UPC, firms must first obtain a GS1 company prefix. The prefix is a five- to ten-digit number that identifies firms and their products in over 100 countries where the GS1 is present. The number of digits in a company prefix indicates different capacities for firms to create UPCs. For example, a ten-digit prefix allows firms to create ten unique UPCs, and a six-digit prefix allows them to create up to 100,000 unique UPCs. See Figure A.1 for examples of different company prefixes. Although the majority of firms own a single prefix, it is not rare to find that some own several. Small firms, for example, often obtain a larger prefix first, which is usually cheaper, before expanding and requesting a shorter prefix. Previous studies, including Broda and Weinstein (2010), have assumed that the first six digits of the UPC identify the manufacturing firm. This assumption is valid for 93% of the products in our sample. Larger firms, on the other hand, usually own several company prefixes due to past mergers and acquisitions. For example, Procter & Gamble owns the prefixes of firms it acquired such as Old Spice, Folgers, and Gillette.

[9]Less than 5 percent of the UPCs belong to prefixes not generated in the US. We were not able to find a

this data set, we can compute the revenue, price, quantity, and quality of each product in a firm's portfolio. We mostly focus on measures of size (number of products, total revenue) and product introduction (frequency, number, and revenue). We also use it to identify entry and exit of firms. In particular, we define entry as the first quarter of sales of the first product(s) by that firm and exit as the quarter after we last observe the last product being sold by that firm. The product-firm baseline dataset allow us to study how size and product introduction change over firm's life cycle.

Table 4 describes the characteristics of products and firms by censoring. For firms, we have less uncensored cases. Among 23,702 total firms in sample period, uncensored firms represent 23.0% of total firms, while both left and right censored firms represent 32.3%. Uncensored firms are smaller than censored firms with lower number of products and total revenue. Both left- and right-censored firms produce 28 products in 4 different product modules per quarter on average. Those firms show stable product entry and exit rates at 3 percent. For firm's life cycle, we will mainly use uncensored and right-censored firms, which represent almost half of total firms (47.7%).

2.3 Measurement of Life Cycle Effects

2.3.1 Baseline Specification

We are interested in identifying the average evolution of sales, price, and revenue as a function of the age of the product. The main sample includes all barcodes sold between 2006Q3 and 2015Q4 and their total revenue, average price, and total quantity at the quarterly level. We observe the barcodes from the moment they are first sold until their exit.

To isolate the effect of age we must account for the fact that at any point in time, we observe products with different ages. Likewise, we want to control for the fact that, for otherwise comparable products, each product might behave differently depending on the timing of their introduction. In order to address such issues, we estimate age effects by implementing age-period-cohort models. These specifications allow us to estimate the evolution of revenue, quantities, and prices since the time the product was first introduced, while accounting for cohort-specific differences in outcomes and any calendar effects specific to the moment when we measure the outcomes (e.g. business cycles affecting all products). This methodology is commonly used in the literature on individuals' life cycle consumption and income dynamics. In the baseline specification, we estimate the outcome of interest (revenue, price, and quantity) (Y) of product j observed at time t, as function of age (a),

firm identifier for those products.

module-period (mt) and cohort (c) fixed-effects:[10]

$$\ln Y_{j,t} = \alpha + \sum_{a=2}^{A} \beta_a D_a + \lambda_{mt} + \theta_c + u_{j,t} \tag{1}$$

We control for heterogeneity by allowing the time fixed-effect to be specific to the type of product.

We are interested in the coefficients β_a that capture the average evolution of the aging process of the product, relatively to the level of the outcome in the first full quarter of activity.

The evolution of the outcomes of products over the life cycle is affected by selection. The main sample includes all barcodes from the moment they are first sold until their respective exits. There are substantial differences in the duration of barcodes, which implies that the estimated effects are conditional on survival if we use all active observations irrespective of their duration. To the extent that products exiting early are different from those that exit later, the unconditional estimated effects will be different from the conditional estimated effects. In order to ensure that the estimation results are not sensitive to selection bias resulting from the inclusion of short-lived products, we repeat the empirical analysis on products that survive more than the median duration of products, and also check robustness to alternative criteria.

2.3.2 Specification Accounting for Duration

We consider an alternative specification that explicitly accounts for selection. To obtain information on the nature of selection, while also isolating true dynamics, we examine how the initial outcomes forecast survival, and also document dynamics conditioning on the ex-post duration. In the alternative specification, we estimate the outcome of interest of product j observed at time t as follows:

$$\ln Y_{j,t} = \alpha + \sum_{d=2}^{D} \sum_{a=1}^{d} \gamma_{ad} D_{ad} + S_{j,t} + \lambda_{mt} + \theta_c + u_{j,t} \tag{2}$$

where λ_{mt} are module-time fixed effects, θ_c are Deaton's normalized cohort effects, $\gamma_{ad} D_{ad}$ are dummies for age interacted with duration, and $S_{j,t}$ is a dummy for observations cen-

[10]Because there is an exact linear relationship between the three effects, we make a normalization of the cohort-effect as suggested in Deaton (1997). The normalization makes the cohort effects average zero over the sample period and orthogonal to cohort trends such that all growth is attributed to age and time effects. In the Appendix we check the robustness of this normalization by considering alternative specifications.

sored observations.[11] Exponentiated, linear combinations of the estimates γ_{ad} allow us to characterize both variation in initial level of the outcome variable, and the evolution with age over the different durations. This approach has some similarities with the approach of Fitzgerald, Haller and Yedid-Levi (2017) working with exporter dynamics and Altonji and Shakotko (1987) to dealing with selection in estimating the effect of job tenure on wages.

We directly evaluate the survival outcomes of products. To do so, we follow much of the literature on duration models and examine the data using a proportional hazard model. In order to account for heterogeneity across products, we specify that the hazard rate of a barcode exiting the market in a given period as the product of two functions: a function of a product's observed and unobserved characteristics; and a function of the time it has spent in the market. This is, we allow for multiplicative unobserved heterogeneity in the level of the hazard function, while estimating the slope of the hazard nonparametrically as Nakamura and Steinsson (2008). Specifically, the hazard is given by:

$$h_{ij}(t) = \bar{h}(t)\theta_i \exp(\boldsymbol{x_{ij}\beta}) \tag{3}$$

where j indexes the products and i the product module. θ_i is a product specific random variable that reflects unobserved heterogeneity in the level of the hazard, $\bar{h}(t)$ is a nonparametric hazard function, $\boldsymbol{x_i}$ is a vector of covariates, and $\boldsymbol{\beta}$ is a vector of parameters. We assume that $\theta_i \sim \text{Gamma}(1, \sigma^2_\theta)$. The model is estimated by maximum likelihood and accounting for right censoring in the last period of our sample (2015Q4). In addition, to further account for heterogeneity, we estimate the hazard separately for each major department in our data.

2.3.3 Robustness Specifications

We consider some alternative approaches to evaluate the robustness of our estimates to alternative assumptions on the data generating process. First, we consider a simplified specification. Because we observe products over time, we can alternatively specify a standard approach with time and product fixed-effects, while exploring the variation within product as follows:

$$\ln Y_{j,t} = \alpha + \sum_{a=2}^{A} c_a D_a + \lambda_t + z_j + u_{j,t} \tag{4}$$

where λ_t and z_j are time and product fixed-effects.

[11] We include a indicator variable for both censored (right and left) to help identify the module-time fixed effects and Deaton's normalized cohort effects.

3 Stylized Facts on the Product Life Cycle

In this section we show the evolution of revenue, prices, quantities over the life cycle of products, as well as the survival patterns of such products. Product life cycle refers to the product's age, i.e. the time since a product first appeared on the market.

3.1 Product Total Revenue

We estimate the baseline specification on equation (1) using the level of quarterly revenue as the dependent variable (in logs) for the sample of products over the first 16 quarters, for products that were active for that entire period. Table 5 reports the estimated age fixed effects. The results presented in column 1 show that the coefficients of the age fixed effects are positive and significant for the first periods, and negative and significant for later periods. We plot the estimated coefficients in Figure 1. Our results show that the revenue of products is mostly declining with age, with the exception of the first 4-5 quarters. By the end of the fourth year of activity, revenue declines by more than 50 percent.

We isolate the role of survival by estimating the specification of equation (2) for products that lasted less than 16 quarters. Figure 2 shows that for short-lived products, revenue declines throughout their entire life cycle until exit, and the negative growth rates are larger among short duration products. Our results show that the sales level at exit is several orders of magnitude smaller than the level observed at entry. This means that products with lower duration, have larger decreases in revenue, even several periods prior to exit. The figure shows the differences in the initial level of revenue normalized relatively to products that lasted only one period. The figure shows that within very narrowly defined types of products, there is substantial heterogeneity in the level of revenue that they generate, as short lasting products generate little revenue immediately after entering.

This is surprising given what it was previously thought about the product life cycle in the management literature (e.g. Levitt (1965)). Nonetheless, in industrial organization, a few case studies have documented similar patterns for the PC retail industry (Copeland and Shapiro (2016)), the semiconductor sector (Byrne, Oliner and Sichel (2015)), and for home electrical appliances and digital consumer electronics (Abe, Ito, Munakata, Ohyama and Shinozaki (2016)). In the result above, we use data from the entire consumer packaged goods sector, and thus we may have heterogeneity across very different types of product, ranging milk to small appliances. Indeed, we study differences in patterns across broad types of products and find that the pattern is common across most of the types.[12]

[12] We use the eight departments in our baseline data: Health and Beauty aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery.

Because these patterns can be affected by staggered entry and exit across stores, we estimate the specification above for the pair barcode-store, and found that increase in sales in the first periods comes mostly from staggered entry, and that the decline in sales is present even at this level of aggregation (see Appendix C for details). We use information on the number of stores selling the product and estimate the baseline specification on equation (1) using the level of quarterly sales per store as the dependent variable (in logs) for the sample of products over the first 16 quarters, for products that were active for that entire period. Figure 3 plots the age fixed-effects. We observe that the average level of sales generated per store declines immediately after entry in the market. We also estimate the baseline specification on equation (1) using the number of stores selling the product as the dependent variable (in logs) and find that the number of stores increases in the first 4-5 quarters, and then declines (Figure 4).

To sum up, our estimated results on sales show that the following stylized facts hold in the data: (1) national product sales decline throughout most of the life cycle of the product, (2) product sales per store decline throughout the entire life cycle, (3) national product sales decline at a larger pace later in life, (4) the rate of decline of sales decreases with product duration, (5) short lasting products have lower initial level immediately at entry. As we show in section 4, these facts have important consequences on firm growth.

3.2 Accounting for Product Duration

We directly evaluate the survival outcomes of products. We start the analysis by studying the survival patterns of barcodes. Figure 5 shows the Kaplan-Meier estimator of the survival function of products, accounting for right censoring in the last period of our sample, 2015Q4. We see that the median product lasts between 3 and 4 years. Overall, we estimate that 25 percent of barcodes exit the market within 4 quarters, more than 60 percent exit before they reach 16 quarters, and 25 percent last more than 40 quarters.

To account for heterogeneity we use proportional hazard model as specified in equation (3). Figure 6 plots the baseline hazard function from the model described by equation 3 for Dry Grocery and for Non-Food Grocery.[13] The shape of the hazard function is of these groups is representative of the shape of the hazard function for most of the major groups. The hazard function is for the first quarters hump-shaped and downward sloping after that. In our data, the median product lasts between 3 and 4 years. Overall, we estimate that 20 percent of barcodes exit the market within 4 quarters, more than 60 percent exit before they reach 16 quarters, and 20 percent last more than 40 quarters. This shows that there is substantial

[13]Appendix B provides details on the estimation.

heterogeneity in product duration. Moreover, while the number of products exiting is larger for short durations, the probability of exit, conditional on survival, is approximately constant.

3.3 Product Price and Quantity

An advantage of our data is that we observe prices and quantities, and hence we are able to determine the contribution of both to the decline of revenue over the product's life cycle. As described in Section 5, variation in sales can be attributed to cost (e.g. scale, learning by doing), and demand differences (e.g. customer capital, appeal). These have different implications for product sales conditional on prices (i.e. marginal cost affects firm revenue through prices, while firm's demand affects firm revenue conditional on prices.). Figure 7 shows the estimated life cycle profile of the price of products (those that last at least 16 quarters). The age fixed-effects show that prices decline 2 percent a year on average. The decline in price happens at a fairly constant pace and, by the end of the 4th year of activity, the price is almost 8 percent lower than the price at entry. Because our empirical specification controls for aggregate effects (e.g. inflation) specific to particular types of products (modules), the decline happens on top of the average fluctuations in prices. Figure 8 shows that the price of products declines as the product gets older regardless of duration. Contrary to the evolution of revenue, product prices decline at a constant pace later in life.

Figures 9 and 10 show the percent decline in quantities sold after the product is introduced. Similar to revenue, quantities decline after the first year of activity. Our results show that 16 quarters after introduction, quantities declined by more than 50 percent relatively to the initial quantities sold when the products were launched. When comparing the magnitudes of the decline in quantities and in prices, we conclude that that the decline in sales, comes mostly from the decline in quantities (Figure 11).

To sum up, our estimated results show that the following stylized facts hold in the data: (1) product sales/quantities/prices decline throughout most of the product life cycle, (2) product sales/quantities decline at a larger pace later in life, while prices decline at a fairly constant pace, (3) the rate of decline of sales/quantities/prices decreases with product duration, and (4) most decline in sales comes from declines in quantities sold, since price reductions are of lower magnitude. As we show in section 4, these facts have important consequences for firm growth.

3.4 Heterogeneity of the Product Life Cycle

We explore product life cycle patterns across different product categories. We use two characteristics: (i) target income groups and (ii) durability.

First, we divide product categories by target income groups. To do so, we use Nielsen Consumer Panel Data and identify high income households earning more than \$100k per year and low income households earning less than \$25k per year.[14] For each product categories, we first calculate expenditure share by these two income groups and take a log difference. When expenditure share is higher from high income group, we call those as luxurious categories. Examples of luxurious categories are men's lotion (.54), oral hygiene appliance (.41), and health snack bars (.34), with log difference of expenditure shares in parenthesis. Categories targeting lower income households are canned fruit (-1.35), powdered milk (-.91) and carbonated soft drink (-.59), with log difference of expenditure shares in parenthesis. Figure 12 shows revenue, price and quantity of product over the life-cycle by category's target income groups. Both price and quantity decreases over product's life-cycle for all categories. In addition, revenue declines faster for luxurious categories, because both price and quantity decline faster than inferior categories. This suggests that consumer's taste approximated by income could matter for product life-cycle.

Second, we divide product categories by durability. In order to proxy durability, we count the number of average shopping trips to purchase each product categories from the Nielsen Consumer Panel Data. We call categories with a few number of trips per year as durable categories. Examples of durable categories are sun exposure detector product (1.00), bathroom scale (1.03) and printers (1.03), with average number of shopping trips per year in parenthesis. Non-durable categories are refrigerated milk (23.61), cigarettes (19.19) and fresh bread (18.76). Note that target income group and durability at the category level are not correlated. Figure 13 shows revenue, price and quantity of product over the life-cycle by category's durability. Both price and quantity decreases over product's life-cycle for all categories. In addition, revenue declines faster for durable categories, because both price and quantity decline faster than non-durable categories. This also suggest that consumer's shopping behavior approximated by the average number of trip could matter for product life-cycle.

[14]The Nielsen Consumer Panel Data comprise a representative panel of households that continually provide information about their purchases in a longitudinal study in which panelists stay on as long as they continue to meet Nielsen's criteria. Nielsen Consumer panelists use in-home scanners to record all of their purchases (from any outlet) intended for personal, in-home use. Consumers provide information about their households and what products they buy, as well as when and where they make purchases. We use the data for 2006 to 2015 where 40,000 to 60,000 panelists are active every year.

4 Implications to the Life Cycle of Firms

We have shown that the sales of a product start declining shortly after its introduction. Such decline in sales at the product level is hard to reconcile with well-documented evidence of firm growth over their life (e.g. Dunne, Roberts and Samuelson (1989) and Hsieh and Klenow (2014)). In order to better understand how the product life cycle affects firm growth, we develop a simple statistical model of firm growth as a function of product vintage within the firm. The purpose of the exercise is to evaluate how the stylized facts on the product life cycle described in Section 3 affect the growth of firms.

4.1 Relationship Between the Life Cycle of Firms and Products

4.1.1 The Size of a Firm as a Function of Products' Vintage

Let S_{ia} represent the sales of firm i of age a, and $R_{j,ia}$ represent the sales of products of vintage j when the firm is age a, such that

$$S_{ia} = \sum_{j=0}^{a} R_{j,ia}$$

the total sales of firm i at age a is the sum of total sales of products of vintage j whose age is $a-j$ across all cohorts $j \leq a$. The oldest cohort of products generates revenue $R_{0,ia}$ when the firm has age a, and the youngest cohort generates revenue $R_{a,ia}$. For simplicity, in what follows we omit the firm subscript i.

We decompose total sales into the number of products T_a and their average revenue s_a. Similarly, we decompose the revenue of each vintage into the number of distinct active products $N_{j,a}$ and their average revenue $r_{j,a}$. We define the survival of products as the ratio of the number of surviving products of vintage j at age $a-j-1$ to those at age $a-j$ as follows:

$$1 - x_{j,a} \equiv \frac{N_{j,a}}{N_{j,a-1}}$$

Likewise, we define the growth in the average revenue of products of vintage j from age $a-j-1$ to age $a-j$ as:

$$1 + g_{j,a} \equiv \frac{r_{j,a}}{r_{j,a-1}}$$

This means that the revenue of each cohort grows according to $G_{j,a} \equiv (1-x_{j,a})(1+g_{j,a}) - 1$.

Using the definitions above, we can recursively define the products and average revenue of each vintage as:

$$N_{j,a} = N_j^E \times \prod_{k=1}^{a-j}(1 - x_{j,j+k}) \qquad r_{j,a} = r_j^E \times \prod_{k=1}^{a-j}(1 + g_{j,j+k})$$

where N_j^E is the number of new products introduced when the firm has age j, and r_j^E is the average revenue of products generated by new products when the firm has age j. Replacing above, we obtain the following expression:

$$S_a = \sum_{j=0}^{a}\left[N_j^E \times r_j^E \times \prod_{k=1}^{a-j}\Big((1 - x_{j,j+k})(1 + g_{j,j+k})\Big)\right] \tag{5}$$

This expression shows that the sales of a firm at age a depends on the number of new products generated until a, their initial average revenue, and the post-entry survival and growth dynamics of each vintage. Using the previous expression, we can express change in sales at age a as follows:

$$S_a - S_{a-1} = N_a^E \times r_a^E + \sum_{j=0}^{a-1}\left[N_j^E \times r_j^E \times \prod_{k=1}^{a-j}(1 - x_{j,j+k})(1 + g_{j,j+k}) \times \Big(-x_{j,a} + g_{j,a} - x_{j,a}g_{j,a}\Big)\right]$$

Using the definition of sales in equation 5, we can write growth of sales at age a, $\frac{S_a - S_{a-1}}{S_{a-1}}$, as

$$\Delta_a = \underbrace{\underbrace{\frac{N_a^E}{T_{a-1}}}_{\text{entry rate}} \times \underbrace{\frac{r_a^E}{s_{a-1}}}_{\text{relative quality}}}_{\text{entrants effect}} + \underbrace{\sum_{j=0}^{a-1}\frac{R_{j,a-1}}{S_{a-1}}G_{j,a}}_{\text{product life cycle effect}} \tag{6}$$

where the first term is the contribution of the newly entrant products, and the second term is the change in the contribution of prior cohorts of products. This second term is determined by the life cycle profile of products, most specifically the evolution of average revenue and the survival, weighted by the revenue level of each vintage at age $a - 1$ in the total sales of the firm. The effect of entrants is the product of the entry rate and the relative revenue of the new products relatively to the average revenue of the products of the firm, which gives us a measure of the quantity versus quality importance within each new vintage of products.

The results of Section 3 allow us to make some predictions about the expected signs of the "product life cycle effect" of equation 6. First, we document that there is substantial exit of products and that the average product (conditional on survival) exhibits declining sales after the first few quarters of activity. The patterns imply that $G_{j,a}$ is likely negative for most vintages of products. Second, because exit is fairly constant and revenue can increase within the first year of activity, only very recent vintages of products have positive $G_{j,a}$. Third, because exit is fairly constant and the decline in sales occurs at a larger pace later in life of products, the term $G_{j,a}$ is likely to be more negative for older vintages. Overall, these patterns imply the following predictions for the "product life cycle effect": (1) most firms will have a negative effect, (2) the effect varies with firm age, and (3) the effect may be positive for young firms and decreases with firm age.

The fact that most firms have negative revenue growth from existing vintages of products, implies that introducing new products is a necessary (but not sufficient) condition for firms' growth. Because our firms exhibit positive revenue growth over their life cycle, we posit that firms must be adding products to their portfolio throughout their life cycle. Moreover, even if firms add products, they must do so at a sufficiently large rate and/or generate sufficiently large revenue in order to compensate the reduction in revenue accruing from previous vintages of products.

4.1.2 Quantifying the Role of Product Life Cycle by Firm Age

We apply the decomposition in equation 6 to the firms in our dataset and compute the annual average across firms for the different components. Column (1) in Table 6 shows that firm sales grow an average of 6% a year among the pooled sample of firms during our sample period. This positive revenue is entirely explained by the introduction of new products (products that did not exist in the previous year) and whose contribution to revenue growth is about 11% a year. As expected, the growth rate of previous vintages is negative. Firms are offsetting this effect by adding products to their portfolio at a rate of 25% a year, and the products that they generate are half of the average revenue of existing products.

Columns (2)-(5) in Table 6 show the average annual growth rates across firms age. The growth paths of the firms in our sample are similar to those of the representative firm in the U.S. economy, i.e. firms grow fast in their initial years of activity but their growth rates subsequently decline as firms become older. Firms in our sample grow more than 30% annually in their first two years of activity but only approximately 10% between ages 5–7. Among firms created before 2006, which include firms older than 7 years old, this value is even smaller. This decline in growth rates results from both a decline in the effect of product life cycle and the contribution of new products. The product life cycle effect is positive among entrant firms (10% on average for firms ages 1 and 2) and becomes -5% for firms between 5-7 years old. The positive value among entrant firms results from the fact the revenue of products increases within the first year with staggered entry and, as a result, the growth rate may be still be positive among very young vintages, which are the only types of vintages that a young firms has in their portfolio. The large decline in the growth of sales as the firm ages is due to the fact that the quick dynamics of product life cycle effect pushes firm's growth down as they get older. In contrast, the effect of entrants declines at a slower pace, from about 22% among very young firms to 16% among firms with ages 5-7, and 10% among firms that already existed in 2006. Most of this decline comes from the reduction of product entry rates as firms get older since the entrants relative quality remains fairly constant over the firm life cycle. The decomposition shows how it is possible to reconcile the decline in sales of products over their life cycle with the increasing revenues observed at the firm level.

4.2 Role of New Products in the Life Cycle of Firms

The decomposition exercise shows that the introduction of new products plays a critical role in sustaining the growth of firm revenue over their life cycle. In this section, we expand our investigation of the role of new products by examining the patterns and determinants of the introduction of new products over time.

We begin by examining the relationship between firms' age and the size of their portfolio of products, which we measure as the number of active barcodes in the market. Figure 14 shows that the total number of products increases over the entire life cycle of firms. Conditional on surviving at least four years, firms increase the number of barcodes in their portfolio by more than 60 percent during that period.[15]

The decomposition that we presented in the previous section shows that the contribution of revenue from new products is very important in explaining the ability of firms to grow. We also show that the impact of revenue of new products on total revenue growth decreases as firms become older. Next, we further examine the relation between firm age and the revenues accruing from new products. We analyze this relation using an empirical specification that accounts for other potential sources of differences in the outcomes of firms, as we did for the outcomes of products. Because firms do not introduce new products every quarter, we also use the inverse hyperbolic sine transformation to implicitly account for zeros in these variables.

Our results show that the total revenues accruing from new products increase in the first year of activity of the firm and then remain mostly constant over time. We also show that the share of revenue of new products in the total revenue of the firm declines substantially with

[15] The estimates are almost identical when we use information on all active firms. The main differences is that with this semi-balanced sample the growth is initially slower and accelerates as firms age. As discussed in the empirical specification section, the differences between the two samples depend on the differences in initial level of products and on the relative growth of the products by duration. Thus we conjecture that the differences are not sufficiently large to generate big gap between estimates.

age (Figures 15 (a) and (b)). The decline itself is not surprising because the share of revenue from new products is, by definition, equal to one in the first quarter of operations of the firm and, as such, can only decline with age. The interesting result is, nonetheless, that the revenue generated from the introduction of new products declines at a very fast pace: after 16 quarters, revenue from new products account for approximately 13% of total revenue on average. These results are in line with the results that we presented in the previous section suggesting that not only the revenue from new products sustains the overall growth of firm revenue, but also that revenues from new products explain a lower fraction of revenue growth as firms grow older. We find that when accounting for zeros using the inverse hyperbolic sine transformation (Figure 15 (c)) the total revenue accruing from new products (in levels) exhibits a decline as firms get older. This pattern indicates that the frequency of product introduction is declining with firm age, even if conditional on introducing a new product the overall level of revenue does not decline.

Next, we investigate if the overall decline in revenue from new products comes from a quantity and/or quality effects. To assess the quantity effect, we study the evolution of the number of new products introduced every quarter as a function of firm age. Figure 16 (b) shows the probability of new product introduction by firm age, using the likelihood of introduction of a product in the first full quarter of activity as a benchmark.[16] The probability that a firm introduces new products declines with age, but such decline is less steep following the first year of activity. However, conditional on introducing new products, the number of new products remains approximately constant as firms become older (Figure 16 (a)). Therefore, the total number of new products introduced every quarter declines approximately 20% in the first 16 quarters of activity (Figure 16 (c)) because the lower frequency of introduction of new products is not compensated by an increase in the intensive margin of the total number of products introduced by firms. Taken together, both the reduction in the number of new products and the overall increase in the total number of products that firms carry in their portfolios contribute to the declining effect of the introduction of new products on revenue growth over the life cycle of firms. Overall, these patterns indicate that the product entry effect on the growth rates of firms declines substantially with age, which contributes to the slowdown in sales growth as firms mature.

To better understand the dynamics of revenue growth of firms, we also evaluate how the quality of new product evolves over the life cycle of firms. We estimate the effect of age on the average revenue of new products in the first full quarter after introduction and we show that, relative to the average revenue at introduction of the original products of the firm,

[16]Note that the likelihood of introduction of new products in the first full quarter of activity of the firm is not necessarily equal to one because, under our definitions, the first product of the firm is introduced during the first quarter of operations, which by definition occurs in the previous quarter.

the average revenue of new products increases in the first few quarters and remains mostly constant thereafter (Figure 17 (a)). We also directly evaluate the effect of age on the ratio between the average revenue of new products and the average revenue of older vintages of products. Figure 17 (b) shows that, relatively to its initial level, this ratio initially declines during the first two years and remains approximately constant thereafter. The results based on this regression framework suggest that new product quality remains largely constant over the life cycle of firms.

The aforementioned results on new product quality are seemingly inconsistent with those of the decomposition of the previous section, which suggested that new product quality slightly increases with age. Such differences are likely explained by the fact that in our regression framework we are able to account for time effects and cohort effects that may be correlated with the cross sectional evidence captured by the decomposition. To further understand the differences between the results of the regression framework and those of the decomposition, we study the life cycle of products at the product-level using age-period-cohort model where we now account for the age of firms. This analysis allows us to compare products of similar characteristics that are created by firms of different ages, and thus is less affected by potential differences in the composition of products that firms roll out as they age. We find that overall dynamics of revenue over the life cycle of products does not depend on the age of the firm when it introduces those new products. Older firms, however, generate a higher initial level of product revenue than that generated by entrant firms, which means that, conditional on the type of product, the average revenue of new products increases with age and the ratio of revenue between new and existing products is also increasing. To reconcile these results, we show that older firms are generating products that generate a higher level of revenue.

Overall, these results allow us to conclude that, as firms get older, the impact of the life cycle of products becomes more negative and the contribution of new products to firm growth declines. Our estimates indicate that the main factor behind the lower contribution of new products to revenue growth is that older firms introduce new products less frequently. But, conditional on introducing new products, the quality of such products does not decrease over time.

The results that we describe above do not distinguish among products based on how innovative they are. A new barcode could belong to a new product that is very similar to others that the firm already holds in its product portfolio or, alternatively, it could be something that is truly unique and innovative. As discussed in Section 2 defining a product as an unique UPC can cause some measurement concerns because even small changes in the product result in a new barcode. These small innovations are plausibly not as meaningful as innovations that substantially alter the range of products offered by firms. We address this issue in two ways. First, we distinguish between two different types of innovation – incremental and extensions. Second, we show that the results reported in the previous sections do not qualitatively change when we consider coarser definitions of products.

Under the first approach, we distinguish between a new product within the main product line of the firm and new products outside the main product line of the firm. Marginal product developments, such as changes in volume and other minor characteristics, are unlikely to involve a lot of resources or have a significant impact on the outcomes of the firm. By contrast, new products that are outside the core business of the firm are likely to involve substantial changes in the production technology with sizable consequences to the outcomes of the firm. We implement a distinction between types of product using the classification system in the Nielsen data set. In particular, we classify a new product at t as an improvement if the firm already has other products of that type, that is, if the firm at $t-1$ already produces goods in the same module as the product being created. We classify a new product as an extension if it represents a new module for the firm. We estimate that the probability that a firm introduces an extension and we find that extensions decrease more than 10 p.p. in the first 16 quarters of the firm (Figure 18 (a)). This decline in the introduction of product extensions as firms grow older is not offset by an increase in the product quality of extensions: the average revenue generated by product extensions is fairly constant throughout the life cycle (Figure 18 (c)). Overall, firms seem to be growing relatively more through product extensions when they are young and through incremental innovations as they age.

As discussed above, the second approach is to coarsen the definition of a product and examine how the number of product lines, measured as the number of product modules, groups, and departments evolve over the life cycle of firms. Figure 19 shows that the average level of the portfolio of products that firms carry also increases with age when we use these alternative measures. Consistent with the analysis above, however, growth is larger for modules than it is for groups and departments. These patterns indicate that most product innovations are happening within the initial portfolio of products and that only a small portion of innovations are new product lines. Finally, in the consumer package goods sector, an important characteristic of the product is their brand. We, therefore, also examine how the number of brands evolve with firm age. Figure 20 shows that the estimated number of brands also increases with firm age.

Overall, we conclude that the number of products, measured either as barcode, brand, or alternative proxies for product lines, increase with firm age. These results together with our previous results on the effect of the life cycle of products, indicate that product introduction is a necessary condition for firm growth.

5 Possible Mechanisms: A Structural Approach

Why are the prices and quantities of products declining after their introduction? To uncover the mechanisms behind these findings, we structurally estimate a model of heterogeneous multiproduct firms and use it to decompose growth over the product life cycle into that attributable to costs, product appeal, scope, and markups. The model follows the framework developed by Hottman, Redding and Weinstein (2016) but focuses on the life cycle growth of a product using a similar approach as the one used by Eslava and Haltiwanger (2017) to study the life cycle growth of firms. In what follows, we first use the theoretical framework to estimate the elasticities of substitution across varieties between and within multiproduct firms. We then use these estimates, along with the structure of the model, to isolate different margins affecting the product life cycle.

5.1 Demand

The model is based on an upper-level Cobb-Douglas demand system across product groups with CES nests below it. Let utility U_t be defined as:

$$\ln U_t = \int_{g\in\Omega^G} \varphi_{gt}^G \ln C_{gt}^G dg, \qquad \int_{g\in\Omega^G} \varphi_{gt}^G dg = 1 \tag{7}$$

where g denotes the product group, φ_{gt}^G the share of expenditure on each product group at time t, and Ω^G is the set of product groups. We assume a continuum of product groups so that each firm is of measure zero relative to the economy as a whole. Thus, the problem becomes separable within product groups as no firm has an incentive to try to manipulate prices in one product group to influence behavior in another product group. Within product groups, we assume two CES nests for firms and UPCs defined as:

$$C_{gt}^G = \left[\sum_{f\in\Omega_{gt}^F} \left(\varphi_{fgt}^F C_{fgt}^F\right)^{\frac{\sigma_g^F-1}{\sigma_g^F}}\right]^{\frac{\sigma_g^F}{\sigma_g^F-1}}, \quad C_{fgt}^F = \left[\sum_{u\in\Omega_{fgt}^U} \left(\varphi_{ut}^U C_{ut}^U\right)^{\frac{\sigma_g^U-1}{\sigma_g^U}}\right]^{\frac{\sigma_g^U}{\sigma_g^U-1}} \tag{8}$$

where the consumption in a product group, C_{gt}^G, is a function of each firm's output, C_{fgt}^F, weighted by the firm's appeal, $\varphi_{fgt}^F > 0$, and adjusted by the elasticity of substitution between firms, $\sigma_g^F > 1$. The output of each multiproduct firm is a function of the consumption of each UPC ,C_{ut}^U, weighted by each product's appeal ,$\varphi_{ut}^U > 0$, and adjusted by the substitutability between UPCs, σ_g^U. The nested CES structure within groups allows for strategic interactions among firms supplying similar products and for the possibility of cannibalization effects.[17] The corresponding exact price indexes for consumption are:

$$P_{gt}^{G}=\left[\sum_{f\in\Omega_{gt}^{F}}\left(\frac{P_{fgt}^{F}}{\varphi_{fgt}^{F}}\right)^{1-\sigma_g^F}\right]^{\frac{1}{1-\sigma_g^F}},\quad P_{fgt}^{F}=\left[\sum_{u\in\Omega_{fgt}^{U}}\left(\frac{P_{ut}^{U}}{\varphi_{ut}^{U}}\right)^{1-\sigma_g^U}\right]^{\frac{1}{1-\sigma_g^U}} \tag{9}$$

where P_{gt}^{G} is the group at time t, P_{fgt}^{F} is the firm price index, and P_{ut}^{U} is the price of UPC u sold by firm f at time t. Using the properties of CES demand, the expenditure share of each group equal the elasticity of the price index of the group with respect to the price index of the firm. Similarly, the expenditure share of the firm equal the elasticity of the price index of the firm with respect to the price of product u as follows:

$$S_{fgt}^{F}=\left(\frac{P_{fgt}^{F}/\varphi_{fgt}^{F}}{P_{gt}^{G}}\right)^{1-\sigma_g^F}=\frac{\partial P_{gt}^{G}}{\partial P_{fgt}^{F}}\frac{P_{fgt}^{F}}{P_{gt}^{G}},\quad S_{ut}^{U}=\left(\frac{P_{ut}^{U}/\varphi_{ut}^{U}}{P_{fgt}^{F}}\right)^{1-\sigma_g^U}=\frac{\partial P_{fgt}^{F}}{\partial P_{ut}^{U}}\frac{P_{ut}^{U}}{P_{fgt}^{F}} \tag{10}$$

Note that, keeping prices constant, products with higher appeal also have higher market share. The demand for the output of product u can be written as:

$$C_{ut}^{U}=\left(\varphi_{ut}^{U}\right)^{\sigma_g^U-1}\left(\varphi_{fgt}^{F}\right)^{\sigma_g^F-1}E_{gt}^{G}\left(P_{gt}^{G}\right)^{\sigma_g^F-1}\left(P_{fgt}^{F}\right)^{\sigma_g^U-\sigma_g^F}\left(P_{ut}^{U}\right)^{-\sigma_g^U} \tag{11}$$

5.2 Technology

The costs of supplying products vary at the product and at the firm level. The total variable cost of firm f in group g of producing UPC u is $a_{ut}\left(Y_{ut}^{U}\right)^{\delta_g+1}$ where a_{ut} is a cost shifter and δ_g is the elasticity of marginal costs with respect to output. In order to allow for entry and exit of both firms and products, each firm faces a fixed cost of production $H_{gt}^{F}>0$ for each product group and a fixed market entry cost for each UPC supplied of $H_{gt}^{U}>0$. Thus, the profits of firm f supplying N_{fgt}^{U} UPCs at time t are given by:

$$\Pi_{fgt}^{F}=\sum_{k=\underline{u}_{fgt}}^{\underline{u}_{fgt}+N_{fgt}^{U}}\left[P_{kt}^{U}Y_{kt}^{U}-a_{kt}\left(Y_{kt}^{U}\right)^{\delta_g+1}\right]-N_{fgt}^{U}H_{gt}^{U}-H_{gt}^{F} \tag{12}$$

[17] We cannot define firm appeal independently of product appeal since the utility function is homogeneous of degree 1 in firm appeal, thus we follow Hottman, Redding and Weinstein (2016) and normalize the geometric means of φ_{fgt}^{F} and φ_{fgt}^{U} to equal 1.

where the UPCs supplied by the firm are indexed from the largest in sales ($\underline{u}_{fgt}$) to the smallest. We assume that firms maximize profits choosing prices under Bertrand competition and subject to $Y_{ut}^U = C_{ut}^U$. Thus, each period the firm chooses its portfolio of UPCs and their prices setting the relative prices of each UPC equal to its relative marginal costs.[18] Given the CES structure we assumed and the fact that there is a finite number of firms in each product group, each firm internalizes the effect of its pricing decisions on the market price indexes. As a result, the equilibrium pricing rule involves variable markups, μ_{fgt}, that are increasing in the expenditure share of each firm. Thus, the firm's pricing rule is:

$$P_{ut}^U = \mu_{fgt}^F (1+\delta_g) a_{ut} \left(C_{ut}^U\right)^{\delta_g} \tag{13}$$

where

$$\mu_{fgt}^F = \frac{\sigma_g^F - (\sigma_g^F - 1) S_{fgt}^F}{\sigma_g^F - (\sigma_g^F - 1) S_{fgt}^F - 1} \tag{14}$$

5.3 The Life Cycle of the Product

It follows from equation 11 that the quantity growth over the product life cycle $\frac{C_{ut}^U}{C_{u0}^U}$, where 0 is the quarter when the product was introduced, can be expressed as:

$$\frac{C_{ut}^U}{C_{u0}^U} = \left(\frac{\varphi_{ut}^U}{\varphi_{u0}^U}\right)^{\sigma_g^U - 1} \left(\frac{\varphi_{fgt}^F}{\varphi_{fg0}^F}\right)^{\sigma_g^F - 1} \frac{E_{gt}^G}{E_{g0}^G} \left(\frac{P_{gt}^G}{P_{g0}^G}\right)^{\sigma_g^F - 1} \left(\frac{P_{fgt}^F}{P_{fg0}^F}\right)^{\sigma_g^U - \sigma_g^F} \left(\frac{P_{ut}^U}{P_{u0}^U}\right)^{-\sigma_g^U} \tag{15}$$

where changes in the quantity growth over the product life cycle can be attributed to changes in the appeal of the product, changes in the appeal of the firm, contributions of product group variables, contributions of firm-group variables, and variation in the price of the product. Thus, after taking logs equation 15, can be written as:

$$\ln\left(\frac{C_{ut}}{C_{u0}}\right) = \left(\sigma_g^U - 1\right) \ln\left(\frac{\varphi_{ut}^U}{\varphi_{u0}^U}\right) - \sigma_g^U \ln\left(\frac{P_{ut}^U}{P_{u0}^U}\right) + \lambda_{fgt} \tag{16}$$

[18] This assumption, that firms choose their portfolio every period, simplifies the problem substantially as it turns the dynamic problem into a series of static ones. As a result, we are able to study a simple static model of optimal price setting and portfolio size decisions to frame our analysis of the product life cycle between the time of the introduction of a product and a future time t. In Appendix F we develop a simple two period model to display the mechanism at play in a dynamic setup.

where it becomes clear that, after controlling for time-varying characteristics of the firms within groups and holding prices constant, the patterns of the product quantities over their life cycle can be attributed to the dynamics of the product appeal. This effect is stronger if the elasticity of substitution within firms σ_g^U is larger. An analogous decomposition applies to the prices of the product. Taking logs of equation 13 we find:

$$\ln\left(\frac{P_{ut}^U}{P_{u0}^U}\right) = \ln\left(\frac{a_{ut}}{a_{u0}}\right) + \delta_g \ln\left(\frac{C_{ut}}{C_{u0}}\right) + \theta_{fgt} \tag{17}$$

where equation 17 shows that the life cycle patterns of the prices of UPC, after controlling for time-varying characteristics of the firms within groups and holding quantities constant, respond to changes in production costs.

Equations 16 and 17 indicate that, given the structure of the model, the main drivers behind the life cycle patterns we uncovered in section 3 are product appeal for quantities and product costs for prices. To validate this conjecture, in what follows, we estimate the model structurally to obtain the values for φ_{ut}^U and a_{ut} up to a normalization. We then describe the evolution of these two variables over the product life cycle.

5.3.1 Structural Estimation

We estimate φ_{ut}^U and a_{ut} in three steps.[19] First, given data on prices (P_{ut}^U) and quantities at the product level (S_{ut}^U), we estimate the elasticity of substitution within firms, σ_g^U, and the elasticity of marginal costs with respect to output, δ_g, using the methodology developed by Feenstra (1994) and Broda and Weinstein (2006). This information is all we need to obtain the unique values of product appeal φ_{ut}^U (up to a normalization) using the shares S_{ut}^U in equation 10. Second, in order to obtain the values for the cost shifter, a_{ut}, we must also estimate the elasticity of substitution across firms σ_g^F. To do so we use the estimated values for φ_{ut}^U to obtain the firm price index P_{fgt}^F. Then, we use the relationship between S_{fgt}^F and P_{fgt}^F along with the instrumental variable approach developed in Hottman, Redding and Weinstein (2016) to estimate σ_g^F. Finally, using our estimated values of σ_g^F and the firm shares S_{fgt}^F, we can obtain estimates for the markups using equation 14. The product costs, a_{ut}, are the residuals from combining information on the prices of the product, P_{ut}^U, and the markup information, μ_{fgt}^F.[20]

[19] Our estimation procedure follows the same steps as those in Hottman, Redding and Weinstein (2016), please refer to their paper for more details on the procedure. Our estimates differ from those found in their paper only because we use a different dataset to estimate the parameters (i.e. Nielsen RMS), which covers more products and firms over a longer time span of data (2006-2015).

[20] Consistent with Hottman, Redding and Weinstein (2016) we find that σ_g^U is always larger than σ_g^F. Our estimates are, nonetheless, slightly higher those those found in their work. This is likely due to the fact that

5.3.2 Product Appeal and Costs over the Product Life Cycle

We begin by describing the patterns of product appeal over the life cycle of the product. Panel A of Figure 21 shows the estimated life cycle profile of product appeal after applying the methodology described in equation 1 to the structural residuals obtained for φ^U_{ut}. The growth of product appeal resembles closely the life cycle patterns of quantities as predicted by equation 16. Surprisingly, the figure shows that the appeal of a product is not across time and declines throughout most of its product life cycle. This indicates that consumers have higher preference for more novel goods and this is the main reason behind the life cycle patterns of product quantities.

The patterns of costs over the product life cycle are similar to those of prices. Panel B of Figure 21 shows that the costs decline at a constant pace as the product gets older. This pattern is true regardless of the product duration. Importantly, the magnitude of the cost declines is much smaller than the decline in product appeal indicating the most of the decline in revenue that we observe over the product life cycle could be explained by declines in the product appeal.

To validate this conjecture, we use the model to decompose the variance of product sales, $E^U_{ut} = P^U_{ut}C^U_{ut}$ over the life cycle of a product, into contributions associated with each if its different components. Using equation 11 and taking logarithms we can write sales as:

$$\ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) = \left(\sigma^U_g - 1\right)\ln\left(\frac{\varphi^U_{ut}}{\varphi^U_{u0}}\right) + \left(\sigma^F_g - 1\right)\ln\left(\frac{\varphi^F_{fgt}}{\varphi^F_{fg0}}\right) + \ln\left(\frac{E^G_{gt}}{E^G_{g0}}\right)$$
$$+ \left(\sigma^F_g - 1\right)\ln\left(\frac{P^G_{gt}}{P^G_{g0}}\right) - \left(\sigma^U_g - 1\right)\ln\left(\frac{P^U_{ut}}{P^U_{u0}}\right) + \left(\sigma^U_g - \sigma^F_g\right)\ln\left(\frac{P^F_{fgt}}{P^F_{fg0}}\right) \quad (18)$$

which decomposes sales into contributions of product appeal (φ^U_{ut}), firm appeal (φ^F_{fg0}), product group variables (E^G_{gt} and P^G_{gt}), the price of the product (P^U_{ut}), and the price index of the firm (P^F_{fgt}). Using the definition of P^F_{fgt} and the pricing rule P^U_{ut} we can write:

the Nielsen RMS cover more firms within a product group and more products per firm than the Nielsen HMS. A detailed comparison between the two data sets can be found in Table A.I.

$$
\begin{aligned}
\ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) &= \left(\sigma^U_g - 1\right)\ln\left(\frac{\varphi^U_{ut}}{\varphi^U_{u0}}\right) - \left(\sigma^U_g - 1\right)\ln\left(\frac{\gamma^U_{ut}}{\gamma^U_{u0}}\right) \\
&+ \ln\left(\frac{E^G_{gt}}{E^G_{g0}}\right) + \left(\sigma^F_g - 1\right)\ln\left(\frac{P^G_{gt}}{P^G_{g0}}\right) \\
&+ \left(\sigma^F_g - 1\right)\ln\left(\frac{\varphi^F_{fgt}}{\varphi^F_{fg0}}\right) - (\sigma^F_g - 1)\ln\left(\frac{\mu^F_{fgt}}{\mu^F_{fg0}}\right) - \left(\frac{\sigma^U_g - \sigma^F_g}{\sigma^U_g - 1}\right)\ln\left(\frac{N^U_{fgt}}{N^U_{fg0}}\right) \\
&- \left(\frac{\sigma^U_g - \sigma^F_g}{\sigma^U_g - 1}\right)\ln\left(\frac{\frac{1}{N^U_{fgt}}\sum_{u\in\Omega^U_{fgt}}\left(\frac{\frac{\gamma_{ut}}{\tilde{\gamma}_{fgt}}}{\varphi^U_{ut}}\right)^{1-\sigma^U_g}}{\frac{1}{N^U_{fg0}}\sum_{u\in\Omega^U_{fg0}}\left(\frac{\frac{\gamma_{u0}}{\tilde{\gamma}_{fg0}}}{\varphi^U_{u0}}\right)^{1-\sigma^U_g}}\right) + (\sigma^U_g - \sigma^F_g)\ln\left(\frac{\tilde{\gamma}_{fgt}}{\tilde{\gamma}_{fg0}}\right)
\end{aligned}
$$

where we multiply and divide by $\left(\frac{\sigma^U_g - \sigma^F_g}{1-\sigma^U_g}\right)\ln\left(\frac{N^U_{fgt}}{N^U_{fg0}}\right)$ to capture the contribution of product scope on the life cycle of sales. Notice that if the products supplied by a firm are more substitutable with each other than with those of other firms (i.e. $\sigma^U_g > \sigma^F_g$), there is a decline in sales after the introduction of a product. This is because the degree of cannibalization depends on the magnitude of σ^U_g. As σ^U_g approaches infinity then the new product takes all the sales of the existing product. In addition, we use that P^U_{ut} can be further decomposed into the contributions of markups μ^F_{fgt}, the contributions of the geometric mean of marginal costs $\tilde{\gamma}_{fgt}$, and the contribution of the relative appeal-adjusted marginal costs across UPCs $\left(\frac{\frac{\gamma_{ut}}{\tilde{\gamma}_{fgt}}}{\varphi^U_{ut}}\right)$ (cost dispersion). The average marginal cost $\tilde{\gamma}_{fgt}$ and the cost dispersion affect the sales of a UPC through the price index of the firm. UPC sales are increasing on P^F_{fgt} if $\sigma^U_g > \sigma^F_g$.

We now decompose the variance of $\frac{E^U_{ut}}{E^U_{u0}}$ into the contributions associated with each of its components. To do so, we first estimate:

$$
\begin{aligned}
\ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) &= \beta_1\ln\left(\frac{\varphi^U_{ut}}{\varphi^U_{u0}}\right) + \beta_2\ln\left(\frac{\gamma^U_{ut}}{\gamma^U_{u0}}\right) + \beta_3\ln\left(\frac{\varphi^F_{fgt}}{\varphi^F_{fg0}}\right) + \beta_4\ln\left(\frac{\mu^F_{fgt}}{\mu^F_{fg0}}\right) + \beta_5\ln\left(\frac{N^U_{fgt}}{N^U_{fg0}}\right) \\
&+ \beta_6\ln\left(\frac{\frac{1}{N^U_{fgt}}\sum_{u\in\Omega^U_{fgt}}\left(\frac{\frac{\gamma_{ut}}{\tilde{\gamma}_{fgt}}}{\varphi^U_{ut}}\right)^{1-\sigma^U_g}}{\frac{1}{N^U_{fg0}}\sum_{u\in\Omega^U_{fg0}}\left(\frac{\frac{\gamma_{u0}}{\tilde{\gamma}_{fg0}}}{\varphi^U_{u0}}\right)^{1-\sigma^U_g}}\right) + \beta_7\ln\left(\frac{\tilde{\gamma}_{fgt}}{\tilde{\gamma}_{fg0}}\right) + \psi_{gt} + \epsilon_{ut} \qquad (19)
\end{aligned}
$$

where we include time effects and allow the coefficients to differ across product groups. We then regress each of the components on log UPC sales as follows:

$$\beta_1 \ln\left(\frac{\varphi^U_{ut}}{\varphi^U_{u0}}\right) = \rho_A \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,A} \tag{20}$$

$$\beta_2 \ln\left(\frac{\gamma^U_{ut}}{\gamma^U_{u0}}\right) = \rho_C \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,C} \tag{21}$$

$$\beta_3 \ln\left(\frac{\varphi^F_{fgt}}{\varphi^F_{fg0}}\right) = \rho_{FA} \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,FA} \tag{22}$$

$$\beta_4 \ln\left(\frac{\mu^F_{fgt}}{\mu^F_{fg0}}\right) = \rho_M \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,M} \tag{23}$$

$$\beta_5 \ln\left(\frac{N^U_{fgt}}{N^U_{fg0}}\right) = \rho_N \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,N} \tag{24}$$

$$\beta_6 \ln\left(\frac{\frac{1}{N^U_{fgt}} \sum_{u\in\Omega^U_{fgt}} \left(\frac{\frac{\gamma_{ut}}{\tilde{\gamma}_{fgt}}}{\varphi^U_{ut}}\right)^{1-\sigma^U}}{\frac{1}{N^U_{fg0}} \sum_{u\in\Omega^U_{fg0}} \left(\frac{\frac{\gamma_{u0}}{\tilde{\gamma}_{fg0}}}{\varphi^U_{u0}}\right)^{1-\sigma^U}}\right) = \rho_{CD} \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,CD} \tag{25}$$

$$\beta_A C \ln\left(\frac{\tilde{\gamma}_{fgt}}{\tilde{\gamma}_{fg0}}\right) = \rho_{AC} \ln\left(\frac{E^U_{ut}}{E^U_{u0}}\right) + \nu_{ut,AC} \tag{26}$$

where, by the properties of OLS, this decomposition allocates the covariance terms between components of UPC sales equally across those components. Thus, it provides a measure of how much of the growth in the sales of a UPC over its life cycle can be attributed to each component and implies that $\rho_A + \rho_C + \rho_{FA} + \rho_M + \rho_N + \rho_{CD} + \rho_{AC} = 1$. We find that almost 90% of the variation in the sales of a product over its life cycle can be attributed to variation in its appeal. This is consistent with the findings of Hottman, Redding and Weinstein (2016) who conduct a similar analysis but decomposing the sales of the firm. They find that at least 76% of the overall firm size distribution can be attributed to firm appeal. This effect is even stronger at the product level, where costs play an even smaller role determining the evolution of sales than they do determining the size of firms.

6 Conclusion

We began the paper asking the following question: what is the contribution of the product life cycle to firm growth? We argue that the evolution of prices and quantities at the product level have important implications for the life cycle growth of firms. Both the profile of prices and quantities decline systematically after a product is introduced. This product life cycle effect pushes the firms' rate of growth downward, particularly, after they have accumulated several generations of products in their portfolio. As a result, firms must constantly add new products in order to maintain positive growth rates. This is the case in our data. Successful firms are constantly adding new products, new brands, and new product lines. However, introducing new products is not a sufficient condition for positive growth. New products must be able to generate a sufficient amount of revenue to be able to compensate for the decline in revenue from previous vintages of products.

In order to identify the mechanisms behind the decline in sales at the product level, we use a structural model of heterogenous multiproduct firms to decompose sales growth into several components: costs, appeal, scope, and markups. We find that almost all of the variation in product sales can be attributed to variation in appeal which systematically decline over the product life cycle. Our findings suggests that demand factors, such as preferences for more up-to-date varieties, are behind the life cycle patterns we document at the product level and have important consequences for firm growth.

References

Abe, Nobuhiro, Yojiro Ito, Ko Munakata, Shinsuke Ohyama, and Kimiaki Shinozaki, "Pricing Patterns over Product Life-Cycle and Quality Growth at Product Turnover: Empirical Evidence from Japan," in "Meeting of the Group of Experts on Consumer Price Indices" 2016, pp. 2–4.

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William R Kerr, "Innovation, Reallocation and Growth," *NBER Working Paper No. 18993*, 2017.

Akcigit, Ufuk and William R Kerr, "Growth Through Heterogeneous Innovations," *NBER Working Paper No. 16443*, 2010.

Altonji, Joseph G and Robert A Shakotko, "Do wages rise with job seniority?," *Review of Economic Studies*, 1987, *54* (3), 437–459.

Alvarez, Fernando and Francesco Lippi, "Price setting with menu cost for multiproduct firms," *Econometrica*, 2014, *82* (1), 89–135.

_ , Katarına Borovicková, and Robert Shimer, "The proportional hazard model: Estimation and testing using price change and labor market data," 2015.

Argente, David and Chen Yeh, "Product's Life Cycle, Learning, and Nominal Shocks," 2017.

_ , Munseob Lee, and Sara Moreira, "Innovation and product reallocation in the great recession," *Journal of Monetary Economics*, 2018.

Arkolakis, Costas and Marc-Andreas Muendler, "The extensive margin of exporting products: A firm-level analysis," *NBER Working Paper No. 16641*, 2010.

Atkeson, Andrew and Patrick J Kehoe, "Modeling and measuring organization capital," *Journal of Political Economy*, 2005, *113* (5), 1026–1053.

Basker, Emek and Timothy Simcoe, "Upstream, Downstream: Diffusion and Impacts of the Universal Product Code," *NBER Working Paper No. 24040*, 2017.

Bhattarai, Saroj and Raphael Schoenle, "Multiproduct firms and price-setting: Theory and evidence from US producer prices," *Journal of Monetary Economics*, 2014, *66*, 178–192.

Bilbiie, Florin O, Fabio Ghironi, and Marc J Melitz, "Endogenous Entry, Product Variety, and Business Cycles," *Journal of Political Economy*, 2012, *120* (2), 304–345.

Broda, Christian and David E Weinstein, "Globalization and the Gains From Variety," *Quarterly Journal of Economics*, 2006, *121* (2), 541–585.

— and — , "Product Creation and Destruction: Evidence and Price Implications," *American Economic Review*, 2010, *100* (3), 691–723.

Byrne, David M, Stephen D Oliner, and Daniel E Sichel, "How fast are semiconductor prices falling?," *Review of Income and Wealth*, 2015.

Copeland, Adam and Adam Hale Shapiro, "Price setting and rapid technology adoption: The case of the PC industry," *Review of Economics and Statistics*, 2016, *98* (3), 601–616.

Deaton, Angus, *The analysis of household surveys: a microeconometric approach to development policy*, World Bank Publications, 1997.

DellaVigna, Stefano and Matthew Gentzkow, "Uniform pricing in us retail chains," *NBER Working Paper No. 23996*, 2017.

Dunne, Timothy, Mark J Roberts, and Larry Samuelson, "The growth and failure of US manufacturing plants," *The Quarterly Journal of Economics*, 1989, *104* (4), 671–698.

Elbers, Chris and Geert Ridder, "True and spurious duration dependence: The identifiability of the proportional hazard model," *The Review of Economic Studies*, 1982, *49* (3), 403–409.

Eslava, Marcela and John Haltiwanger, "The Life-cycle Growth of Plants in Colombia: Fundamentals vs. Distortions," 2017.

Feenstra, Robert C, "New Product Varieties and the Measurement of International Prices," *American Economic Review*, 1994, *84* (1), 157–177.

— and John Romalis, "International prices and endogenous quality," *The Quarterly Journal of Economics*, 2014, *129* (2), 477–527.

Fitzgerald, Doireann, Stefanie Haller, and Yaniv Yedid-Levi, "How exporters grow," *NBER Working Paper No. 21935*, 2017.

Foster, Lucia, John Haltiwanger, and Chad Syverson, "The slow growth of new plants: Learning about demand?," *Economica*, 2016, *83* (329), 91–129.

Garcia-Macia, Daniel, Chang-Tai Hsieh, and Peter J Klenow, "How Destructive is Innovation?," *NBER Working Paper No. 22953*, 2016.

Gilbert, Laurien, "Gains from Product Variety and the Local Business Cycle," 2017.

Gowrisankaran, Gautam and Marc Rysman, "Dynamics of consumer demand for new durable goods," *Journal of political Economy*, 2012, *120* (6), 1173–1219.

Heckman, James and Burton Singer, "The identifiability of the proportional hazard model," *The Review of Economic Studies*, 1984, *51* (2), 231–241.

_ and _ , "A method for minimizing the impact of distributional assumptions in econometric models for duration data," *Econometrica*, 1984, pp. 271–320.

Hottman, Colin J, Stephen J Redding, and David E Weinstein, "Quantifying the sources of firm heterogeneity," *Quarterly Journal of Economics*, 2016, *131* (3), 1291–1364.

Hsieh, Chang-Tai and Peter J Klenow, "The life cycle of plants in India and Mexico," *The Quarterly Journal of Economics*, 2014, *129* (3), 1035–1084.

Klette, Tor Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5).

Lentz, Rasmus and Dale T Mortensen, "An empirical model of growth through product innovation," *Econometrica*, 2008, *76* (6), 1317–1373.

Levitt, Theodore, "Exploit the Product Life Cycle," 1965.

Manova, Kalina and Zhiwei Zhang, "Export prices across firms and destinations," *The Quarterly Journal of Economics*, 2012, *127* (1), 379–436.

Mayer, Thierry, Marc J Melitz, and Gianmarco IP Ottaviano, "Market size, competition, and the product mix of exporters," *American Economic Review*, 2014, *104* (2), 495–536.

Melitz, Marc J, "The impact of trade on intra-industry reallocations and aggregate industry productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Midrigan, Virgiliu, "Menu costs, multiproduct firms, and aggregate fluctuations," *Econometrica*, 2011, *79* (4), 1139–1180.

Minniti, Antonio and Francesco Turino, "Multi-product Firms and Business Cycle Dynamics," *European Economic Review*, 2013, *57*, 75–97.

Nakamura, Emi and Jón Steinsson, "Five facts about prices: A reevaluation of menu cost models," *The Quarterly Journal of Economics*, 2008, *123* (4), 1415–1464.

Timoshenko, Olga A, "Product switching in a model of learning," *Journal of International Economics*, 2015, *95* (2), 233–249.

Table 1: Summary Statistics of Products by Censoring

The table reports summary statistics of products included in the baseline sample. For each product, we determine if the product has sales in 2006Q1 (left-censored) and in 2015Q4 (right-censored), and we compute descriptive statistics for observations that entered and were discontinued in the period under analysis ("Complete"), for observations for which we can determine entry but not exit ("Right-censored"), for observations for which we do not observe entry but we observe exit ("Left-censored"), and for observations for which both entry and exit cannot be determined ("Both-censored"). We report the total observations in each category, statistics on duration, and statistics on sales, for pooled sample for the period 2006Q1-2015Q4. The duration refers to the number of quarters for which we observe the products. Only for the can of the "Complete" its refers to the length of life the products. Also, for definition, "Both-censored" have duration equal to 40. The statistics for the revenue is computed by determining the average quarterly sales (in thousands of dollars) across all stores and weeks of the quarter, deflated by the Consumer Price Index for All Urban Consumers. The table reports the average and distribution statistics of this variable.

	Complete	Right-censored	Left-censored	Both-censored
Total # of products	225,583	214,554	128,424	86,644
Duration (quarters)				
mean	7.4	13.3	13.1	40.0
less than 4 (%)	52.0	28.7	31.4	0
less than 16 (%)	90.2	70.9	70.2	0
above 28 (%)	1.3	10.6	11.0	100
Revenue (quarterly, $1,000)				
mean	27.0	105.2	25.1	179.5
25th percentile	0.2	1.0	0.1	2.2
median	1.9	7.7	1.0	13.3
75th percentile	12.7	53.8	7.7	88.0
90th percentile	56.1	233.2	42.3	406.7
95th percentile	121.9	482	106.8	832.5

Table 2: Summary Statistics of Products by Sample

The table reports summary statistics of products included in the baseline samples. For each product, we determine if it is part of the baseline balanced sample ("Balanced"), and part of the semi-balanced sample ("Semi-Balanced"). Details are provided in the text. We report the total observations in each category, statistics on duration, and statistics on sales, for pooled sample for the period 2006Q1-2015Q4. The duration refers to the number of quarters for which we observe the products. The statistics for the revenue is computed by determining the average quarterly sales (in thousands of dollars) across all stores and weeks of the quarter, deflated by the Consumer Price Index for All Urban Consumers. The table reports the average and distribution statistics of this variable.

	Balanced	Semi-balanced
Total # of products	80,638	179,223
Duration (quarters)		
mean	25.7	15.7
less than 4 (%)	0	22.4
less than 16 (%)	0	55
above 28 (%)	28.1	12.6
Revenue (quarterly, $1,000)		
mean	126.8	75.1
25th percentile	1.5	0.6
median	10.5	4.6
75th percentile	69.3	31.3
90th percentile	294.9	147.7
95th percentile	584.2	332.1

Table 3: Summary Statistics of Products by Censoring

The table reports summary statistics of products included in the baseline sample. For each product, we determine if the product has sales in 2006Q1 (left-censored) and in 2015Q4 (right-censored), and we compute descriptive statistics for observations that entered and were discontinued in the period under analysis (”Complete”), for observations for which we can determine entry but not exit (”Right-censored”), for observations for which we do not observe entry but we observe exit (”Left-censored”), and for observations for which both entry and exit cannot be determined (”Both-censored”). We report the total observations in each category, statistics on duration, and statistics on sales, for pooled sample for the period 2006Q1-2015Q4. The duration refers to the number of quarters for which we observe the products. Only for the can of the ”Complete” its refers to the length of life the products. Also, for definition, ”Both-censored” have duration equal to 40. The statistics for the revenue is computed by determining the average quarterly sales (in thousands of dollars) across all stores and weeks of the quarter, deflated by the Consumer Price Index for All Urban Consumers. The table reports the average and distribution statistics of this variable.

	Complete	Right-censored	Left-censored	Both-censored
Total # of firms	4425	4726	6107	7680
Duration (quarters)				
average	10.6	16.9	16.4	40
less than 4 (%)	35.0	18.1	20	0
less than 16 (%)	80.7	58.1	61.0	0
above 28 (%)	3.9	17.9	17.8	100
Revenue (quarterly, $1,000)				
average	8.4	23.6	111.4	3425.1
25th percentile	0.1	0.1	1.3	8.9
median	0.5	1.1	6.8	56.8
75th percentile	3.3	7.7	36	365.9
90th percentile	14.8	35.9	161.6	2218.1
95th percentile	32	86.9	349.8	7387.4
Products (quarterly)				
average	2.1	3.2	5.3	27.2
25th percentile	1	1	1.3	2.7
median	1	1.8	3	6.7
75th percentile	2.5	3.5	5.5	18.4
90th percentile	4.2	6.7	10.3	51.8
95th percentile	5.8	10	16	98

Table 4: Summary Statistics of Firms by Censoring

The table reports summary statistics of firms included in the baseline sample by censoring. The variables are defined either for entire sample period or at the quarter level for the period 2007Q1-2014Q4. The revenue is the total sales (in dollars) across all stores and weeks of the quarter, deflated by the Consumer Price Index for All Urban Consumers.

	uncensored	left censored	right censored	both censored
For entire sample period:				
Total # of firms	5,461	4,726	5,838	7,677
Average duration of firms	7.77	15.86	16.04	39
Quarterly average:				
Active # of firms	1,343	1,853	2,196	7,467
# of products per firm	2.64	3.81	5.33	28.36
# of modules per firm	1.32	1.54	1.82	4.28
# of groups per firm	1.16	1.27	1.42	2.41
# of departments per firm	1.04	1.07	1.11	1.31
Product entry rate	0.15	0.03	0.13	0.02
Product exit rate	0.08	0.11	0.03	0.03
Revenue	10,719.3	32,396.8	133,387.1	3,533,932.9
Revenue from entering products	571.3	324.0	2,194.0	3,004.5
Revenue from exiting products	131.4	172.8	89.16	180.4

Table 5: The Life Cycle of Products: Revenue, Price, and Quantity

		(1)		(2)		(3)
VARIABLES	logrevenue	logrevenue	logprice	logprice	logquantity	logquantity
2.age		0.210***		-0.00988**		0.220***
		(0.0138)		(0.00428)		(0.0144)
3.age		0.259***		-0.0120***		0.271***
		(0.0139)		(0.00431)		(0.0145)
4.age		0.360***		-0.0168***		0.376***
		(0.0140)		(0.00434)		(0.0146)
5.age		0.358***		-0.0252***		0.384***
		(0.0140)		(0.00434)		(0.0146)
6.age		0.275***		-0.0311***		0.306***
		(0.0141)		(0.00438)		(0.0147)
7.age		0.203***		-0.0333***		0.237***
		(0.0142)		(0.00440)		(0.0147)
8.age		0.209***		-0.0380***		0.247***
		(0.0142)		(0.00442)		(0.0148)
9.age		0.142***		-0.0448***		0.187***
		(0.0143)		(0.00443)		(0.0149)
10.age		0.00952		-0.0483***		0.0579***
		(0.0144)		(0.00446)		(0.0149)
11.age		-0.108***		-0.0505***		-0.0575***
		(0.0144)		(0.00448)		(0.0150)
12.age		-0.149***		-0.0544***		-0.0946***
		(0.0145)		(0.00451)		(0.0151)
13.age		-0.255***		-0.0623***		-0.193***
		(0.0146)		(0.00453)		(0.0152)
14.age		-0.442***		-0.0676***		-0.375***
		(0.0147)		(0.00458)		(0.0154)
15.age		-0.605***		-0.0681***		-0.537***
		(0.0149)		(0.00463)		(0.0155)
16.age		-0.694***		-0.0753***		-0.619***
		(0.0152)		(0.00471)		(0.0158)
Constant	8.847***	8.864***	-0.591***	-0.551***	9.438***	9.415***
	(0.00237)	(0.0103)	(0.000731)	(0.00321)	(0.00246)	(0.0108)
Observations	1,290,208	1,290,208	1,290,208	1,290,208	1,290,208	1,290,208
R-squared	0.192	0.200	0.789	0.789	0.386	0.391
Coh&Mod&Time FE	Yes	Yes	Yes	Yes	Yes	Yes

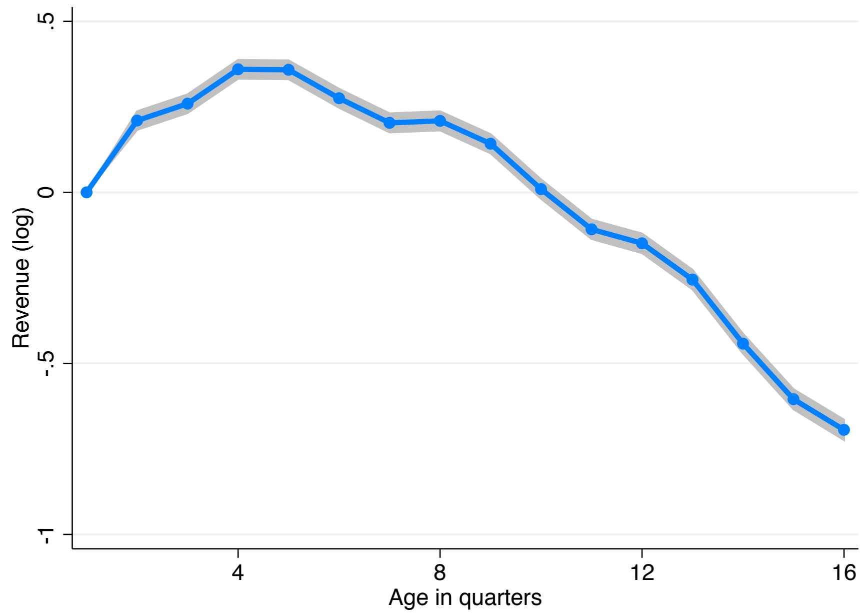
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Decomposition of Sales Growth over Firm's life cycle

The table reports decomposition results using the equation 6. All numbers are annual average across firms.

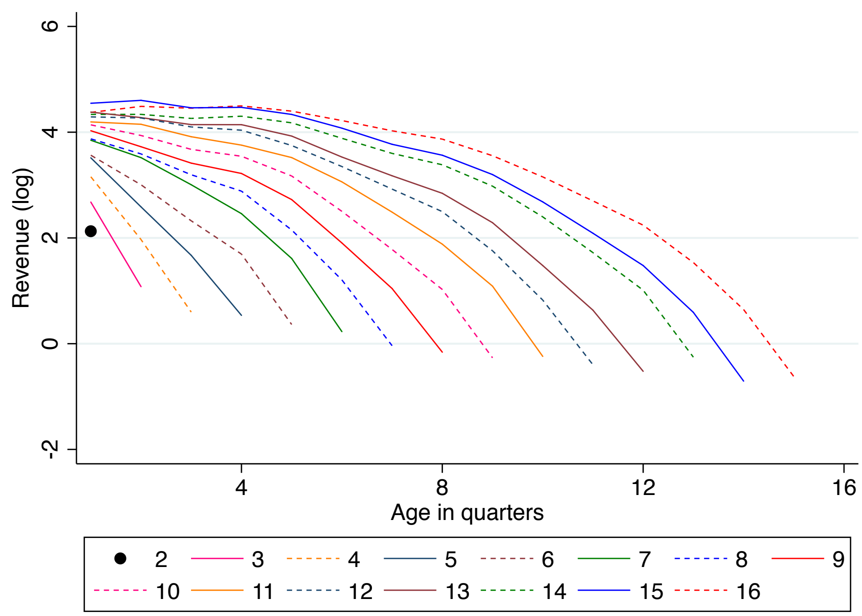
	(1) all	(2) ages 1-2	(3) ages 3-4	(4) ages 5-7	(5) Censored
Data:					
Growth Sales	0.06	0.32	0.14	0.11	0.03
Decomposition:					
Product Life Cycle Effect	-0.06	0.10	-0.03	-0.05	-0.07
Entrants Total Effect	0.11	0.22	0.16	0.16	0.10
Entrant Rate	0.25	0.52	0.38	0.35	0.22
Entrants Relative Quality	0.49	0.44	0.48	0.53	0.49

Figure 1: Revenue of product over the life cycle



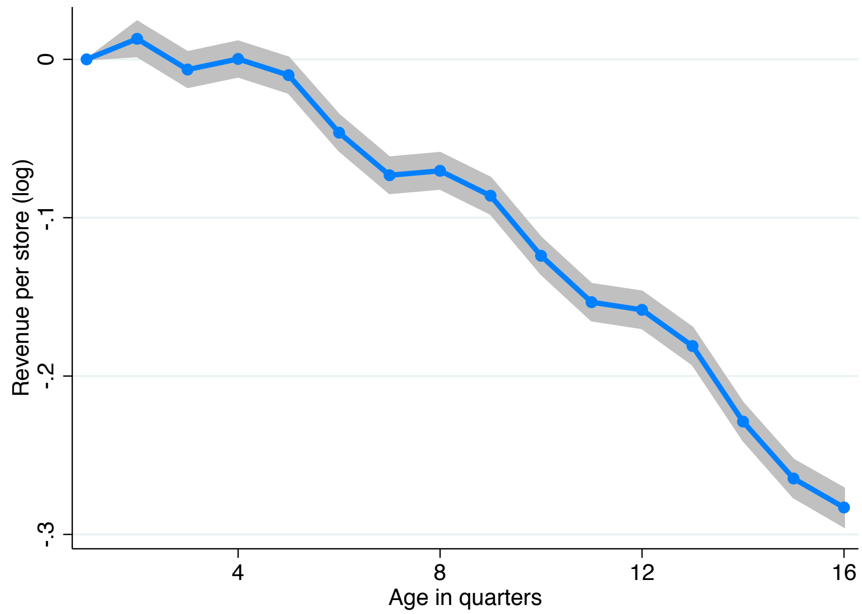
Note: These figures show revenue, price and quantity of long-lasting product over the life cycle. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

Figure 2: Revenue of product over the life cycle: by duration



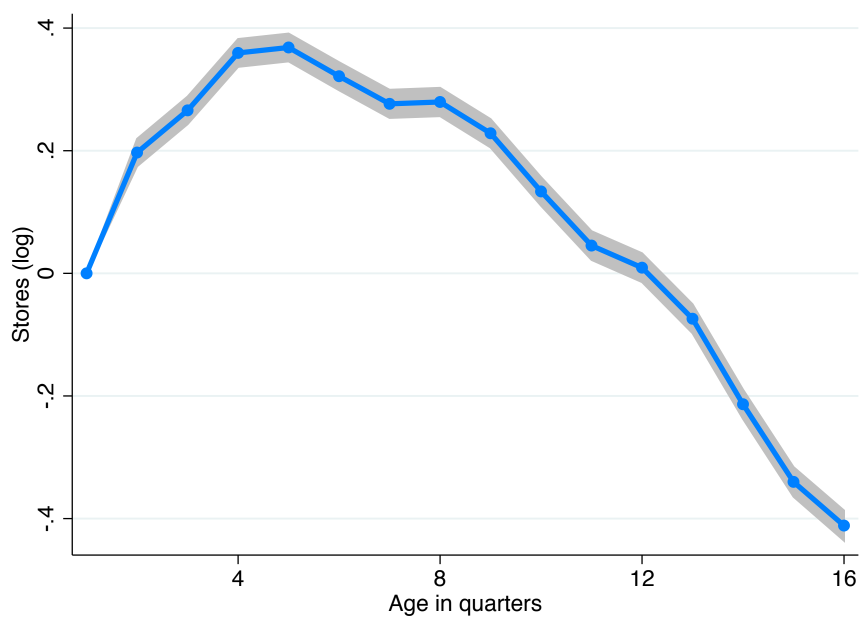
Note: This figure shows revenue of product over the life cycle by duration in quarters.

Figure 3: Revenue of product per store over the life cycle



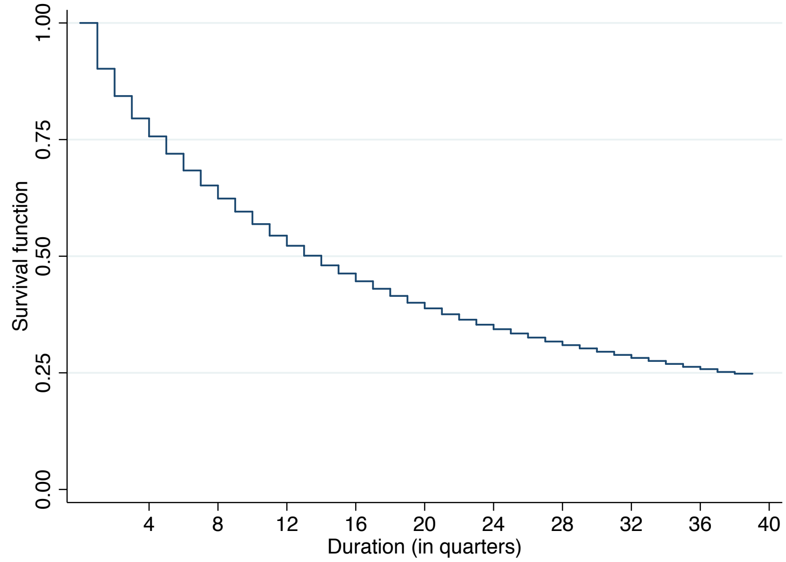
Note: This figure shows revenue of product over the life cycle by duration in quarters.

Figure 4: Stores selling the product over the life cycle



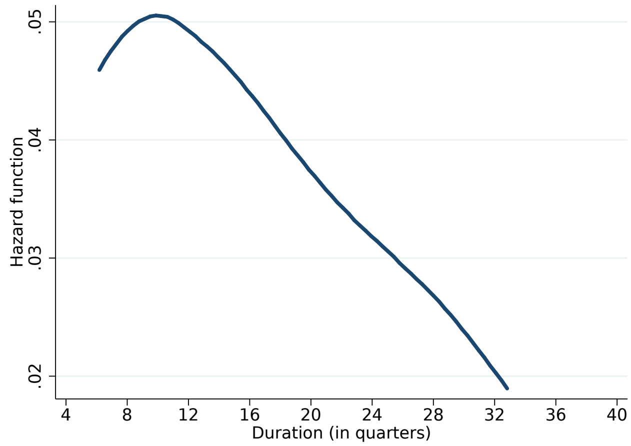
Note: This figure shows revenue of product over the life cycle by duration in quarters.

Figure 5: Unconditional Kaplan-Meier Survival Function

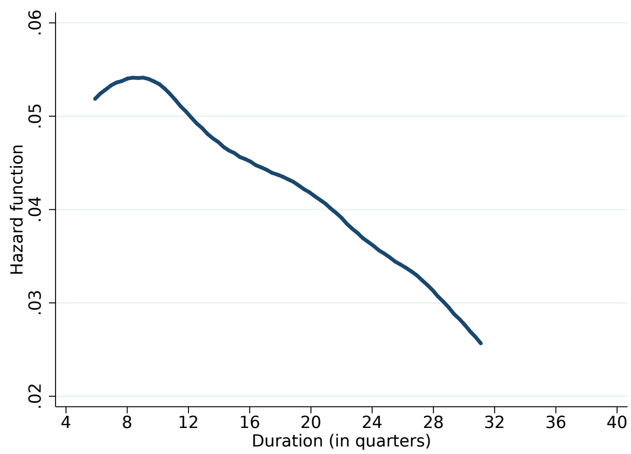


Note: This figure shows unconditional Kaplan-Meier survival function.

Figure 6: Hazard Function Dry Grocery and Non-Food Grocery



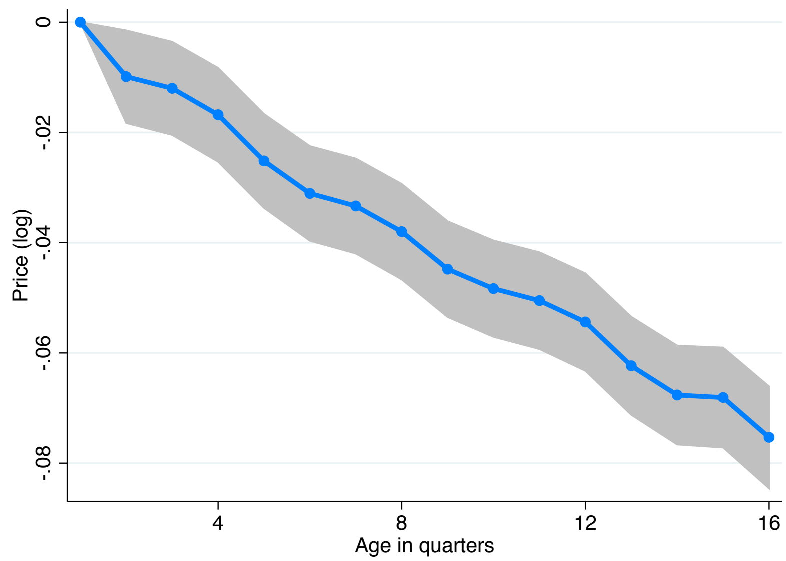
(a) Dry Grocery



(b) Non-Food Grocery

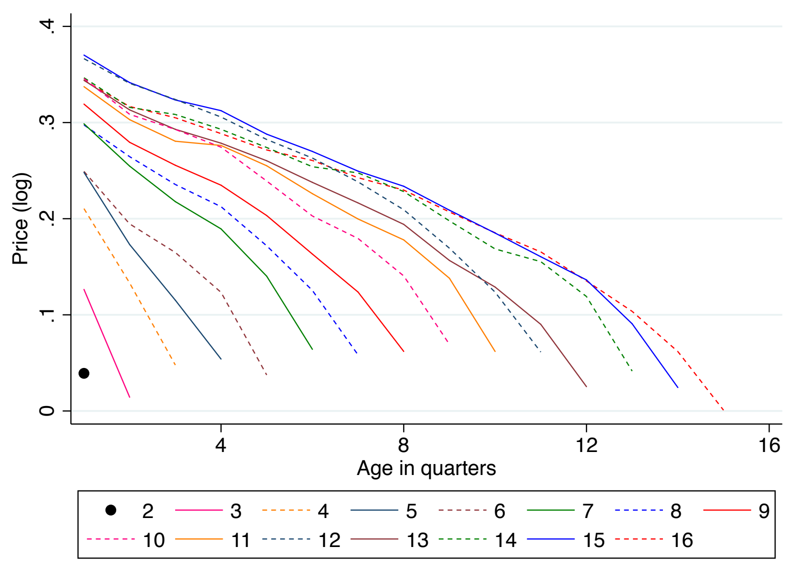
Note: These figures show the hazard function for two department in the Nielsen data: Dry Grocery and Non-Food Grocery. The hazards are estimated using a proportional hazard model. Across product modules the random effects are assumed to be gamma distributed and the age for the firm at the time the product is launched is used as covariate.

Figure 7: Price of product over the life cycle



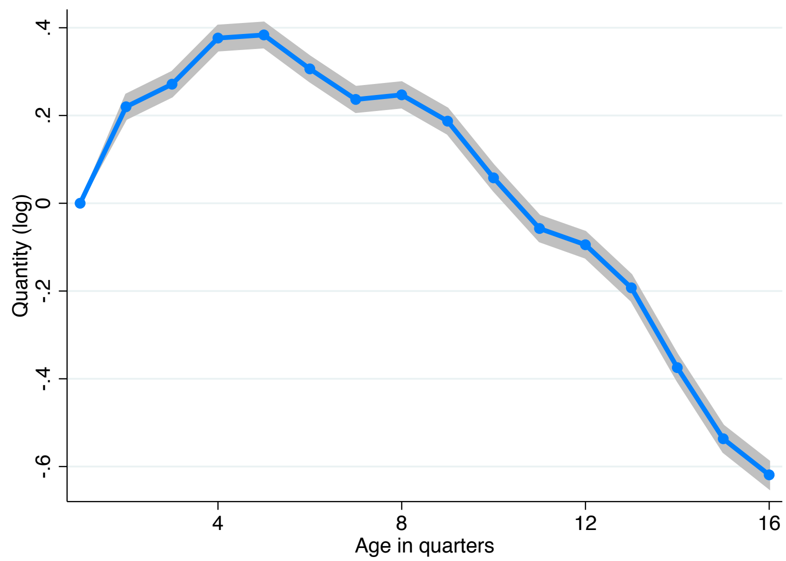
Note: These figures show revenue, price and quantity of long-lasting product over the life cycle. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

Figure 8: Price of product over the life cycle: by duration



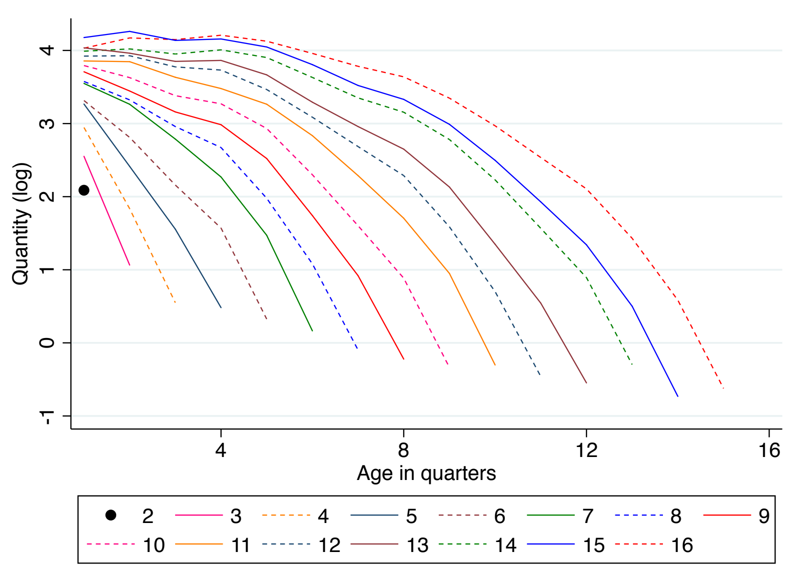
Note: This figure shows estimated age fixed effects ($\hat{\beta}_a$) of price over the life cycle of products, computed using equation 1 by duration.

Figure 9: Quantity of product over the life cycle



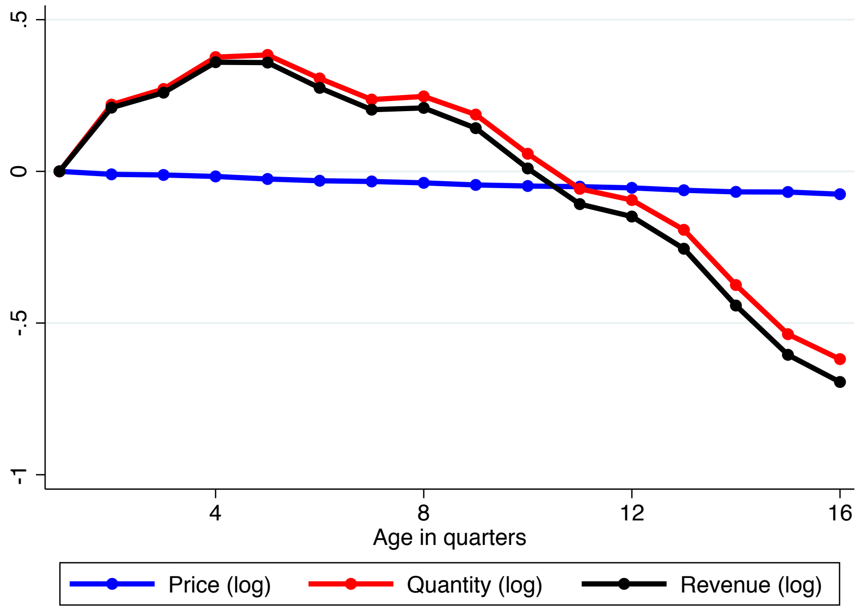
Note: These figures show revenue, price and quantity of long-lasting product over the life cycle. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

Figure 10: Quantity of product over the life cycle: by duration



Note: This figure shows estimated age fixed effects ($\hat{\beta}_a$) of quantity over the life cycle of products, computed using equation 1 by duration.

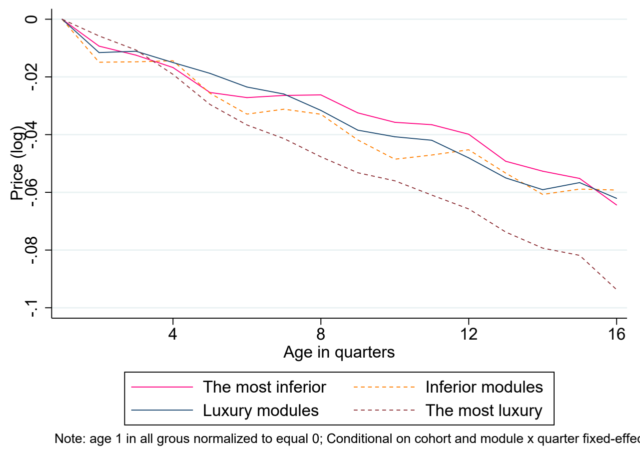
Figure 11: Price, quantity and revenue of product over the life cycle: by duration



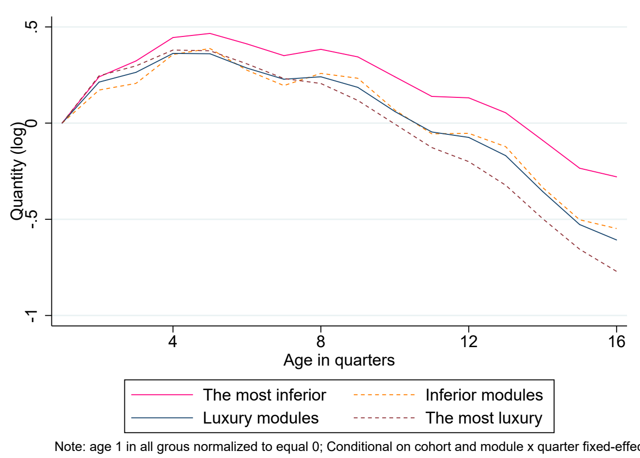
Note: This figure shows quantity of product over the life cycle by duration in quarters.

Figure 12: Revenue, Price and Quantity of product over the life cycle: by Category's Target Income Groups

(a) Revenue of Product



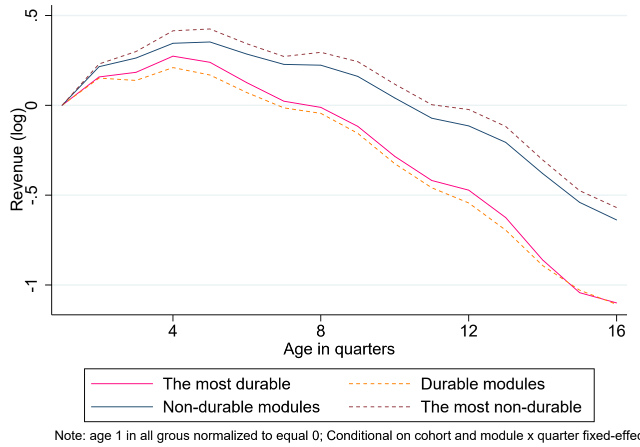
(b) Price of Product



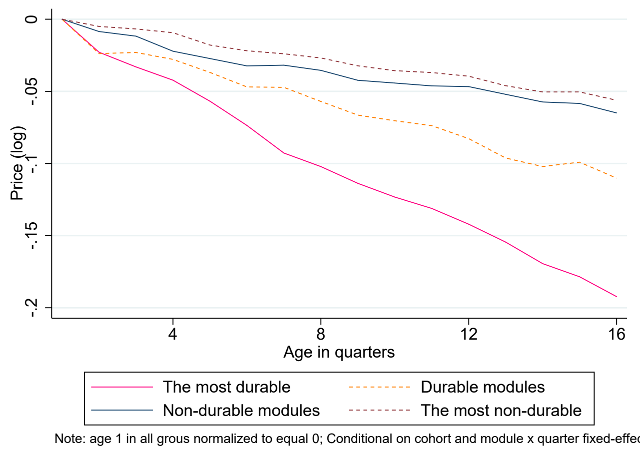
(c) Quantity of Product

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity over the life cycle of products, computed using equation 1 by category's target income groups. We keep balanced sample with 16 quarters or above duration.

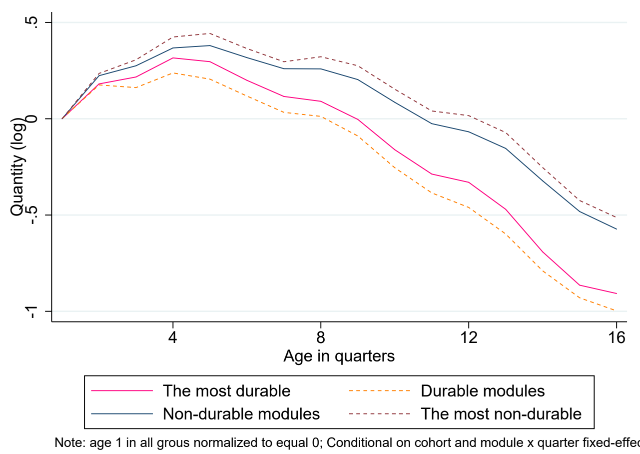
Figure 13: Revenue, Price and Quantity of product over the life cycle: by Category's Durability



(a) Revenue of Product



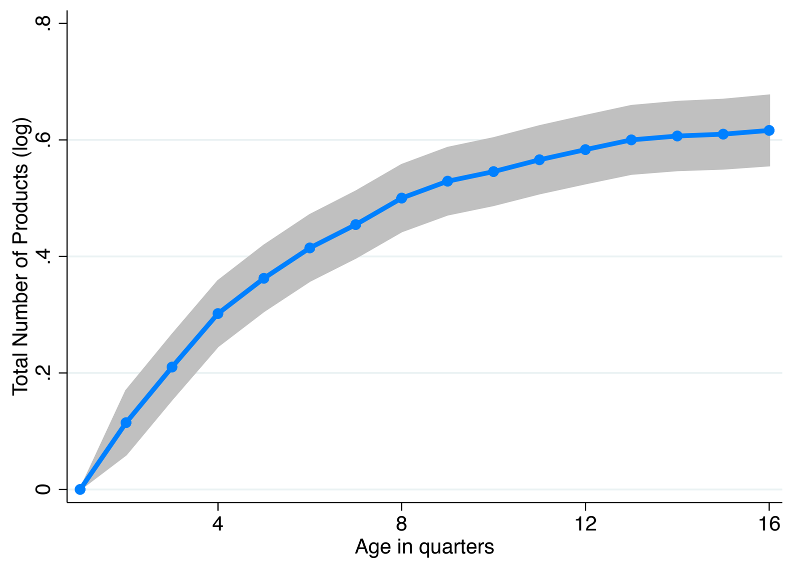
(b) Price of Product



(c) Quantity of Product

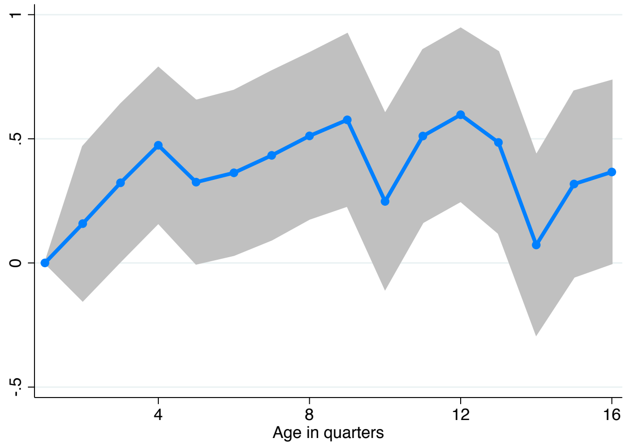
Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity over the life cycle of products, computed using equation 1 by category's durability. We keep balanced sample with 16 quarters or above duration.

Figure 14: Total Number of Products over Firm Life Cycle

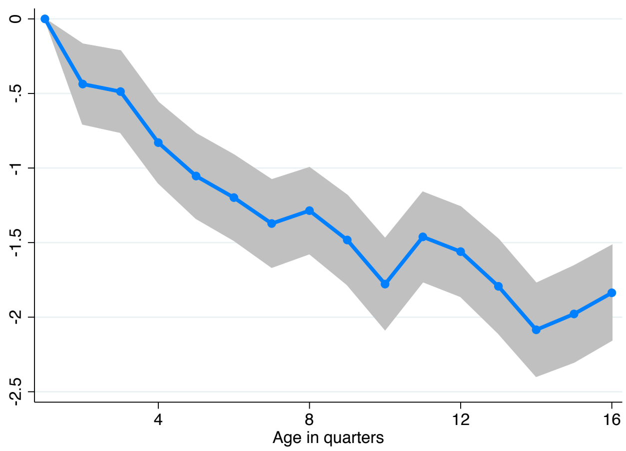


Note: This figure shows estimated age fixed effects ($\hat{\beta}_a$) of total number of products over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

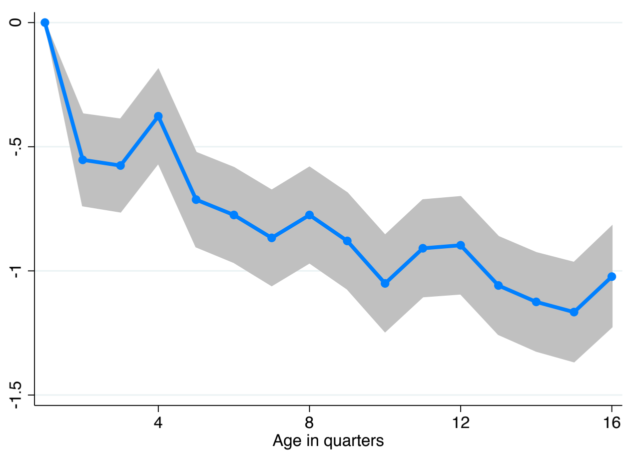
Figure 15: Total Revenue of New Products over Firm Life Cycle



(a) Revenue of new products (in logs)



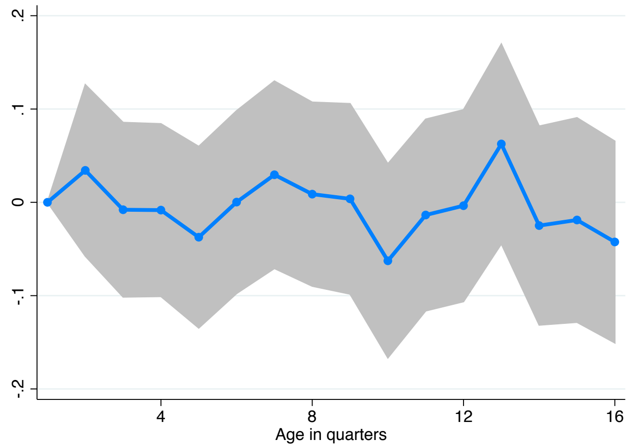
(b) Share of revenue of new products (in logs)



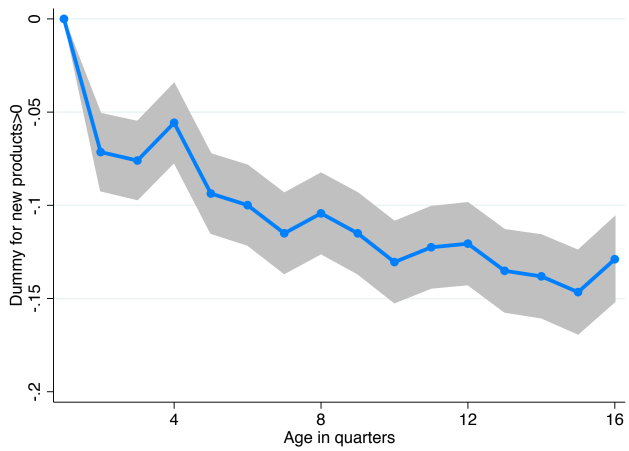
(c) Revenue of new products accounting for zeros (in logs)

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of total revenue of new products over the life cycle of firms, computed using equation 1. Revenue of new products accounting for zeros use an inverse hyperbolic sine transformation. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

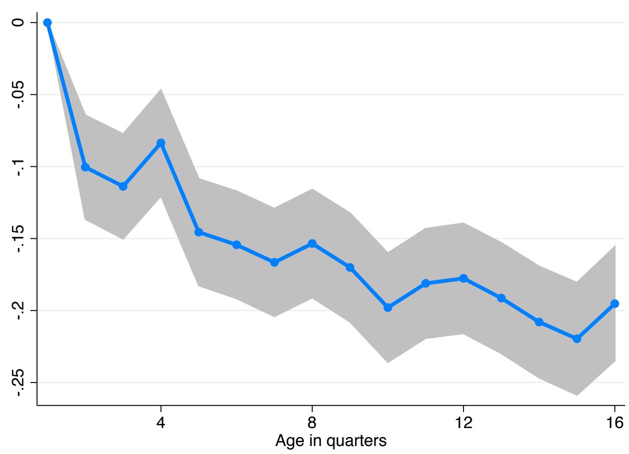
Figure 16: Total Number of New Products over Firm Life Cycle



(a) Number of new products



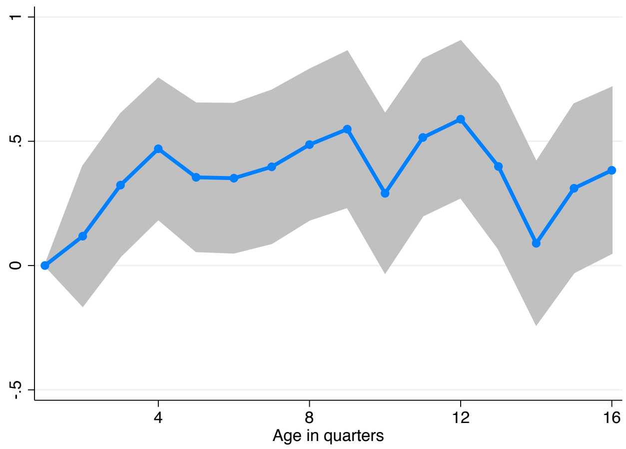
(b) Probability of introducing new products



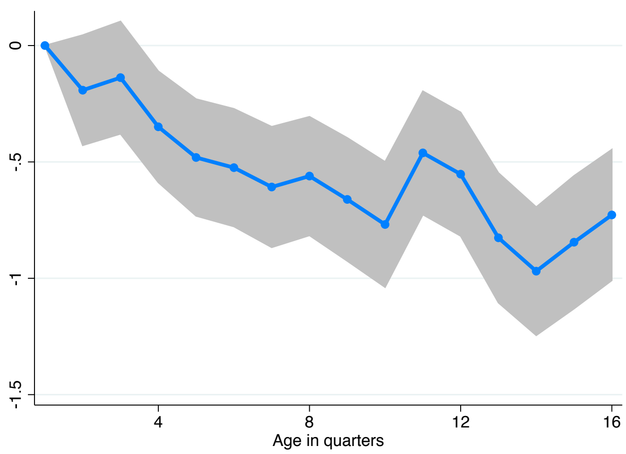
(c) Number of new products accounting for zeros (in logs)

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of total number of new products over the life cycle of firms, computed using equation 1. The number of new products is calculated conditional on introducing products. The number of new products accounting for zeros use an inverse hyperbolic sine transformation. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

Figure 17: Average Revenue of New Products



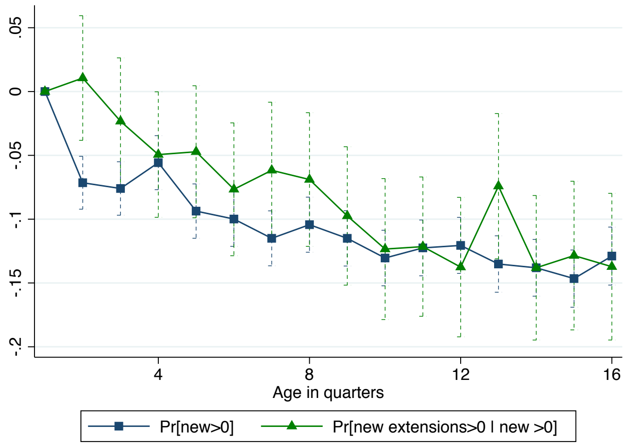
(a) Average revenue of new products (in logs)



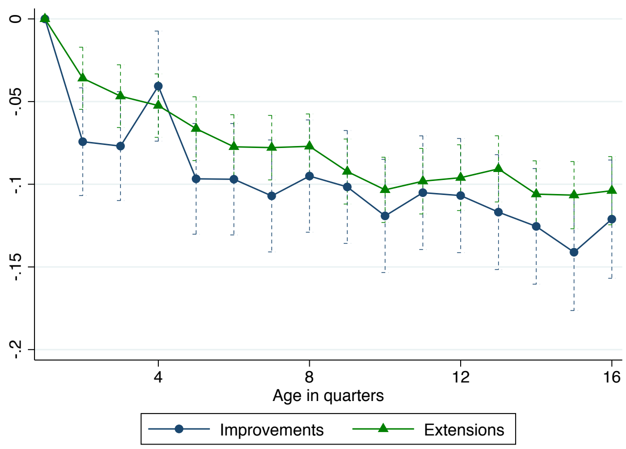
(b) Ratio of revenue of new to all products (in logs)

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of average revenue of new products over the life cycle of firms, computed using equation 1. Revenue of new products are calculated from the first full quarter in the market. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

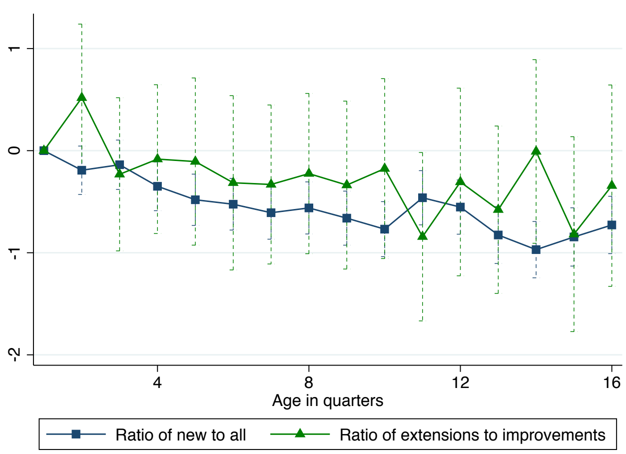
Figure 18: Introduction of improvements and extension products



(a) Probability of creating an extension



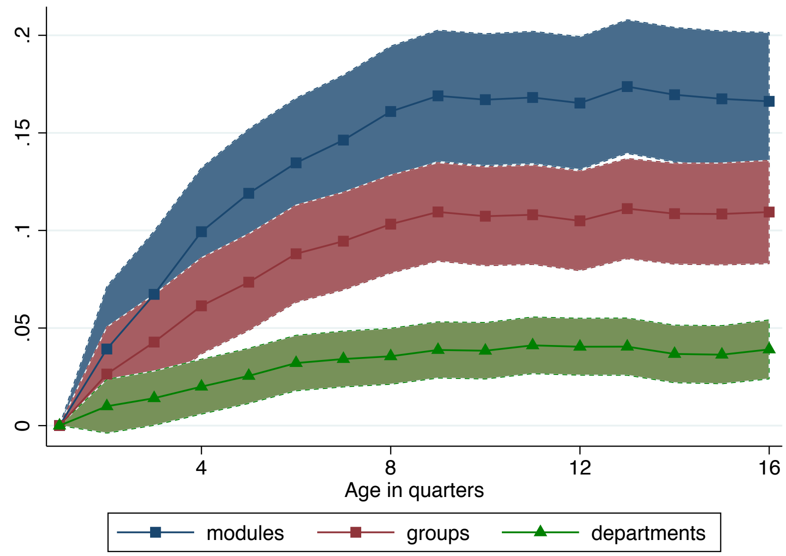
(b) Number of new products accounting for zeros (in logs)



(c) Relative average revenue

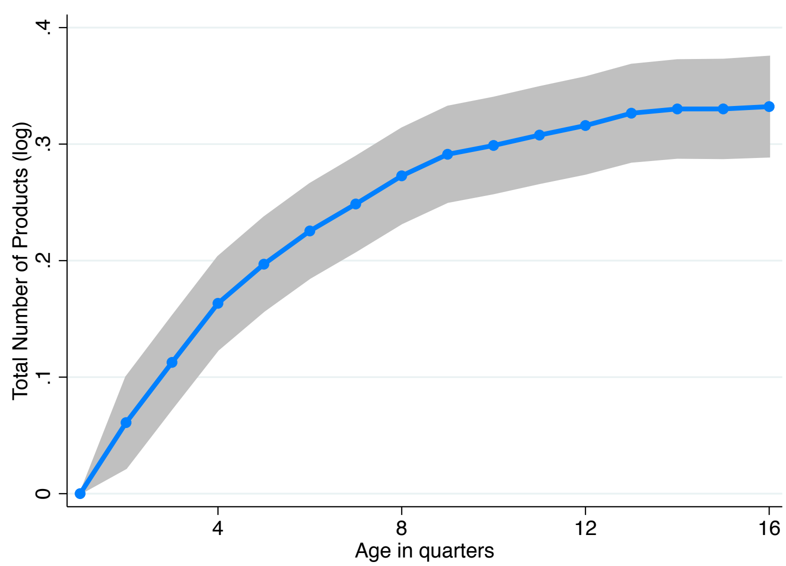
Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of introduction of improvements and extension products over the life cycle of firms, computed using equation 1. The number of new products accounting for zeros use an inverse hyperbolic sine transformation. We keep balanced sample with 16 quarters or above duration. Vertical bar represents 95 percent confidence interval.

Figure 19: Extensions over Firm Life Cycle



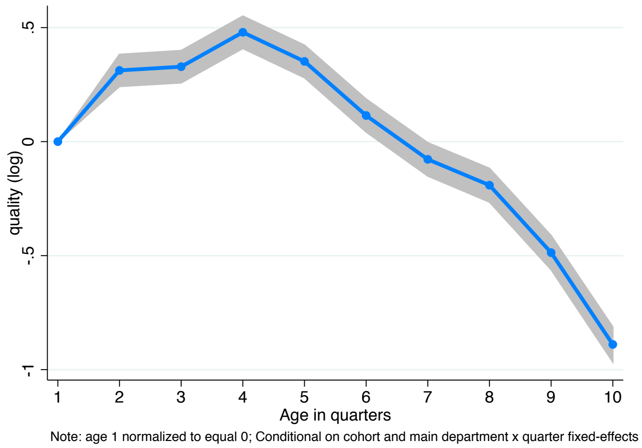
Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of total number of module, group, and department over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

Figure 20: Total Number of Brands over Firm Life Cycle

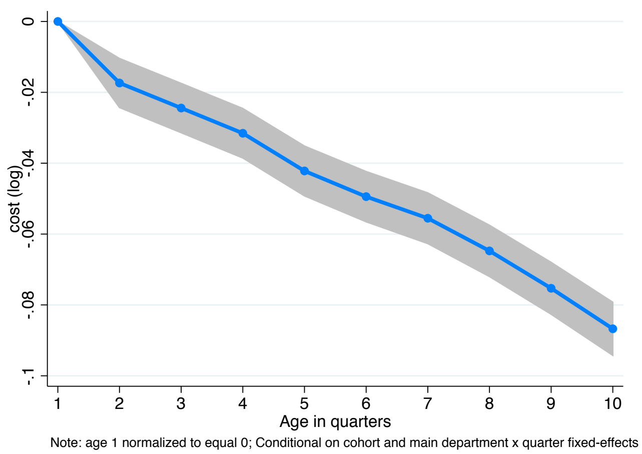


Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of total number of brands over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

Figure 21: Product Appeal and Costs Over the Product Life Cycle



(a) Product Appeal



(b) Product Cost

Note: These figures show the product appeal and the product cost of long-lasting products over the life cycle. Product appeal and costs are estimated as structural residuals of the model developed in section 5. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

APPENDIX – FOR ONLINE PUBLICATION ONLY

A Appendix Tables and Figures

Table A.I: Comparison between Three Barcode-level Data-sets

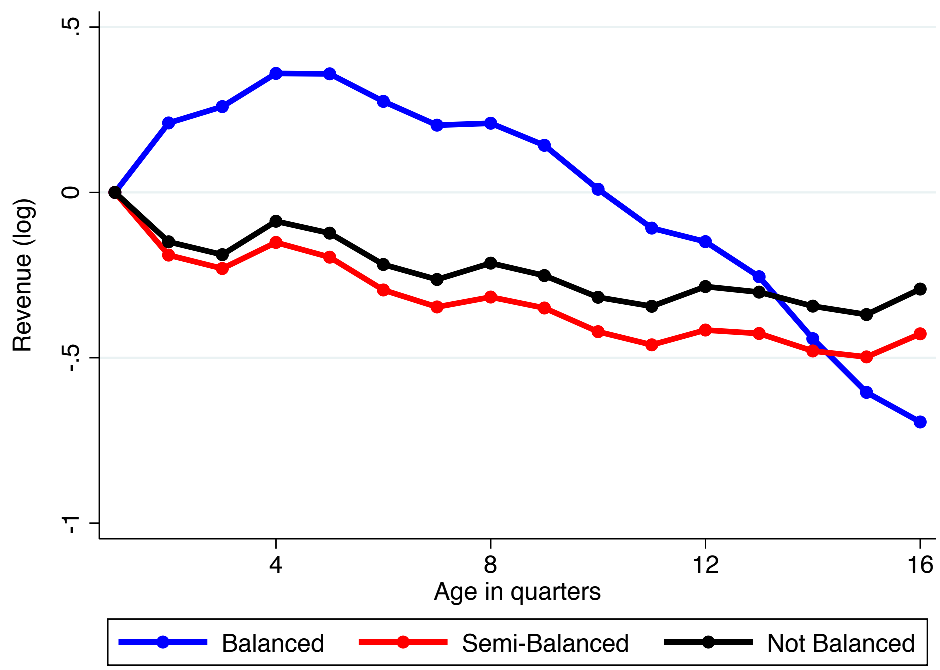
The table compares three data sets: the Nielsen Retail Measurement Services (RMS), Nielsen Homescan (HMS), and the IRI Symphony. The three data sets report barcode transactions. The RMS and the IRI data sets are collected at the store level. The HMS is collected directly from households. The 31 categories in the IRI represent roughly 143 modules in the Nielsen data sets.

	RMS	HMS	IRI
Time period	2006-2015	2004-2015	2001-2012
Coverage	1,071 modules, 114 groups	1,077 modules, 115 groups	31 categories
Observational units	Store	Households	Store
# of stores/households	35,510 stores	61,557 households	2,945 stores
# of states	49	49	43
# of counties	2,550	2,699	503
# of products in 2006	724,211	392,455	50,434
Frequency	Weekly, average	Daily, by transaction	Weekly, average
Tag on temporary sales	none	deal flag by household	sales flag by IRI

Figure A.1: Example of a Company Prefix

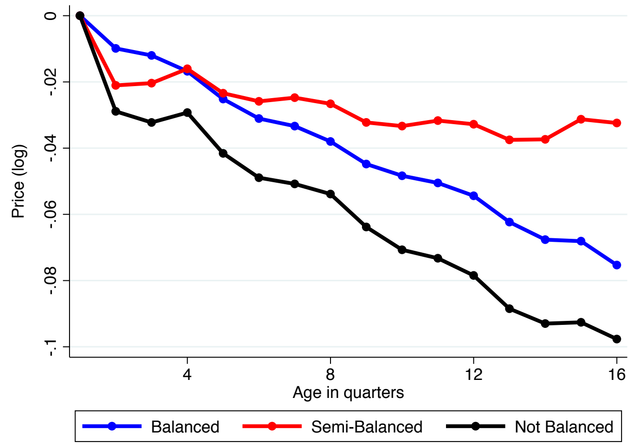
Note: This figure shows examples of a 6- and a 9-digit firm prefix. The source is the GS1-US website (http://www.gs1-us.info/company-prefix).

Figure A.2: Revenue of product over the life cycle: alternative samples

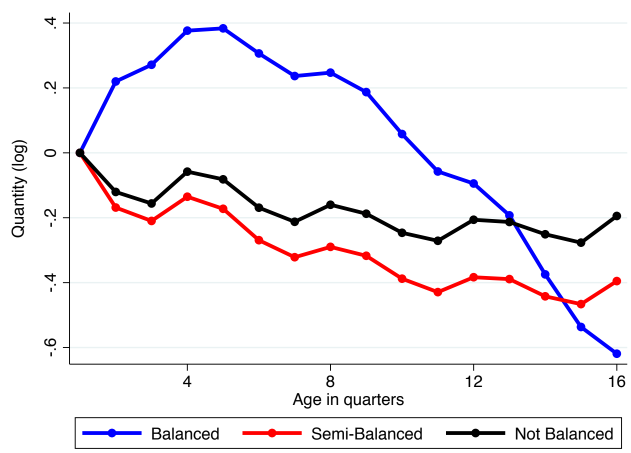


Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity over the life cycle of products, computed using equation 1. We keep balanced sample with 16 quarters or above duration.

Figure A.3: Price and Quantity of product over the life cycle: alternative samples



(a) Price of product



(b) Quantity of product

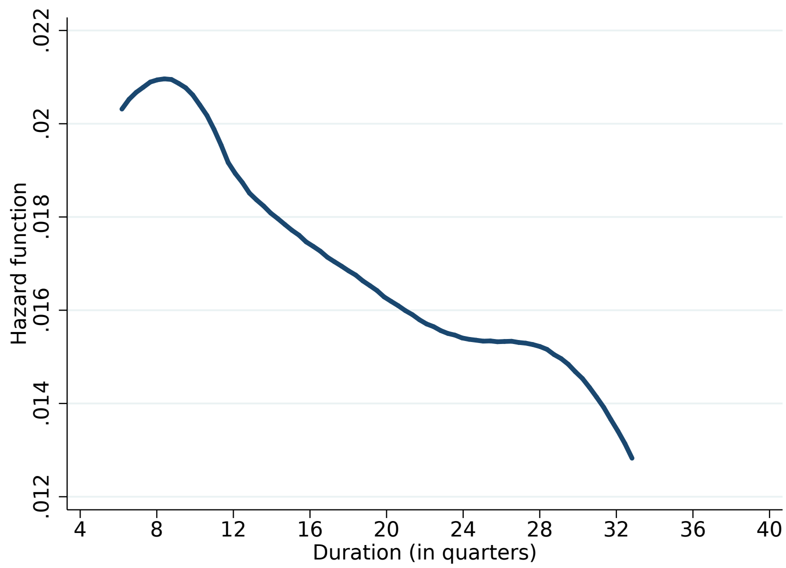
Note: These figures show price and quantity of long-lasting product over the life cycle. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

B Duration

B.1 Firm Survival

Data on firms in the U.S. economy shows that the median firm lasts almost 5 years. Products in the consumer packaged goods sector have lower durations than the average firms in the U.S. economy. This is both true for the US economy as a whole, and in our sample of firms that sell products in the consumer packaged goods sector (see Figure B.1). Because our firms are bundles of products, firm exit occurs in our sample when the last product that the firm sell ceases activity. The fact that the pace of product exit is faster than that of firms is, therefore, not surprising. The converse could occur, however, if the products of firms with large portfolios last substantially longer than those of single-product firms.

Figure B.1: Firm Level Hazard Function



Note: These figures show the hazard function of firms in the Nielsen data. The hazard function is estimated using a proportional hazard model. Across product modules the random effects are assumed to be gamma distributed.

B.2 Age of the Firm as Covariate

Next, we study whether the survival of products depends on the life cycle of the firm. To do so convincingly we follow both a parametric and a nonparametric approach. We begin by estimating the proportional hazard model imposing parametric restrictions on the distribution of product characteristics just as in the previous section. This approach allows us to estimate the hazard functions for young and old firms, holding the value of the rest of the covariates at their mean value. Panel A in figure B.2 shows the estimated hazard functions of products sold by firms that have been in the market one complete quarter (new firms) at the time they launch the product, firms in the market for 8 quarters (2 years)l, and those in the market for 20 quarters (5 years). The figure shows small differences, but not significant, differences in the probability of exit of products launched by firms of different ages. The median duration of a product sold by a firms with 5 years of experience is 1-2 quarters larger. This suggests that firms become only slightly better at launching products that last longer in the market as they age.

Given that imposing the wrong parametric functional form might lead us to understate the importance of heterogeneity – as emphasized by Heckman and Singer (1984b) – we also consider a nonparametric approach to identify the importance of the firm life cycle on the hazard function of products. More precisely, we follow Elbers and Ridder (1982) and Heckman and Singer (1984a) and assume that a product's hazard is the product of three terms, a baseline hazard, an unknown function of observed covariates, and a product fixed effect which is orthogonal to the covariates.

Under the assumption of continuous time and continuous space, Alvarez, Borovicková and Shimer (2015) show that the survivor function can be used to identify the contribution of the observed covariates. Assume that the hazard of a product i is given by

$$h_i(t) = \theta_i \bar{h}(t)\psi(x_i) \tag{27}$$

where x_i is an observable characteristic of a product i. Let $S(t,x)$ be the share of products with characteristics x that last t periods in the market. Then,

$$S(t,x) = \int \exp\left(\theta\psi(x)\int_0^t \bar{h}(s)ds\right) g(\theta)d\theta \tag{28}$$

After differentiating with respect to t,

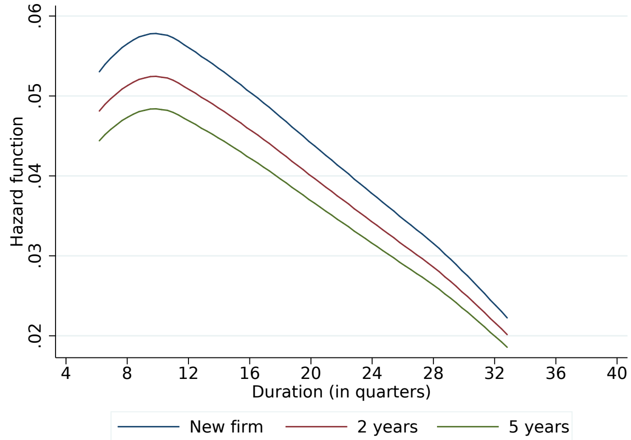
$$S_t(t,x) = -\psi(x)\bar{h}(t)\int \theta\exp\left(-\theta\psi(x)\int_0^t \bar{h}(s)ds\right) g(\theta)d\theta \tag{29}$$

After evaluating this expression at $t = 0$ and normalizing the baseline hazard up to a scale ($\bar{h}(0) = \int \theta g(\theta)d\theta = 1$), equation 29 identifies $\psi(x)$. We choose the age of the firm at the beginning of the product life cycle as our covariate x, drop left-censored spells, and consider only firms that have been in the market for at least one full quarter. Then for each x, we record the number of spells as $n(t,x)$. The survivor function $S(t,x)$ is obtained for each x and $t \leq T$ as:

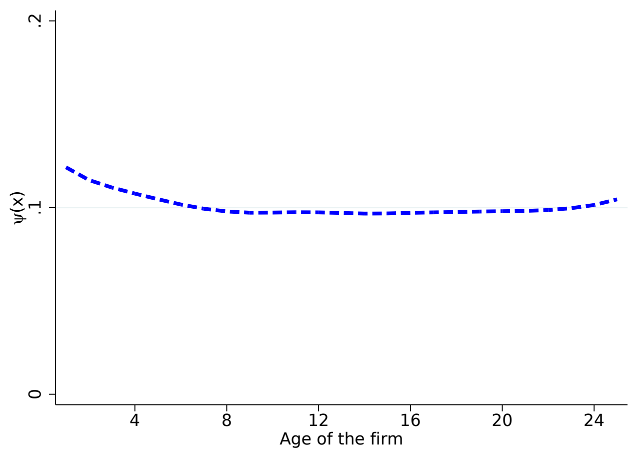
$$S(t,x) = \frac{\sum_{s \geq t} n(s,x)}{\sum_{s} n(s,x)} \tag{30}$$

Panel B of figure B.2 shows the estimated $\psi(x)$ for each quarter of firms' age. Our findings are consistent with the parametric approach. Our estimates of $\psi(x)$ is flat for all firm ages. Thus, we do not find strong evidence that older firms launch products that last longer in the market.

Figure B.2: Firm Age as Covariate: Parametric and Non-Parametric Approach



(a) Parametric Hazard



(b) Estimated function $\psi(x)$

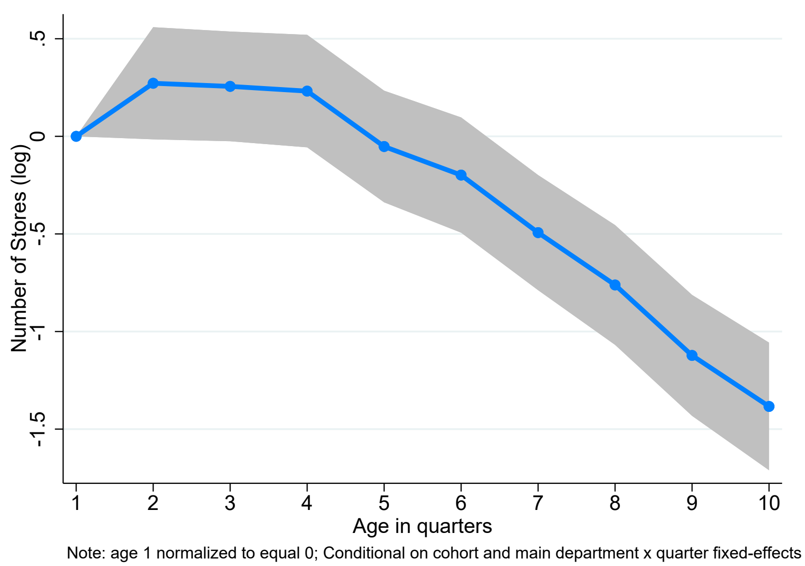
Note: Panel A shows the hazard function of products using the firm age at the entry time of a product as covariate. The figure shows the hazard evaluated at different ages of the firm. A new firm is a firm that has been in the market for at least one full quarter. The hazards are estimated using a proportional hazard model. Across product modules the random effects are assumed to be gamma distributed. Panel B shows the non-parametric estimation of $\psi(x)$ where the age of the firm at the beginning of the spell is the chosen covariate.

C Geographical Spread of New Products

In this paper, we studies aggregate price, quantity and revenue of products at the national level. However, pricing behavior and consumer demand might be affected by geographical spread of new products. Potential concern is that life-cycle patterns in price, quantity and revenue might be associated with this lagged local market penetration.

In this section, we investigate the number of stores over product's life-cycle. As Figure C.1 shows, the number of stores over product's life cycle is the highest during the first year of product introduction, in an example of detergent. This is consistent to multi-city retailers who introduce new products simultaneously in all cities in which they operate and set prices not at local-level (DellaVigna and Gentzkow, 2017; Gilbert, 2017). Therefore, product entry decision is made at the national level, and not associated with local market conditions.

Figure C.1: The Number of Stores over Product's life cycle: Detergent



Note: This figure shows estimated age fixed effects ($\hat{\beta}_a$) of the number of stores over the life cycle of products, computed using equation 1 in an example of product module, detergent. We keep balanced sample with 16 quarters or above duration. Grey area represents 95 percent confidence interval.

D Case Studies

D.1 Tide Pods

The portfolio of brands of Procter & Gamble, a large conglomerate firm, includes the brand "Tide", which in turn encompasses powder, liquid, and pods laundry detergents products. Tide Pods are palm-size, liquid detergent-filled tablets that include concentrated detergent and other products, designed to be tossed in the washer, without the need for measurements. Tide Pods has launched in 2012 and it is known has the biggest innovation in laundry in the last few decades.

We start by identifying the UPCs that refer to Tide Pods. We use the Nielsen's products clean file and identify the Tide Pods using the variable "brand" and selecting those observations that include strings for both "TIDE" and "PODS".[21] We identify 113 barcodes (115 barcodes if we consider multiple versions).[22] Among them, 4 UPC are included in the module 7003 - "Detergents- packaged", and 109 are included in "Detergents - Heavy duty - liquid". These UPCs are classified into three brands "TIDE + PODS - H-D LIQ", "TIDE PODS - PCK", and "TIDE PODS- H-D LIQ".

After identifying the UPCs, we explored information about the characteristics of the UPCs, and we identify that, in this module, the most important characteristics are container, scent, and size. We organize the 83 UPCs, with no missing product characteristics into 18 categories, according to 7 scents (4 launched in 2012, and 3 launched in 2014 and 2015), 2 containers (tub and bag), and 3 group sizes (small, medium, and large). Bags can be small and medium, and tubs can be medium and large.[23] After identifying the "Tide Pods" products and their characteristics, we use our balanced store dataset (sample A) to study their evolution. In this dataset, we identify 80 out of the 83 barcodes with characteristics.[24]

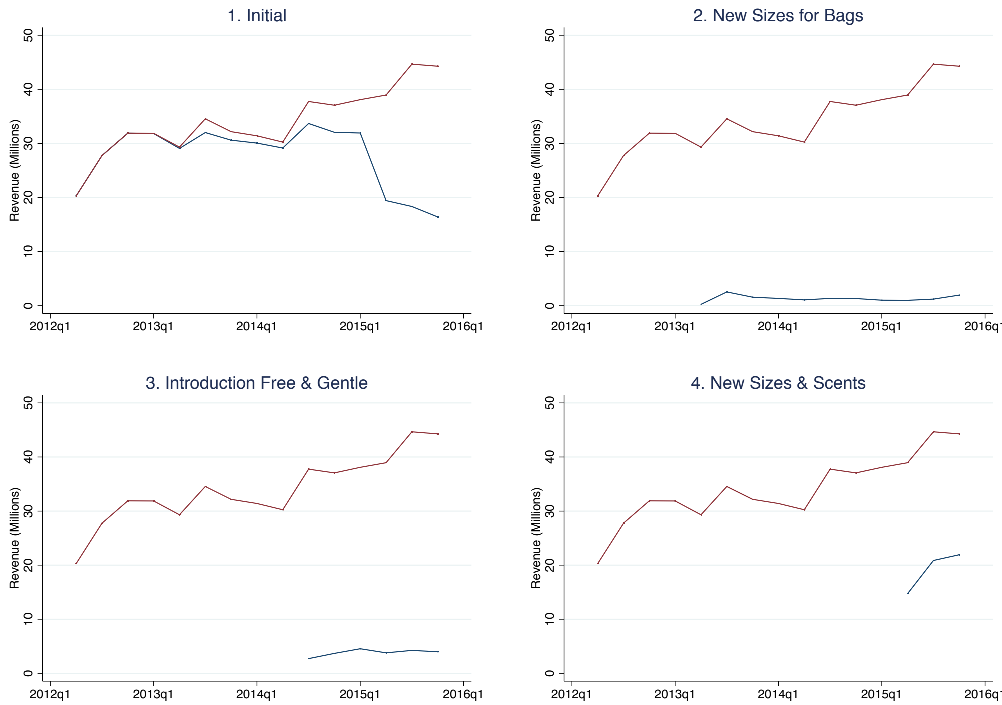
[21] The text "TIDE PODS" does not include all UPC.

[22] No UPC appears only in Nielsen HMS.

[23] In this period, Tide Pods suffered some negative press due to safety concerns of children eating the pods, and as a response P&G changed containers/bags changed color (from transparent to orange) and latch system (double latch lid in 2012, and free safety latches in 2013). We do not observe any change in the UPCs as a consequence of these changes.

[24] The non-matched UPC from the characteristics file are combinations of characteristics that are shared with matched UPCs.

Figure D.1: Revenue of "Tide Pods" Products



Note: The figure plots the evolution of total revenue of the UPCs for each of the four groups (blue line) and the total revenue of "Tide Pods" UPCs (red line). Details on the groups of UPC in each group are given in the Appendix

When we study the introduction of UPCs in our dataset, we identify four distinctive periods. "Tide Pods" products are introduced early in 2012 with 39 distinct UPCs, under the scents "Spring Meadow", "Alpine Breeze", "Mystic Forest", and "Ocean Mist", and various sizes for bags and tubs.[25] After that, there was a period of low product introduction, with only 6 new barcodes introduced between 2013 and early 2014.[26] In 2014, 10 new barcodes are introduced for a new line, "Free & Gentle", that was substantially different from other lines. Finally, there is a new period of rapid product introduction with 26 new UPCs with two new scents "Botanical Rain" and "Original", and new tub and bag sizes for the main scents.[27] Figure D.1 shows the evolution of quarterly revenue for these four groups of barcodes, and their aggregate revenue. The plots show that the initial set of products generate most of the revenue of "Tide Pods" until 2015. In 2015, there is a big decline in the revenue of the 2012 vintage of products, around the introduction of the products created in 2015. Our

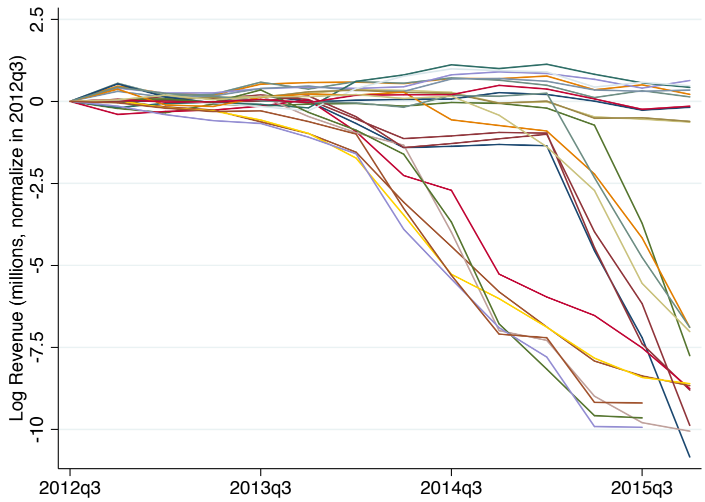
[25] One barcode was introduced early in 2008, with low revenue, and with missing quarters. Two barcodes were observed in the 3rd quarter of 2011, and 4 in the last quarter of 20012.

[26] And these new barcodes are very similar to the initial UPCs, with only differences in sizes.

[27] These new scents seem to be replacing the scents "Ocean Mist" and "Mystic Forest" that experienced rapid revenue decay in the previous quarters.

interpretation of this result is that P&G cannibalizes existing detergents when it introduced these new products. This also implies that the decline in revenue of the initial products may result solely from the introduction of these new products.

Figure D.2: Revenue of the Initial Cohort of "Tide Pods" Products

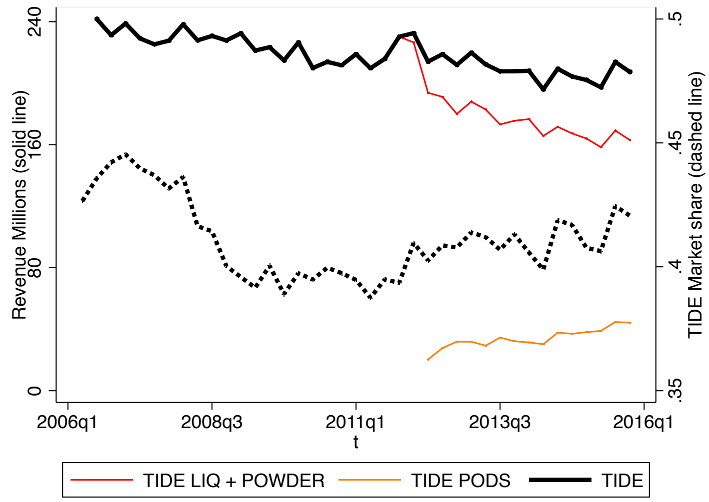


Note: The figure plots the log revenue of top 25 UPCs of Tide Pods products created in early 2012. The values are normalized to the revenue level in 2012q2.

Figure D.2 shows the evolution of revenue for the most important barcodes of the first generation of "Tide Pods" relative to the revenue level at entry (normalized to 2012q2). The plot shows that there is a lot of heterogeneity across barcodes. There are some UPCs that exhibit large declines well before the introduction of the new barcode, others decline around the time of the introduction of the new generation, and some others that remain at a level similar to the entry revenue. We find that total revenue with "Tide Pods" (Figure D.1) increased in the first 4-5 quarters after entry, and remained fairly constant until mid-2014, when the introduction of "Free & Gentle" and the new scents and sizes in 2015 brought another considerable revenue increase. Our interpretation of these patterns is that P&G decided to introduce new UPCs as a response to the slowdown and decline in revenue accruing from the first generation of UPCs. The evidence suggests the new generations boosted sales of "Tide Pods" and without the introduction of these new products total Tide Pods revenue would not have increased as much.

The introduction of "Tide Pods" occurs in a context where Tide was losing substantial market share (from around 45% to 39% around the recession period). Figure D.3 shows that upon introduction, the sales of Tide liquid and powder detergent decline further, which may be a consequence of cannibalization effects of "Tide Pods" together with the prior trend

Figure D.3: Revenue of "Tide Pods" and the revenue and market share of "Tide"



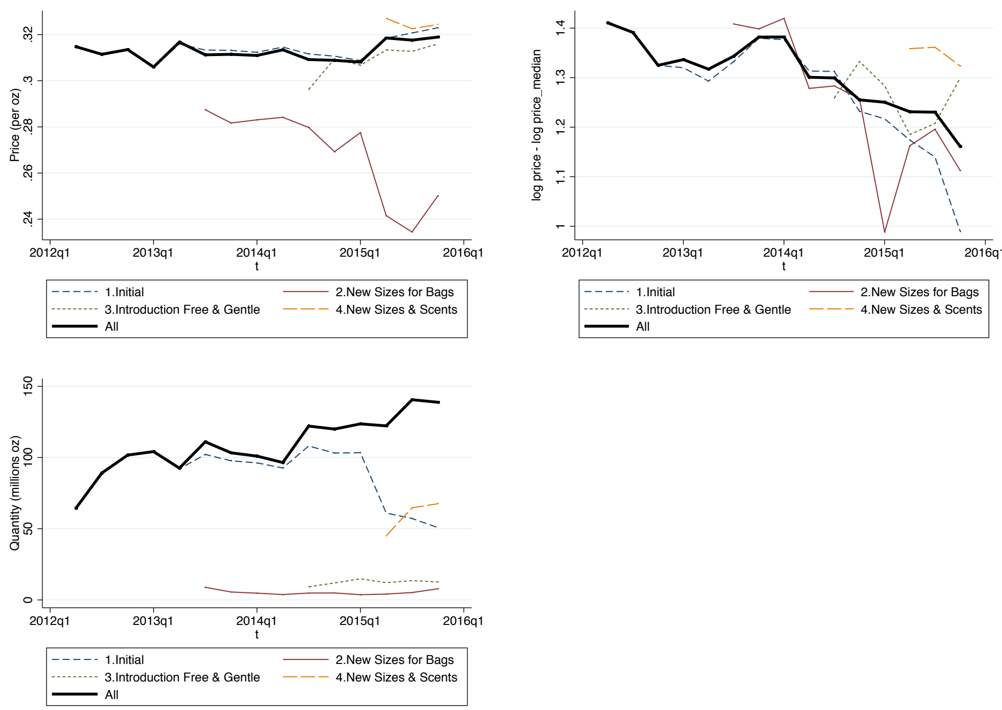
Note:

of declining revenue. With the introduction of "Tide Pods" the revenue of Tide recovers relatively to the revenue of other brands (market share increases from 39% to 42%)), which is suggestive evidence that Tide Pods helped P&G to slow down the aggregate decline in revenue that characterized the pre-introduction period.

Besides revenue, we also compare the price and quantity of "Tide Pods" across different generations (Figure D.4). The results indicate that there are small differences in prices across the different generations of products (with exception of the products created in the second period), and that the price level of the second wave of scents and sizes created in 2014 starts at a higher level. The average price of "Tide Pods" and of each generations of products is declining relatively to the median price of detergents.

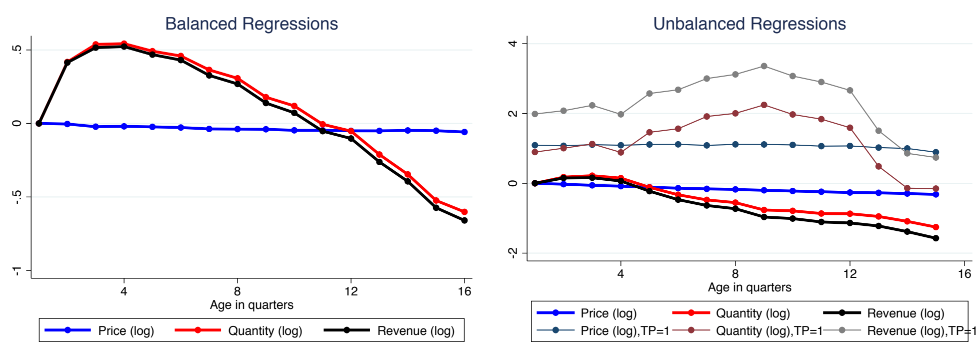
We estimate the equations above just for the detergents market, and we observe that this market behaves similarly to the aggregate CPG sector (Figure D.5).

Figure D.4: Price and Quantity of "Tide Pods" products



Note:

Figure D.5: The quantity, price, and revenue lifecyle patterns of detergents



Note: The left plot shows the estimated age fixed-effects when we estimate equation X for log price, log quantity and log revenue to a balanced sample of detergents that survive at least 16 quarters. The controls in these regressions are time fixed-effects, and cohort Deaton-normalized cohort-effects. The right plot shows the equivalent regressions but for the sample of unbalanced detergents, where we add age fixed-effects interacted with a dummy for "Tide Pods". For this exercise we have to use the unbalanced sample because there is not "Tide Pods" products that have at least 16 quarters of activity during the sample period.

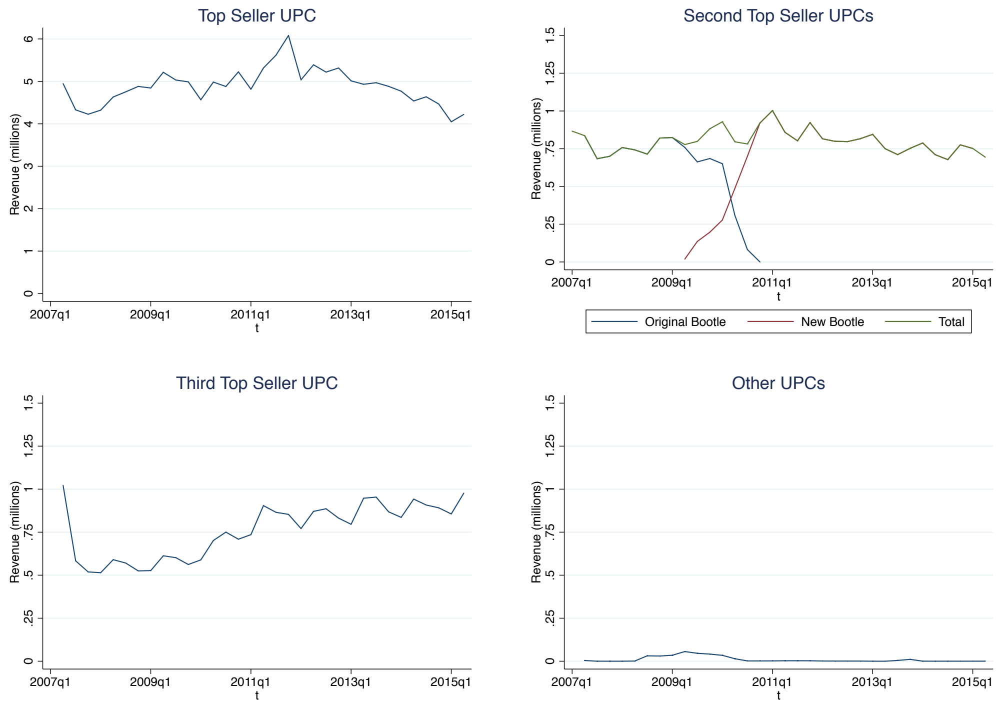
D.2 Coca-Cola Cherry Zero

Coca-Cola Cherry Zero is a flavored variation of Coca-Cola Zero introduced in the first quarter of 2007. Coca-Cola products are carbonated soft drinks produced by The Coca-Cola Company. There are several types of drinks under the "Coca-Cola" brand, including Coca-cola, Diet Coke (introduced 1982), Caffeine-Free Coca-Cola (introduced 1983), Coca-Cola Cherry (introduced 1985), and Coca-Cola Zero (introduced 2005), among others. In our data, we identify 780 barcodes under this brand name, divided in two modules (340 "soft drinks - carbonated", and 440 "soft drinks - Low Calorie"), among which 93 barcodes refer to "Coca-Cola Zero" and 110 barcodes refer to "Coca-Cola Cherry". Coca-Cola Cherry Zero includes 16 barcodes, that differ in container (can or bootle), size of container, and number of units in package.

After identifying the Coca-Cola Cherry Zero products and their characteristics, we use our balanced store dataset (sample A) to study their evolution. In this dataset, we identify 11 out of the 13 barcodes with characteristics in the products clean file. Most barcodes (7 out of 11) appear for the first time in our dataset around early 2007, and the post introduction UPCs are very small, with an exception. Only about 3 products have relatively high sales: a standard can in 12 units package, a 20oz bottle, and a 2l bootle (Figure D.6). With the exception of the top 3 UPCs, the products exhibit an evolution of revenue similar to the evolution described in the stylized facts above, i.e. a few periods of growth followed by decline. Another interesting feature is that the two barcodes for the 2l bottle show that upon entry the new UPC starts with a higher level of revenue than the previous UPC for the 2l bottle.

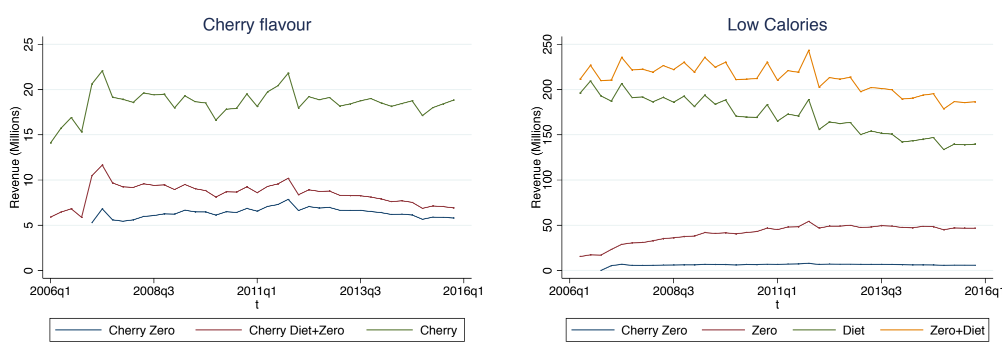
tbc

Figure D.6: Revenue of Coca-Cola Cherry Zero products



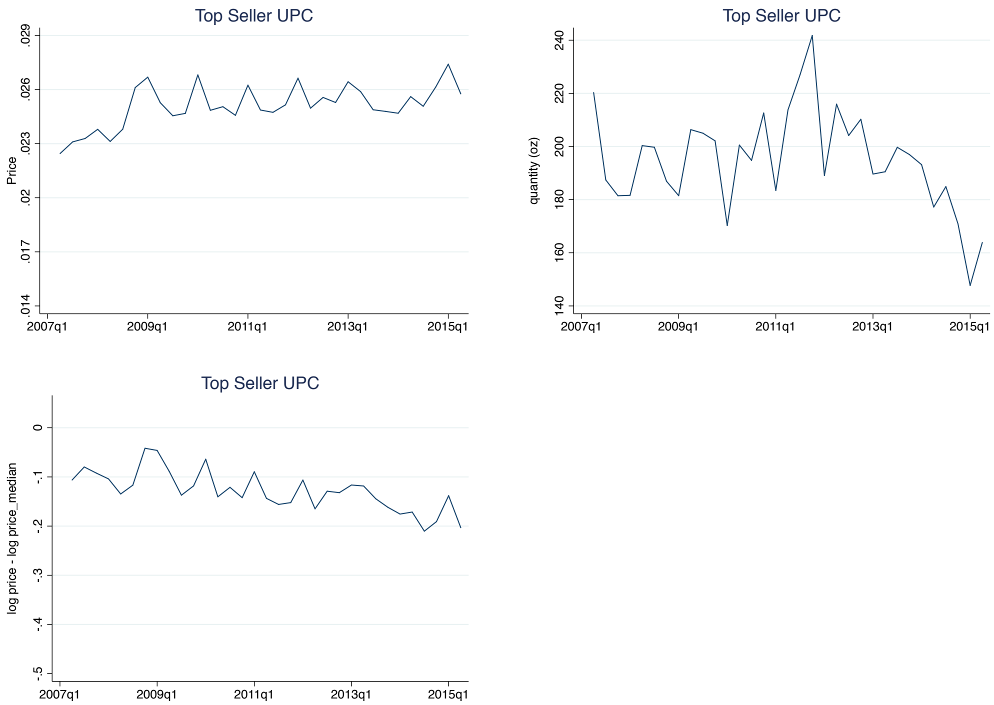
Note: The top ranked product is the UPC of 12oz can, in a 12 package. The second ranked product is a 2l product. During this period the 2l version of of this product changed, but the characteristics (container, size, and number of units) remained constant. The third ranked barcode is a 20oz bootle.

Figure D.7: Revenue of Coca-Cola Cherry and Coca-Cola Zero products



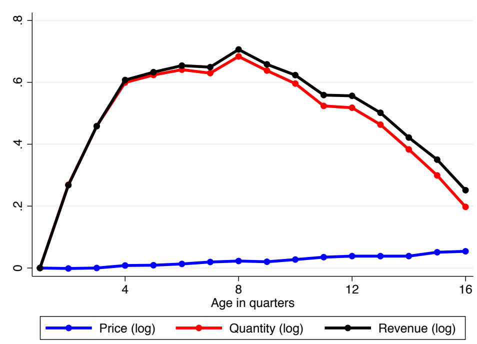
Note:

Figure D.8: Price and quantity of the largest revenue barcode of Coca-Cola Cherry



Note:

Figure D.9: The quantity, price, and revenue lifecyle patterns of sodas



Note: The left plot shows the estimated age fixed-effects when we estimate equation X for log price, log quantity and log revenue to a balanced sample of sodas that survive at least 16 quarters. The controls in these regressions are time fixed-effects, and cohort Deaton-normalized cohort-effects.

E Heterogeneity in the Product Life Cycle by Firm Type

In Section 3.4 we showed that the decline in revenue over product life cycle holds across very heterogeneous groups of products. This means that firms that produce very distinct products are subject to the same forces affecting their growth. Nevertheless, it remains important to show if there are important differences as a function of firm characteristics. We start by evaluating how the products of entrant, young incumbents, and mature incumbents differ. Figure E.1 shows that products launched by entrants and young incumbents generate substantial lower revenue than products launched by mature incumbents in the same product category (even after controlling for cohort and time effects). This evidence on how products differ according to the age of the firm shows substantial differences in initial level, but not a big difference in the life cycle patterns once the differences in initial levels are accounted for.

Moreover, when looking at revenues and quantities separately, we see that the initial difference in revenue results solely from the fact that mature firms sell substantially larger quantities of each barcode, since their price is several orders of magnitude lower than the price of young firms (Figure E.2). We interpret this pattern through the lens of the framework developed above, where young firms will introduce relatively more products (larger entry rate) but they generate lower revenue per barcode. This may also indicate that entrants and young firms may be creating products that are more appealing to small niches to whom they may be able to charge a larger premium.

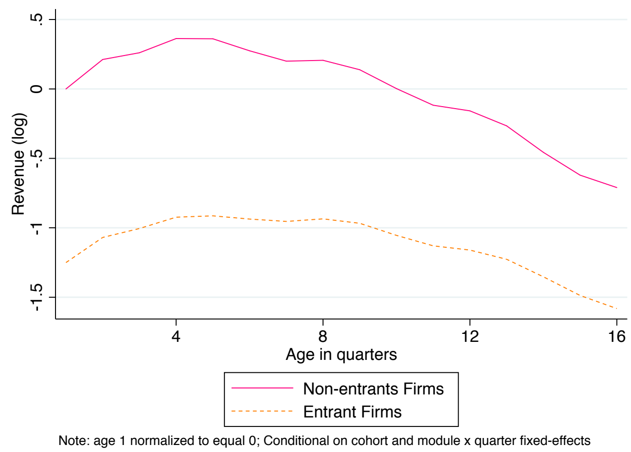
Another source of heterogeneity in the analysis presented above pertains to the diversification of firms. Mature incumbent firms are more likely to be producing different types of products. We implement a distinction between types of product by using the Nielsen classification system of consumer packaged goods to determine the degree of diversification of firms. We then evaluate how the level of diversification correlates with the life cycle patterns we observe. Figure E.3 shows the estimated results. The initial revenue accruing from new products created by highly diversified firms is larger than that of non-diversified firms (single product, or single module firms). The subsequent evolution of revenue is, however, very similar across diversified and non-diversified firms. Differences in revenue come entirely from large differences in quantities sold, since prices are lower among more diversified firms (Figure E.3).

We also study the characteristics of new products that belong to the core product line of the firm (defined as the product group that generates most revenue). Our results show that the initial level of revenue is almost 50 percent higher when the product is created within that product line, relative the revenue of other products created outside the main product lines (Figure E.4), and that there are no differences in the product life cycle path of revenue after one year of activity. The difference in initial revenue comes from both a difference in quantity and price (Figure E.4). Both prices and quantities of products created within the core business of the firm are higher than equivalent products created by firms for whom those products are not in their main line of business.

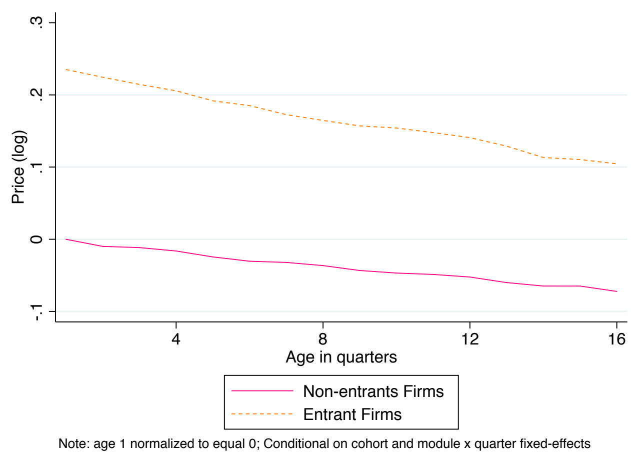
The positive association between initial level of revenue of new barcodes and how close those products are from the core business of the firm, can also be seen when we separate the life cycle paths of products depending on whether they are in a new group to the firm or within the same group (Figure E.5) . Our results show that products generated in groups where the firms are already present generate higher initial level of revenue. These differences come entirely from quantity differences since initial prices display similar magnitudes.

Overall, we observe that while there is substantial differences in the initial level of revenue of new barcodes as a function of the characteristics of the firms that introduce them, the empirical result that revenue is mostly declining holds across different types of products, with small differences in the pace of the decline.

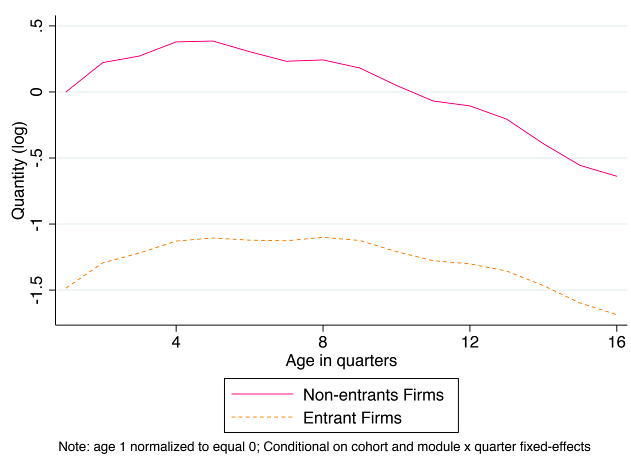
Figure E.1: Revenue, Price and Quantity of Product over the Life Cycle: entrant and incumbernt firms



(a) Revenue of Product



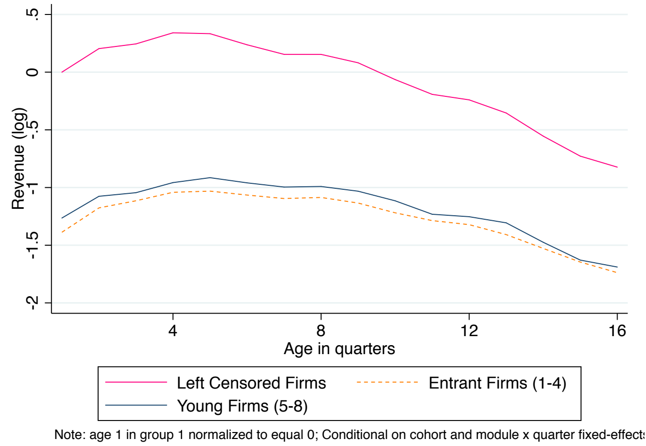
(b) Price of Product



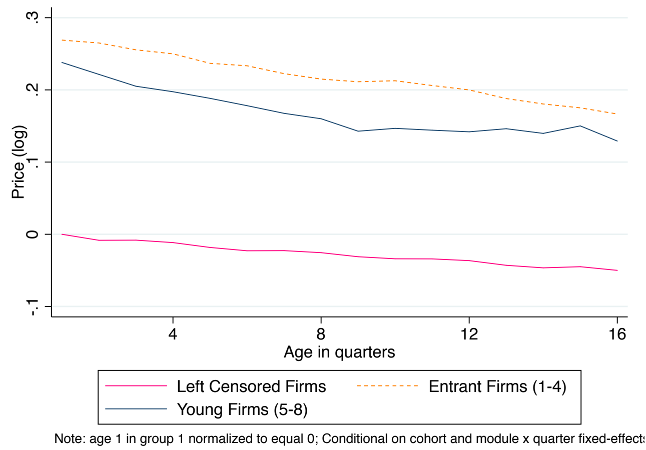
(c) Quantity of Product

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity of product introduced by entrant and incumbent firms over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration.

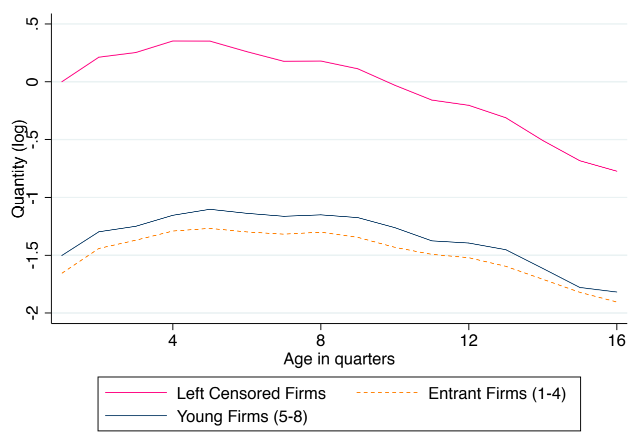
Figure E.2: Revenue, Price and Quantity of Product over the Life Cycle: young and old firms



(a) Revenue of Product



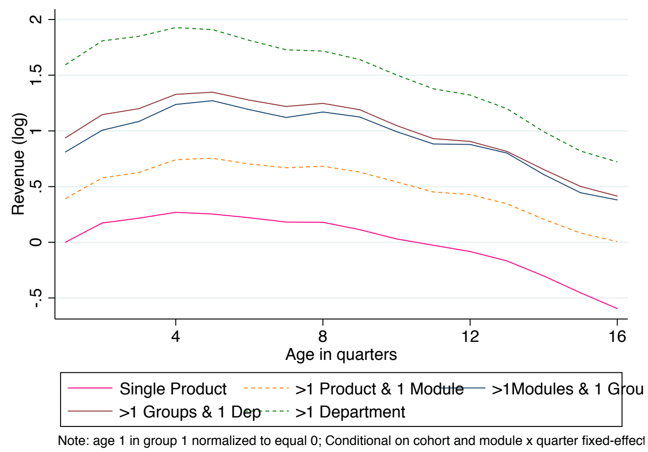
(b) Price of Product



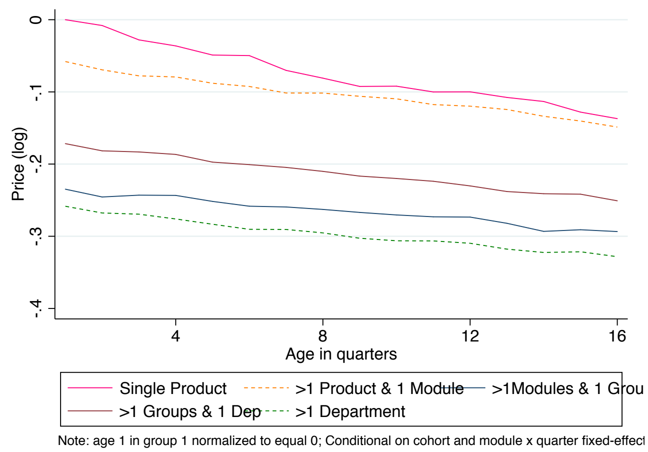
(c) Quantity of Product

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity of product introduced by young and old firms over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration.

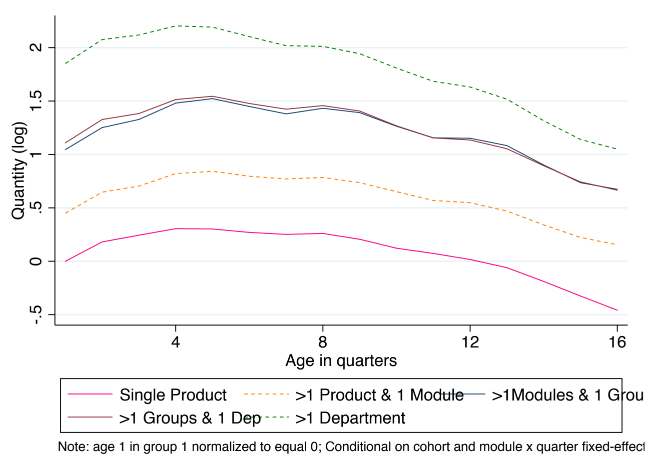
Figure E.3: Revenue, Price and Quantity of Product over the Life Cycle: diversification of firm



(a) Revenue of Product



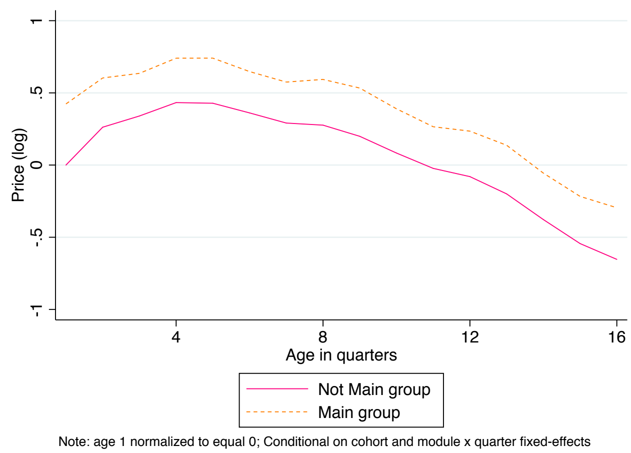
(b) Price of Product



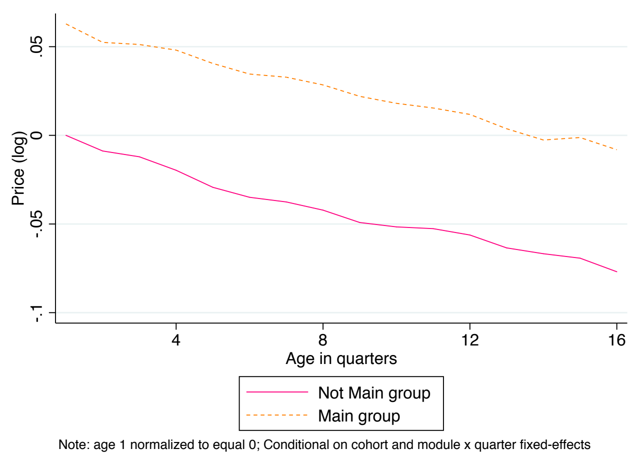
(c) Quantity of Product

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity of product introduced by level of firm's diversification over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration.

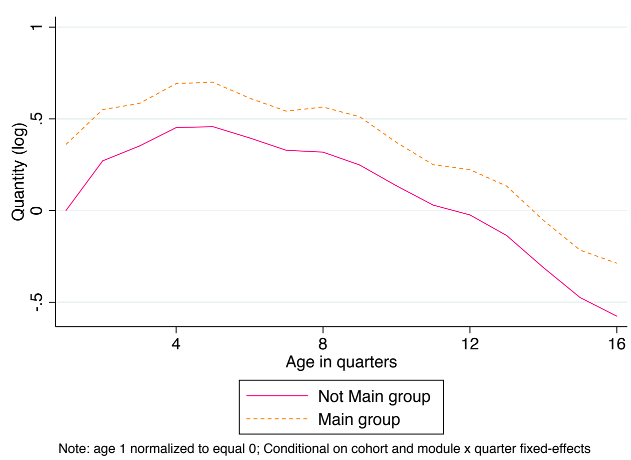
Figure E.4: Revenue, Price and Quantity of Product over the Life Cycle: how close product is from firm's original portfolio



(a) Revenue of Product



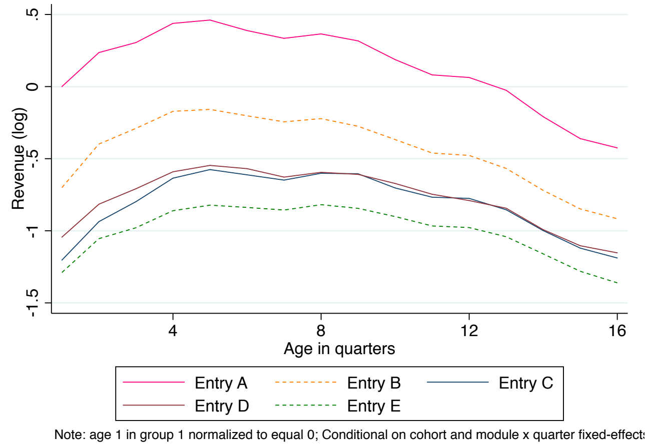
(b) Price of Product



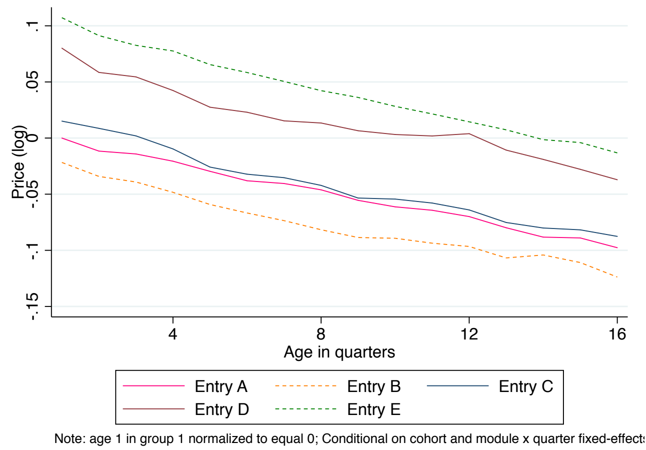
(c) Quantity of Product

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity of product introduced by how close product is from firm's original portfolio over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration.

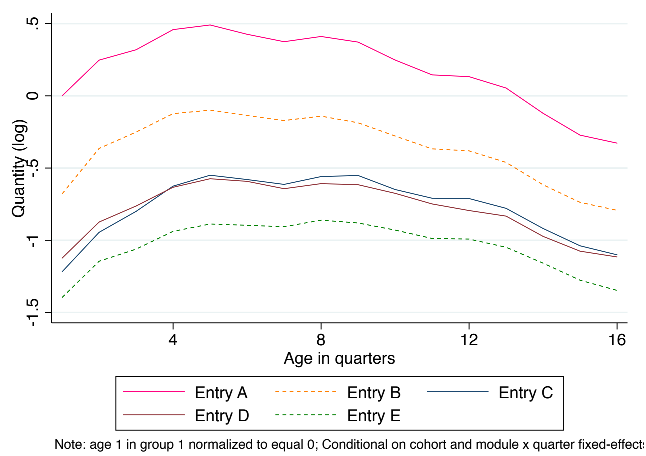
Figure E.5: Revenue, Price and Quantity of Product over the Life Cycle: incremental or radical innovation



(a) Revenue of Product



(b) Price of Product



(c) Quantity of Product

Note: These figures show estimated age fixed effects ($\hat{\beta}_a$) of revenue, price and quantity of product introduced by incremental or radical innovation over the life cycle of firms, computed using equation 1. We keep balanced sample with 16 quarters or above duration.

F Two Period Model of Firm and Product Life Cycle

To display the mechanisms of a dynamic model of a multiproduct firm as clearly as possible, we use a model with only two periods. Each firm is small relative to the aggregate economy, thus within a group the firm's problem is separable. Each firm starts with one product and maximizes profits. At the end of each period, the firm gets a random draw of product appeal and decides whether to add/drop a product. The firm can add at most one product each period. The firm then chooses the price of each UPC to minimize the cost of supplying real output and sets the relative prices of UPCs equal to their relative marginal costs.

To simplify the state space, we normalize $\varphi^F_{fgt} = 1$. In this specification, product appeal is identical up to scale to a combination of firm and product appeal: $\hat{\varphi}^U_{ut} = \left(\varphi^U_{ut}\right)^{\sigma^U - 1}\left(\varphi^F_{fgt}\right)^{\sigma^F - 1}$. Furthermore, we assume that the cost shifter a_{ut} only varies at the firm level (i.e. $a_{ut} = a_{fgt},\ \forall\, u \in \Omega_{fgt}$).[28] At the beginning of the first period, each firm chooses its price for the final consumer to maximize its profits. The firm then gets a random draw of product appeal and decides whether to add a product or not.

Second Period

We proceed backwards. At the beginning the second period, the firm's problem is summarized by the following equation:

$$V_2(\hat{\varphi}^U_{12}, \hat{\varphi}^U_{22}, N^U) = \max\left\{V_2^{N^U}(\hat{\varphi}^U_{12}, N^U), V_2^{N^U+1}(\hat{\varphi}^U_{12}, \hat{\varphi}^U_{22}, N^U + 1), 0\right\} \tag{31}$$

where $V_t^{N^U}$ is the value function of firm f and time t when it sells N^U products (in this example $N^U = 1$). Given the product appeal of its product in period 2, φ^U_{12}, and their draw of product appeal in the second period, $\hat{\varphi}^U_{22}$, the firm might decide to add a product or drop its current one and exit the market. In this case the firm gets 0 value. By construction, in period 2, the firm only cares about maximizing its period return function. If the firm does not exit the market and does not adds a product it maximizes:

$$V_2^{N^U}(\hat{\varphi}^U_{12}, N^U) = \max_{P^U_{12}}[P^U_{12} - a_2(Y^U_{12})^{1+\delta}] - N^U H^U - H^F \tag{32}$$

The optimal price in the second period P^U_{12} is:

[28]For simplicity, in this section we omit the subscript g and f.

$$P_{12}^U(\hat{\varphi}_{12}^U, N^U) = \left[a_{12}\left(\left(\hat{\varphi}_{12}^U\right)^{\sigma^U-1} E_2^F \left(P_2^F\right)^{\sigma^F-1}\left(P_2^F\right)^{\sigma^U-\sigma^F}\right)^{\delta}(1+\delta)\frac{\sigma^F-(\sigma^F-1)S_2^F}{\sigma^F-(\sigma^F-1)S_2^F-1}\right]^{\frac{1}{\delta\sigma^U}}$$

where the price index of the firm, P_2^F, the share of the firm, S_2^F, and the price index of the group, P_2^G, depend on the number of products, N^U, and on the product appeal φ_{12}^U. If the firms decides to add a product, the firm maximizes:

$$V_2^{N^U+1}(\hat{\varphi}_{12}^U, \hat{\varphi}_{22}^U, N^U+1) = \max_{P_{12}^U, P_{22}^U} \sum_{k=1}^{N^U+1} P_{k2}^U Y_{kt}^U - a_{k2}(Y_{kt}^U)^{1+\delta} - (N^U+1)H^U - H^F \tag{33}$$

The optimal price of product k is:

$$P_{k2}^U(\hat{\varphi}_{12}^U, \hat{\varphi}_{22}^U, N^U) = \left[a_{k2}\left(\left(\hat{\varphi}_{k2}^U\right)^{\sigma^U-1} E_2^F \left(P_2^F\right)^{\sigma^F-1}\left(P_2^F\right)^{\sigma^U-\sigma^F}\right)^{\delta}(1+\delta)\frac{\sigma^F-(\sigma^F-1)S_2^F}{\sigma^F-(\sigma^F-1)S_2^F-1}\right]^{\frac{1}{\delta\sigma^U}} \tag{34}$$

First Period

In the first period the firm starts with only one product and it solves:

$$V_1^{N^U}(\hat{\varphi}_{11}^U, N^U) = \max_{P_{11}^U}[P_{11}^U Y_{11}^U - a_{11}(Y_{11}^U)^{1+\delta}] - N^U H^U - H^F + \beta\int_{\varphi} V_2(\hat{\varphi}_{12}^U, \hat{\varphi}_{22}^U, N^U)dF(\varphi) \tag{35}$$

where $F(\varphi)$ denotes the distribution over product qualities and β is the discount factor. It is clear from this setup that the price of the same product in the second period is different depending on whether the firm decides to add a product or not. Given that firms are large relative to a product group, they internalize the effects of their decisions (both launching a new product and choosing prices) on the price index of the group. Thus, a new product affects both the price index of the firm and the share of the firm which, in turn, affects the markup of the firm within a product group. In order to understand the impact of the introduction of a new product on the pricing decisions of the firm, in section F.1 we derive the cannibalization effects on the price of a UPC.

F.1 Cannibalization Effects on the Price

We assume that the number of UPCs is large and can be approximated by a continuous variable. In that case, the effect of a change in the number of products within the firm on the price of product u is:

$$\frac{\partial P^U_{ut}}{\partial N^U_{fgt}} = \left(\frac{\sigma^F - 1}{\sigma^U}\right) \frac{P^U_{ut}}{P^G_{gt}} \frac{\partial P^G_{gt}}{\partial P^F_{fgt}} \frac{\partial P^F_{fgt}}{\partial N^U_{fgt}} + \left(\frac{\sigma^U - \sigma^F}{\sigma^U}\right) \frac{\partial P^F_{fgt}}{\partial N^U_{fgt}} \frac{P^U_{ut}}{P^F_{fgt}} + \left(\frac{1}{\delta\sigma^U}\right) \frac{P^U_{ut}}{\mu^F_{fgt}} \frac{\partial \mu^F_{fgt}}{\partial S^F_{fgt}} \frac{\partial S^F_{fgt}}{\partial P^F_{fgt}} \frac{\partial P^F_{fgt}}{\partial N^U_{fgt}} \tag{36}$$

Note that if σ^U is very large, the cannibalization rate is equal to 1 meaning that the sales of a new UPC come entirely from existing products. In this case the effect of the introduction of a new product on the price of UPC u is the same its impact on the firm price index P^F_{fgt}. If $\sigma^U > 1$ is finite, there exists product differentiation within firms. In this case after dividing and multiplying by N^U_{fgt} and using the definition of S^F_{fgt} we get:

$$-\frac{\partial P^U_{ut}}{\partial N^U_{fgt}} \frac{N^U_{fgt}}{P^U_{ut}} = \left[\frac{(\sigma^F - 1)S^F_{fgt}}{(\sigma^U - 1)\sigma^U} + \frac{\sigma^U - \sigma^F}{(\sigma^U - 1)\sigma^U} + \frac{1}{\delta\sigma^U(\sigma^U - 1)} \left[\frac{\partial \mu^F_{fgt}}{\partial S^F_{fgt}} \frac{S^F_{fgt}}{\mu^F_{fgt}}\right] \left[\frac{\partial S^F_{fgt}}{\partial P^F_{fgt}} \frac{P^F_{fgt}}{S^F_{fgt}}\right]\right] N^U_{fgt} S^U_{N^U_{fgt}}$$

where we use that the elasticity of the firm price index (P^F_{fgt}) with respect to the number of products of the firm (N^U_{fgt}) is $\frac{N^U_{fgt} S^U_{N^U_{fgt}}}{(1-\sigma^U)}$. The first term on the right captures cannibalization across firms: The introduction of the new UPC reduces the product-group price index (P^G_{gt}), which reduces the price of existing UPCs if varieties are more substitutable within product-groups than across product- groups ($\sigma^F > 1$). The second term captures cannibalization within firms: the introduction of a UPC reduces the firm price index (P^F_{fgt}), which reduces the price of existing UPCs if varieties are more substitutable within firms than across firms (e.g $\sigma^U > \sigma^F$). The third terms captures the change in the markup. The introduction of a new product decreases the firm price index which increases the share of the firm. As the share of the firm increases, the markup of the firm increases as well. This can be seen in the following elasticities:

$$\frac{\partial S^F_{fgt}}{\partial P^F_{fgt}} \frac{P^F_{fgt}}{S^F_{fgt}} = -(\sigma^F - 1)(1 - S^F_{fgt}) < 0$$

$$\frac{\partial \mu^F_{fgt}}{\partial S^F_{fgt}} \frac{S^F_{fgt}}{\mu^F_{fgt}} = \frac{(\sigma^F - 1)S^F_{fgt}}{(\sigma^F - (\sigma^F - 1)S^F_{fgt})(\sigma^F - (\sigma^F - 1)S^F_{fgt} - 1)} > 0$$

The effects of cannibalization on the price of a UPC are:

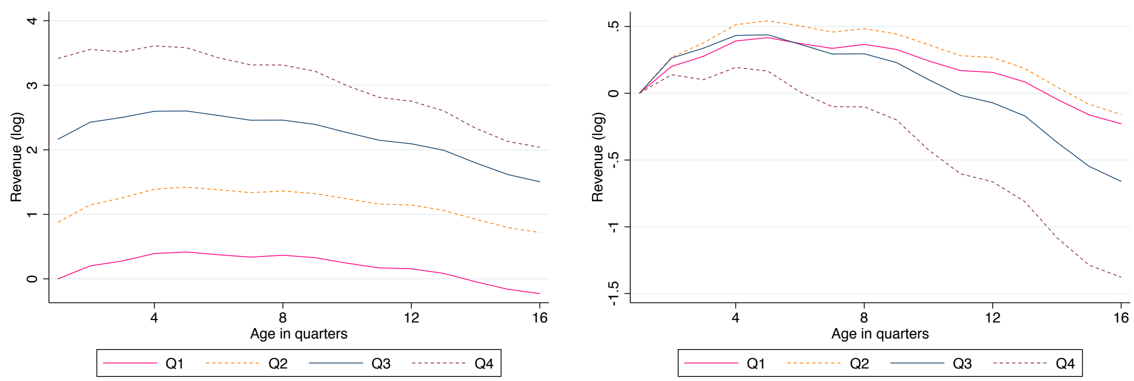
$$-\frac{\partial P_{ut}^U}{\partial N_{fgt}^U}\frac{N_{fgt}^U}{P_{ut}^U} = \left[\frac{(\sigma^F-1)S_{fgt}^F}{(\sigma^U-1)\sigma^U} + \frac{\sigma^U-\sigma^F}{(\sigma^U-1)\sigma^U} + \frac{1}{\delta(\sigma^U-1)\sigma^U}\left[\frac{-(\sigma^F-1)^2 S_{fgt}^F(1-S_{fgt}^F)}{(\sigma^F-(\sigma^F-1)S_{fgt}^F-1)^2\mu_{fgt}}\right]\right] N_{fgt}^U S_{N_{fgt}^U}^U$$

where the right-hand side is positive if and only if

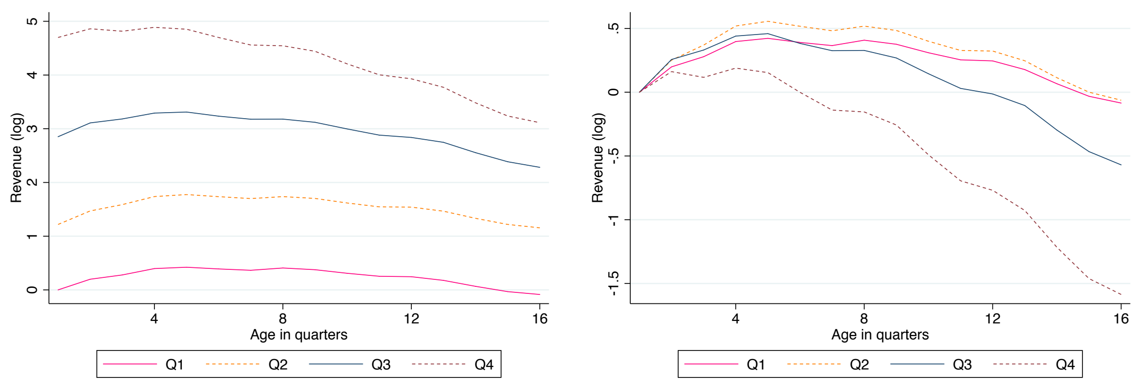
$$(\sigma^F-1)S_{fgt}^F + \sigma^U - \sigma^F > \frac{1}{\delta}\left[\frac{-(\sigma^F-1)S_{fgt}^F}{((\sigma^F-1)S_{fgt}^F-\sigma^F)}\right]$$

G Cannibalization

Figure G.1: Life Cycle Revenue of New Products by Intensity of Product Introduction



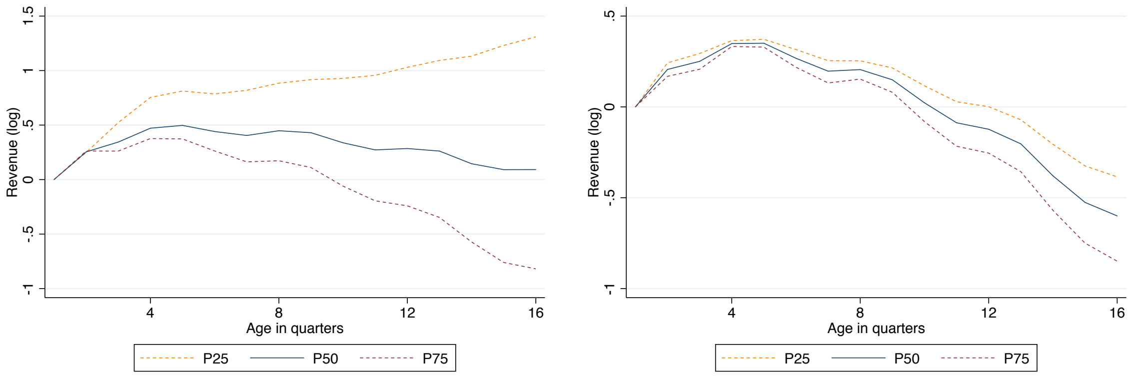
(a) Number of New Product Introduced Post Entry (quartiles)



(a) Revenue of Number of New Product Introduced Post Entry (quartiles)

Note: For each product j introduces in t_0 by firm i in group g, we compute the cumulative number of new products (revenue of new products) introduced by the firm in the same group for all quarters after entry of j, $t_0 + t$. We estimate equation X allowing for the age fixed-effects and for age fixed-effects interacted with (log) revenue of new products. The regressions are conducted on the baseline balanced sample of products that lasted at least 16 quarters. The different lines represent the estimated effect of age evaluated at percentile 25/50/75 of the variable. The left-side plot shows the effect when we use log revenue pf new products. The right-side plots shows the effect when we use increase in product introduction relative to increase in revenue.

Figure G.2: Life Cycle Revenue of New Products by Intensity of Product Introduction



Note: For each product j introduces in t_0 by firm i in group g, we compute the cumulative number of new products (revenue of new products) introduced by the firm in the same group 16 quarters after entry of j, $t_0 + 16$. Using this variable we create a categorical indicating the quartiles, and estimate equation X allowing for the age fixed-effects to be heterogeneous across those four groups. The regressions are conducted on the baseline balanced sample of products that lasted at least 16 quarters. Q1 indicates the quartile with least product introduction post entry, and Q4 indicates the quartile with most product introduction. The left-side plots shows the age fixed effects normalized to having group Q1 equal to zero at entry. The right-side plots show the age fixed effects with all quartiles normalized to zero at entry.