Product Market Strategy and Corporate Policies*†

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Abstract

How does product life cycle affect investment and financing? To answer this question, we structurally estimate a dynamic model where the firm chooses product portfolio characteristics that influence cash flow dynamics and shape corporate policies. In the model, the firm trades off higher profitability of newer products versus product introduction costs. Using disaggregated product-level data, we find that the product dimension is critical in quantitatively explaining cash flow dynamics, investment and financing, and has materially important valuation effects. In particular, we show that product introductions and capital investment act as complements and that product dynamics induce stronger precautionary savings motives. Our estimates reveal that the product life cycle effect is more pronounced for firms with smaller product portfolios, supplying less unique products, and competing more intensely.

JEL Classification: G31, G32

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1. Introduction

Firms use products to translate their ideas into profits. Product introductions alter firms' product portfolios, which, in turn, influence their cash flows. As such, product dynamics and cash flow dynamics are closely related. Empirical evidence suggests that within-firm product creation and destruction is substantial. For example, firms in the consumer goods sector introduce or withdraw on average 10.8% of products in their portfolios every year (Argente, Lee, and Moreira, 2018).[1] The large extent of product creation and destruction can be attributed to product life cycle, as firms' revenue growth crucially depends on either developing current product lines or introducing novel products (e.g. Levitt, 1965; Argente, Lee, and Moreira, 2019b). Thus, the product-level variation is bound to influence cash flow dynamics and to impact firms' policies. Moreover, as firms choose not only their product portfolio but also the way in which it is financed and implemented in their real activities, product dynamics must be related to investment and financing decisions.

The importance of product dynamics induced by product life cycle raises a number of novel questions for financial economists. First, how does product life cycle influence corporate policies? Second, to what extent do firms' product portfolio choices affect their investment and financing decisions? Third, which product characteristics are vital in determining firms' exposure to product life cycle? Finally, how quantitatively important are product dynamics for corporate policies?

In this paper, we demonstrate both empirically and quantitatively that corporate valuations and policies are better understood when taking into account the characteristics of products, which microfound firms' cash flows. First, we describe the empirical relation between product portfolio age and firms' investment and financing decisions. Second, we develop and estimate a dynamic model to understand and quantify the influence of the economic mechanisms underpinning the empirical results. By doing so, we document that product life cycle has significant and economically meaningful implications for corporate policies.

To analyze the implications of product life cycle, we reconstruct firms' product portfolios by using detailed and disaggregated product data from Nielsen Homescan. We focus on firms'

[1] Product dynamics contribute much more to macroeconomic fluctuations than the effects of labor markets or establishment entry and exit (Broda and Weinstein, 2010).

product portfolio age, measured by the share of products that exceed half of their lifespan. Product portfolio age is related to product life cycle due to the negative relationship between product-specific revenue and age (e.g. Argente et al., 2019b). An important result of the paper is to show that this relationship aggregates to product portfolio level, because product portfolio age is negatively associated with firms' profitability. Crucially, the effect of product portfolio age on cash flow is markedly different from that of *firm* age. We also document that the product life cycle channel results in a negative relationship between the market-to-book ratio and product portfolio age, which implies that managing product portfolios has direct implications for firm value. As such, product decisions of value-maximizing firms should be reflected in their investment and financing choices: empirically, both net leverage and capital investment are also negatively related to product portfolio age.[2]

We rationalize these empirical patterns by developing and estimating a dynamic model of the firm which makes investment, financing and product decisions. In the model, the firm combines capital and products to generate revenue. It finances its activities with current cash flow, net debt subject to a collateral constraint and costly external equity. Consistent with the product life cycle channel, each product follows a life-cycle pattern: new products provide higher revenue than old ones and are expected to last longer, because old products can exit. When deciding on introducing a new product to its portfolio, the firm trades off the benefits, associated with higher and more durable revenue of a younger product portfolio, versus product introduction costs. The fact that the firm can adjust its product portfolio has direct implications for cash flow dynamics, and thus connects the firm's real, financial, and product decisions.[3]

The model provides economic rationale to the empirical stylized facts. First, it shows that capital investment and product introductions are complements rather than substitutes, meaning that the firm expands its product lines while also investing in production capacity. The firm increases capital investment when introducing new products, because a higher level

[2]Using an alternative, text-based approach, Hoberg and Maksimovic (2019) document that firms in the late stage of their product life cycle have a higher investment-q sensitivity. Our data suggests that investment policy of firms with older product portfolios is more sensitive to Tobin's q.

[3]In related research, Livdan and Nezlobin (2017) argue that controlling for the vintage composition of capital stock can help explain firms' investment decisions, as the age of capital affects its profitability. In this paper, a product's age affects its revenue as well. However, product introductions are different from capital investment.

and durability of revenues associated with a younger product portfolio increases its incentives to invest in physical capital. However, the firm tends to invest less as its product portfolio ages, because its revenues decline and become more risky as they are expected to diminish quicker. Thus, the model rationalizes the negative relationship between investment and product portfolio age observed in the data.

Second, the model documents that product life cycle induces stronger precautionary savings motives. In particular, when the product portfolio ages, the firm has higher incentives to preserve its debt capacity. This happens because the firm wants to avoid issuing costly external financing to fill the revenue gap created by old products becoming obsolete. The firm, however, also tends to increase its leverage when introducing new products, as they are predominantly financed with debt. As such, the model sheds light on the economic mechanism driving the negative empirical relationship between leverage and product portfolio age. Notably, these effects are absent in standard dynamic model of the firm that do not account for product portfolio structure.

To quantify the importance of product life cycle on corporate policies, we estimate the structural parameters of the model by matching a set of model-implied moments to their empirical counterparts. Crucially, the estimation procedure relies on using the product portfolio data, as firms' product portfolio structure is indicative of the importance of the product life cycle channel. Thus, the observable product portfolio characteristics help identify the two key parameters governing the firm's product decisions: the old product revenue discount and the product introduction cost. We find that the estimated model quantitatively matches key features of the data, particularly different moments of product portfolio age. Moreover, the estimates suggest that the product life cycle channel is quantitatively important, with each old product providing only 52.8% of a new product's revenue and the cost of introducing each new products being equal to 0.75% of assets, that is $7.64m for a typical sample firm. Both estimates are significant and substantial in magnitude, suggesting that product-level economic forces are sizeable.

To understand which features of the data help explain the exposure to the product life cycle channel, we study the cross-sectional implications of the model. We do so by estimating the model on subsamples of firms varying along key characteristics. By doing so, we examine whether the model successfully captures differences across product dimensions that might not be directly represented in product data that is aggregated to the firm level. We also investigate how the magnitude of the product life cycle channel changes along dimensions not explicitly captured by the model.

First, we demonstrate that firms whose products are more sensitive to life cycle effects are also more exposed to the product life cycle channel. These firms have a larger estimated old product revenue discount, invest more in physical capital and adopt lower leverage. Hence, the results are in line with the model's prediction that stronger product life cycle effects induce higher precautionary savings incentives, and that firm complement product introductions with capital investment. The results from this sample split also serve as a 'sanity check' for the model setup, as they indicate that the model can rationalize discrepancies across firms with markedly different product characteristics, despite using data aggregated to firm-level.

Second, we analyze whether a number of vital product characteristics help explain the magnitude of the product life cycle channel. In particular, we document that firms with smaller product portfolios are more exposed to the product life cycle channel, as they face more pronounced old product revenue discount and higher product introduction costs. As their cash flows are effectively riskier, these firms adopt lower leverage ratios. At the same time, firms supplying many products tend to have younger product portfolios, which results in higher, but less volatile profits, highlighting that firms may also use their product lines as means of revenue diversification.

We also show that competition strengthens the product life cycle channel. Specifically, firms operating in more competitive environment are more sensitive to product-level economic forces, as their products become obsolete faster. This leads to a higher rate of product introductions, which translates into their product portfolio structure and feeds back to investment and financing decisions.

Furthermore, we show that firms supplying more durable products can benefit from their products for a longer period of time but also face higher product introduction costs. This is a result of two opposing forces: on the one hand, these firms are more exposed to product life cycle, in that their products lose a larger chunk of their revenue when ageing. On the other hand, more durable products also tend to last longer, the effect of which dominates.

Finally, we demonstrate that firms with more unique products have higher product introduction costs, but are less exposed to product life cycle. Given that we use cost of sales as proxy for product uniqueness, this result means that firms try to influence the exposure to product life cycle by managing costs such as advertising. We provide evidence that firms do so because their products have lower durability, which incentivizes them to prolong the products' life cycle.

Overall, the cross-sectional results highlight that the estimated model provides insights concerning how the different dimensions of firms' product characteristics affect corporate policies. The empirical evidence shows that both between- and within-firm product market forces are an important determinant of investment and financing decisions.

The last contribution of the paper is to provide evidence that the product life cycle channel has quantitatively important implications for corporate policies. First, by means of variance decomposition, we show that product dynamics explain as much as 20% of the variation in leverage and investment in the model. Second, counterfactual experiments related to the severity of life cycle effects suggest that eliminating the revenue gap between new and old product increases firm value by 4.48%. Similarly, lowering the product introduction costs by 50% results in a 7.85% increase in firm value, indicating that costs related to product introduction are economically significant. Hence, the counterfactual experiments imply that managing the life cycle of products, by means of introduction cost or sensitivity to ageing, yields material benefits to firms. Third, we demonstrate that product characteristics largely influence the precautionary savings incentives of the firm. More severe product life cycle effects result in stronger precautionary savings motives, as the firm can lose a large fraction of revenue when its products age. Similarly, less frequent product introductions lower the firm's incentives to preserve debt capacity, because product introductions require less financing. These effects are large: for example, when eliminating the product life cycle channel, the firm would essentially double its leverage ratio.

All in all, the results further highlight the fact that firms' internal product setting, which can be difficult to observe in the data or may be concealed as a firm fixed effect, matters for firm value, and that the effects of product characteristics are large.

1.1. Related literature

This paper contributes to several strands of literature. First, the paper adds to the literature that uses dynamic models to quantitatively explain corporate investment and financing policies. Recent examples include Gomes (2001), Hennessy and Whited (2005, 2007), DeAngelo, DeAngelo, and Whited (2011), Morellec, Nikolov, and Schürhoff (2012, 2018), Nikolov and Whited (2014), Wu (2018) or Nikolov, Schmid, and Steri (2018). We contribute to this literature by explicitly considering firms' product portfolio decisions. In particular, we show that product dynamics influence firms' cash flow dynamics and matter quantitatively for firms' investment and financing decisions.

To this end, the paper is also related to the growing literature on the relationship between corporate strategy and corporate policies, e.g. Titman (1984), Hellmann and Puri (2000), Parsons and Titman (2008), Gourio and Rudanko (2014), Clayton (2017), D'Acunto, Liu, Pflueger, and Weber (2018) or Hoberg and Maksimovic (2019). We differ from this literature by focusing explicitly on firms' product market strategy and showing that cash flow dynamics and corporate policies are affected by firms' product portfolio characteristics other than pricing policy, as documented by e.g. D'Acunto, Liu, Pflueger, and Weber (2018). In that respect, this paper is most closely related to Hoberg and Maksimovic (2019), who infer firms' life cycle stage from a text-based measure of product life cycle and study its implications for investment. Hoberg and Maksimovic (2019) document that product life cycle matters for firms' investment-q sensitivity, as the investment policy of firms in the late stage of their product life cycle is more sensitive to Tobin's q. Our papers offers a complementary view on the importance of the product dimension for corporate policies by directly using disaggregated product-level data and by providing quantitative evidence of its significance.

The paper also adds to the literature on how product market characteristics affect corporate financing policy, e.g. Spence (1985), Maksimovic (1988), Phillips (1995), Chevalier (1995a,b), Kovenock and Phillips (1995, 1997), MacKay (2003), Frésard (2010), and Valta (2012). In contrast to these papers, we focus on *within-firm* product market characteristics, that is the product market strategy, rather than *between-firm* effects such as competition and we argue that internal product market setting is an important determinant of corporate investment and financing policies.

Finally, the paper is related to the literature on multiple-product firms such as Broda and Weinstein (2010), Bernard, Redding, and Schott (2010), Hottman, Redding, and Weinstein (2016), Argente, Lee, and Moreira (2018); Argente, Hanley, Baslandze, and Moreira (2019a); Argente, Lee, and Moreira (2019b), who study the reasons why firms choose to supply multiple goods. In contrast to these papers, we analyze the corporate finance implications of product portfolio choice.

2. Data and Stylized Facts

In this section, we analyze the empirical relation between product life cycle and corporate policies. we focus on product portfolio age as the measure of firms' exposure to product life cycle, which by itself implies a negative relationship between product-specific revenue and product age (e.g. Levitt, 1965; Argente et al., 2019b). We show that the product-level life cycle effects naturally translate to the product portfolio level, resulting in a negative relationship between product portfolio age and profitability. We document that both corporate investment and financing policy are negatively related to product portfolio age when controlling for other firm characteristics, indicating that product life cycle constitutes an important and novel source of variation in corporate policies.

2.1. Data sources

We use the data from Nielsen Homescan to reconstruct firms' product portfolios. The dataset contains information on prices and quantities of nondurable consumer goods sold in the US over the period of 2004 to 2018. The product data is comprehensive, covering about 66% of CPI expenditures (Broda and Weinstein, 2010), and detailed, as it contains vastly more information about products than other datasets such as BLS. We merge the Nielsen data with the accounting data of US public firms from quarterly Compustat. Appendix A provides a detailed description of the data as well as of the merging procedure. Appendix B contains the definitions of variables used throughout the paper.

2.1.1. *Defining a product*

We focus on the UPC-level definition of a product, as it allows to investigate the life cycle of each individual product and to construct a precise measure of product portfolio age.[4]

[Table 1 about here.]

Table 1 presents the summary statistics of several product characteristics of firms in three different samples: the Nielsen Homescan, all matched public firms, and the final sample of firms used in the paper. Firms vary substantially in the number of supplied products, with an average public firm supplying roughly 11 times more products and operating in 3 times more markets than an average firm in the sample. Their average net product entry and net product creation rates, however, are lower than those of private firms, given the size of their product portfolios. Table 1 also documents that while public firms supply $\approx 17\%$ of all products in the market, their sales of these products constitute $\approx 48\%$ of total product revenue. This result highlights that analyzing product market strategies of public firms remains of great importance, even though there are relatively fewer public than private firms. Moreover, while public firms operate in roughly 7.4 markets at once, their average market share in these markets is fairly low, 1.4% on average, which reinforces the notion that nondurable consumer good market in the US is fairly competitive. This is no longer true, however, when looking at particular markets, in which as little as 5 firms often enjoy a combined market share of roughly 60%.

2.2. *Product portfolio age*

To measure product portfolio age, we follow Melser and Syed (2015) and Argente et al. (2018, 2019b). We define the proxy as the weighted share of *old* products, whose age exceeds half of their lifespan, in the firm's product portfolio, where the weights correspond to product-

[4] In principle, the data used allows for many definitions of a product. For example, one could use a very wide notion of a product that is often implicitly assumed by researchers, namely that firms supply a representative good. While in many cases reasonable, this approach would neglect the product-level dynamics that we study in this paper. The stylized facts are qualitatively robust to employing a coarser definition, e.g. one that associates brands in a given consumer good category with a product ('brand-modules'). In Appendix A we revisit the issue of product definition in more detail.

specific revenue:

$$\text{age}_{it} = \frac{\text{weighted \# of products with age exceeding 50\% of lifespan}(it)}{\text{total \# of products}(it)}. \tag{1}$$

As such, this measure captures the effective age of firm's i product portfolio in quarter t. We measure product portfolio age this way, as it allows us to directly link the data to the model.[5]

[Table 2 about here.]

Panel A of Table 2 indicates that the average firm in the sample has 44.5% of old products. Product portfolio age varies substantially as its standard deviation is 0.33 and a further variance decomposition into within- and between-firm effects suggests that as much as 79% of the variance can be attributed to within-firm variation. The average product portfolio age is slightly higher when products are not weighted by their revenues (0.512) and when products are defined at a brand-module rather than UPC level (0.519). Taking a higher threshold for the proxy results in a smaller share of older products (0.315 for 75% threshold and 0.202 for 90% threshold), but the variation between- and within- firms remains fairly high.

[Fig. 1 about here.]

The large variation in product portfolio age is also noticeable in Fig. 1, which shows that the distribution of product portfolio age is spread out. In particular, there are many firms with only new and only old products. Finally, product portfolio age and firm age are only weakly positively related, with the correlation coefficient of 0.03. This suggests that product portfolio age can provide additional information above and beyond standard firm characteristics such as firm age. This result is expected given e.g. the evidence of Hoberg and Maksimovic (2019), who document that firms transition from being an 'old' product life cycle firm to 'new.'

[5]Using alternative breakpoints or an unweighted measure of product portfolio age generates qualitatively and quantitatively similar results. In the Internet Appendix we document that these different measures of product portfolio age produce qualitatively similar relationships with corporate policies. For example, Argente et al. (2019b) also document the decline in product-specific revenue can start as early as at the end of the first year for products lasting at least 4 years and that it varies with product duration. As such, using half of the lifespan is more conservative.

2.2.1. *Other product portfolio characteristics*

While product portfolio age is of key importance for measuring the effects of product life cycle, there also exist other important product portfolio characteristics that may interact with product life cycle as well. Table 2 provides additional information about two such characteristics: product portfolio size and adjustments.

First, a comparison between Tables 1 and 2 suggests that the average *effective* number of products (58) is much lower than the raw one (441).[6]. This implies that not only do public firms differ in the number of products they supply, but also that the majority of firms' revenues can be attributed to a small number of products, supporting the notion that product revenues are fairly concentrated. Moreover, product portfolio size and product portfolio age are negatively correlated, implying that firms with older product portfolios have on average fewer products.

Second, we report that the average net product entry amounts to 0.26% each quarter. This corresponds to an average sample firm introducing 3.5 products each quarter, which increase its retail sales by roughly 1.2%, suggesting that within-firm product-level dynamics have important implications for cash flow dynamics. Moreover, the firm-specific average net product creation is more than 3 times lower than the aggregate one reported in Table 1, implying that a vast majority of product creation and destruction takes place in private firms. Finally, product portfolio adjustments are negatively related to product portfolio age. This means that, intuitively, firms with older product portfolios also introduce new products less often.

In the Internet Appendix we provide further empirical evidence about the relationship between these product portfolio characteristics and corporate policies.

2.3. *Product life cycle matters for profitability*

An important result of the paper is to show that the notion of product life cycle of Levitt (1965) and Abernathy and Utterback (1978) can be generalized to the firm level. The left graph in Panel A of Fig. 2 documents that firms with older product portfolios have lower

[6] The effective number of products equals the inverse of their product revenue concentration measured using the normalized HHI of each firm's product revenue, see Appendix B for details.

profitability. This means that individual-product life cycle and product portfolio age are closely related. As such, the proxy passes the natural 'sanity check' of matching the findings of Argente et al. (2019b) using firm- rather than product-level data. Therefore, the product life cycle provides a natural channel through which product-level economic forces interact with corporate policies.

[Fig. 2 about here.]

The fact that product portfolios consist of individual products, together with product life cycle, implies that firms' cash flow should be directly affected by both product portfolio age and product introductions. We show in two ways that this is indeed the case.

First, the right graph in Panel A of Fig. 2 shows that product portfolio age is tightly related to product sales growth, which declines as product portfolio ages. The economic significance is substantial: product revenues of firms with younger product portfolios grow by about 1.6% annually, largely due to new product introductions. On the other hand, revenue growth of firms with old product portfolios is close to zero. These numbers are consistent with the observed decline in profitability.

Product life cycle has important implications for other firm characteristics as well. The left graph in Panel B of Fig. 2 documents that firms with youngest and oldest product portfolios have on average higher cash flow volatility. This result stem from the fact that older products carry higher risk, due to both the decline in revenue as well as the chance of becoming obsolete. Finally, the cost of sales, presented in the bottom right graph, is a u-shaped function of product portfolio age. Provided that this variable proxies for firms' marketing expenses, the shape is intuitive: firms with younger products have to devote more resources to introducing new products and advertising. In the same manner, firms with older products may try to prolong the lifespan of their products by devoting more resources to marketing, or to increasing their R&D expenses, which are also contained in this measure (Peters and Taylor, 2017).

Importantly, product life cycle has *different* implications for firm characteristics than firm life cycle, as proxied by *firm* age in Panel C of Fig. 2. Both profitability and product sales growth behave tend to increase, on average, as firm age increases. As such, we provide further evidence that product and firm life cycle could generate different patterns for firms, similarly to Argente et al. (2019b).

[Table 3 about here.]

Second, if the influence of product dynamics on corporate policies operates through firms' cash flow dynamics, the effect of product introductions on cash flow should be substantial. To investigate this claim, we check how firms' profitability and sales change in quarters when firms introduce new products. Table 3 shows that when taking into account firm and time fixed effects, the average log sales are 4.2% higher in quarters when the number of products increases, while the average profitability is 4.0% higher and the average log product sales are 12.5% higher. These effects are even stronger when conditioning on the number of products introduced, e.g. average log sales are 5.9% rather than 4.2% higher when firms introduce more products than a typical firm in a given quarter. Finally, the effects of product introduction on cash flow are persistent, but tend to become weaker over time. For example, a product introduction is associated with 3.3% higher average log sales 8 quarters after the introduction took place, thus 21% lower than the contemporaneous effect.

2.4. Product portfolio age and corporate policies

Having documented that product portfolio portfolio age is negatively associated with firms' profitability, the natural question that arises is whether product life cycle also has implications for firm value. In other words, do value-maximizing firms care about managing product portfolio age?

[Fig. 3 about here.]

To answer this question, the top graph in Panel A of Fig. 3 presents the relationship between product portfolio age and the *unexplained* part of the market-to-book ratio. The figure documents that firm value declines with the share of old products, except for firms with very old product portfolio.[7] In other words, product portfolio age has direct implications for firm value. The fact that the relationship survives when taking into account other firm characteristics (as in Loderer, Stulz, and Waelchli, 2017) again highlights the incremental

[7]This finding is largely explained by risk. For example, Fig. 2 indicates cash flow volatility is a u-shaped function of product portfolio age.

information conveyed by product portfolio characteristics.[8]

As product life cycle influences the behavior of value-maximizing firms, it should also have an effect on firms' investment and financing policy. The middle and bottom graphs in in Panel A of Fig. 3 indicate that both residualized investment and net book leverage tend to decline with product portfolio age. Importantly, the fact that the lines are not flat indicates that product portfolio age provides economically significant additional explanatory power in standard leverage or investment regressions. For example, the within-R^2 of the leverage regression, with specification identical to the one employed in Fig. 4, increases from 4.9% to 5.5%, that is by roughly 11%. For investment regression it increases by 6%.

Finally, as a robustness check, in Panel B of Fig. 3 we verify whether additionally controlling for firm age changes the relationship between product life cycle and corporate policies. With the exception of market-to-book, the figures look fairly similar. This result is the consequence of two facts: firm age being closely correlated with other firm characteristics such as firm size, hence providing limited additional explanatory power, and firm age and product portfolio age being fairly uncorrelated. However, the slightly flatter relationship between product portfolio age and residualized market-to-book indicates that controlling for firm age could be important as well, which is also the point made by Loderer et al. (2017). Overall, the results in Panel B of Fig. 3 suggest that controlling for product life cycle is important above and beyond the effects of *firm* life cycle. In the Internet Appendix we show explicitly that firm age is differently related to residualized investment and leverage, as both tend to increase on average as firms age.

The empirical relationships are also intuitive. The decline in the investment rate is consistent with the notion that product and capital investment are complements, that will be later formally confirmed by the model. The rationale behind the decline in net leverage is twofold. First, when firms' product portfolios age, that is when they do not replace their ageing products by new ones, firms are at risk of abruptly losing their revenues and prefer to pursue a more conservative financing policy in case their revenues vanish. Second, it also makes firms more risky. These effects result in a substitution between debt and cash financing: cash

[8]Fig. A.2 in the Internet Appendix presents the raw relationships between product portfolio age, firm value, investment and net leverage.

holdings increase and debt issuance decreases and hence net leverage declines.[9]

[Fig. 4 about here.]

One remaining question to address is whether the magnitude of the reduced-form relationships in Fig. 3 is economically meaningful. To show that the effects of product portfolio age are indeed significant, we compare how other firm characteristics, that are considered standard determinants of investment and capital structure, fare in explaining residualized investment or leverage, when controlling for all other variables.For each policy, we focus on two such characteristics: size and market-to-book for investment as well as profitability and tangibility for leverage. The results are presented in Fig. 4. The graphs show that each variable correlates with the corresponding policy in an intuitive way, e.g. investment and market-to-book are positively related, while profitability is negatively related to leverage. More importantly, the graphs suggest that the economic magnitude of product portfolio age is larger than that of size and comparable to those of market-to-book for investment, while at least comparable to that of tangibility, and slightly smaller than that of profitability for leverage. Therefore, the results again reinforce the notion that product portfolio age constitutes an important and novel source of variation in corporate policies.

In summary, the stylized facts presented in this section showcase a non-trivial relationship between product life cycle, as captured by product portfolio age, and corporate policies. However, the presented empirical evidence makes it difficult to make statements regarding the quantitative importance of product characteristics. Isolating product-level forces is challenging in a reduced-form setting because financial data is essentially observed at the firm- rather than product-level. As such, in the remainder of the paper we examine the quantitative implication of product life cycle for financing and investment through the lens of a structural model. The structural approach allows to investigate the importance of frictions driving product portfolio adjustments and how they translate to variation in corporate policies.

[9]Focusing on the investment policy as an example, in Fig. A.1 in the Internet Appendix, we investigate the robustness of these results by using other definitions of product portfolio age. The results imply that all different measures produce qualitatively similar relationship between product portfolio age and investment.

3. Model

In this section, we develop a discrete-time dynamic model in which a firm makes optimal financing, investment, and product portfolio decisions.

3.1. Technology

The risk-neutral firm is governed by managers whose incentives are fully aligned with shareholders and who discount cash flows at the rate r. The firm produces homogeneous output, which can be structured into many different products, using a decreasing returns-to-scale technology. For example, one could think of the firm producing the same kind of product but marketing it to different market niches or tastes by exploiting differentiation, i.e. altering its branding, appearance, prices. The products are thus ex ante identical, but each product follows a life cycle pattern, which is the key feature of the model. Hence, the products are different ex post to the extent that they are in a different stage of their life cycle.[10] The product life cycle implies that old products contribute *less* to the firm's revenue than new products, in line with empirical evidence of Argente, Lee, and Moreira (2019b). Given capital stock K and profitability shock Z, the firm generates revenue equal to

$$ZK^{\theta} \times (1 - \phi(1 - \xi)), \tag{2}$$

where ϕ is the share of old products in the firm's product portfolio and $\xi \in [0, 1]$ is the old product-specific revenue discount; these are discussed in detail in the following section. As such, the model specification implies that the firm's maximum capacity is ZK^{θ} and that, absent product life cycle (i.e. when $\xi = 1$), the model would collapse to the standard neoclassical benchmark.[11] The profitability shock Z follows an AR(1) process in logs,

$$\log(Z') = \rho \log(Z) + \sigma\varepsilon', \ \varepsilon' \sim N(0, 1). \tag{3}$$

[10] The model does not distinguish between vertical and horizontal differentiation explicitly, but is more consistent with the latter, given that all product varieties are priced in the same way and only differ in their features.

[11] The firm's revenue is the sum of the revenue generated by new and old products, i.e. $ZK^{\theta} \times (1-\phi(1-\xi)) = (1 - \phi)ZK^{\theta} + \xi\phi ZK^{\theta}$. Here the implicit assumption is that it is not the number of products per se that matters for the firm's revenue, but rather its product portfolio structure.

Given gross investment I, the next-period physical capital stock evolves according to

$$K' = I + (1-\delta)K \tag{4}$$

with capital depreciation rate $\delta \in [0,1]$. Depreciation expense is tax deductible. When the firm adjusts its capital stock, it incurs convex capital adjustment costs defined as

$$\Psi(K,K') = \psi\left[K' - (1-\delta)K\right]^2/2K. \tag{5}$$

3.2. Product dynamics

In the model, each product follows a life-cycle pattern and can be in one of four states: 'introduction,' 'new,' 'old,' and 'exit.' New and old products are different, as each old product provides only $100 \times \xi\%$ of the revenue of a new product, consistent with product life cycle. A product that exits contributes nothing to the firm's revenue. The graphical illustration of an individual product's life cycle is presented in Figure 5.

[Fig. 5 about here.]

A product that is introduced immediately becomes new, which corresponds to t_n in Figure 5. Every period, a new product can transition to being an old product with probability $p_{n\to o}$, which happens at time t_o in Figure 5, or remains new with probability $p_{n\to n} \equiv 1 - p_{n\to o}$. Similarly, every period an old product can either remain old with probability $q_{o\to o}$, or exits with probability $q_{o\to e} \equiv 1 - q_{o\to o}$, which happens at time t_e in Figure 5. A product that exits remains in that state forever. The product life cycle of a single product can thus be characterized by a transition matrix

$$\begin{array}{c c} & \begin{array}{cccc} \text{intr}_t & \text{new}_t & \text{old}_t & \text{exit}_t \end{array} \\ \begin{array}{c} \text{intr}_{t+1} \\ \text{new}_{t+1} \\ \text{old}_{t+1} \\ \text{exit}_{t+1} \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 \\ 1 & p_{n\to n} & 0 & 0 \\ 0 & p_{n\to o} & q_{o\to o} & 0 \\ 0 & 0 & q_{o\to e} & 1 \end{bmatrix} \end{array} \tag{6}$$

At the beginning of each period, the firm owns P_n new products and P_o old products, and decides whether to introduce Δ_P new products. It does so by trading off the benefits of a younger product portfolio, that is higher current revenue and higher durability of revenue, versus product introduction costs equal to $\eta K \cdot \Delta_P$. The product introduction costs capture the fact that introducing new products is costly, as it requires the firm to conduct market research, repurpose its production technology, or hire workers to market the products. Thus, the stock of new products P_n can change in two ways: the firm can introduce more products or existing new products can become old. The stock of old products P_o changes due to the ageing of new products and because old products can exit. As such, the transition probability for the firm's end-of-period product portfolio state $\Phi \equiv (P_n, P_o)$ (also called the product portfolio structure) can be expressed by a transition matrix T_Φ, which contains the probability that the firm's products transition to the state $\Phi' = (P'_n, P'_o)$ conditional on being in the state $\Phi = (P_n, P_o)$. The construction of the product portfolio transition matrix T_Φ is described in detail in the Internet Appendix.[12]

Given the structure of product dynamics in the model, we can compute the share of old products in the firm's product portfolio as:

$$\phi \equiv \phi(\Delta_P, \Phi) = \frac{P_o}{P_n + \Delta_P + P_o}, \tag{7}$$

which is tightly linked to the empirical proxy for product portfolio age developed in Section 2. Furthermore, the transition matrix allows to infer the expected lifetime of each product,

$$m^{(\text{intr.,exit})} = \frac{1}{1 - p_{n\to n}} + \frac{1}{1 - q_{o\to o}}. \tag{8}$$

Formally, Eq. (8) is the expected hitting time of state 'exit' of a product starting at state 'introduction' and it implies that each product is expected to remain 'new' for $1/(1 - p_{n\to n})$ periods and 'old' for $1/(1 - q_{o\to o})$ periods. Given that we can observe the left-hand side of

[12] In the model, the firm does not have the possibility to *remove* a product from its portfolio, meaning that product exit is purely stochastic. This modelling choice captures the notion of product exit being driven by exogenous customer demand forces: the firm would withdraw the product when it contributes nothing to revenue. Allowing the firm to retire a product early would require incorporating a more granular product state, as otherwise firms could artificially increase their product portfolio age by retiring old products rather than introducing new ones.

Eq. (8) in the data, and given the break point assumption used to create the measure of product portfolio age, the model can be tightly linked to the data using this definition of product portfolio age.

3.3. Financing frictions

The firm's financing choices consist of internal funds (cash and current profits), risk-free debt, and costly external equity. Since in the model it is never optimal for the firm to hold both debt and cash at the same time, we define the stock of net debt D as the difference between the stock of debt and the stock of cash.

Debt takes the form of a riskless perpetual bond incurring taxable interest at a rate $r(1-\tau)$. As in Hennessy and Whited (2005) and DeAngelo, DeAngelo, and Whited (2011), the stock of debt is subject to a collateral constraint proportional to the depreciated value of capital

$$D \leq \omega(1-\delta)K, \tag{9}$$

where ω is the collateral constraint parameter such that $\omega \in [0,1]$. Alternatively, the firm may choose to hoard liquid assets to save on the costs of external equity issuance or to avoid depleting its debt capacity. However, the interest the firm earns on its cash balance is equal to $r(1-\tau)$, meaning that liquid assets earn a lower rate of return than the risk-free rate.

The cost of raising external equity is modeled in reduced form, similar to Hennessy and Whited (2005, 2007)

$$\Lambda(E(\cdot)) = \lambda E(\cdot)\mathbb{1}_{\{E(\cdot)<0\}}, \tag{10}$$

where E is the firm's cash flow, implying that the firm has to bear a proportional equity financing cost λ if it issues external equity.

3.4. The firm's cash flow

This setup implies the firm's cash flows E, which is a function of $(\Delta_P, K, K', D, D', \Phi, Z)$, consists of operating, investment, and financing cash flow

$$
\begin{aligned}
E(\cdot) = {} & \underbrace{(1-\tau)[ZK^{\theta} \times (1-\phi(1-\xi)) - \eta K \cdot \Delta_P]}_{\text{after-tax operating profit}} + \underbrace{\tau\delta K}_{\substack{\text{depreciation}\\ \text{tax credit}}} \\
& - \underbrace{I}_{\text{investment}} - \underbrace{\psi I^2/2K}_{\substack{\text{capital}\\ \text{adjustment cost}}} \\
& + \underbrace{D' - [1+r(1-\tau)]D.}_{\substack{\text{net debt issuance}\\ \text{less interest expense}}}
\end{aligned}
\tag{11}
$$

This formulation implies that the firm issues external equity if its cash flow is negative or pays out a dividend otherwise.[13]

3.5. Recursive formulation

The firm's problem is to maximize the present value of its future cash flows by choosing the investment, debt and product policies, subject to the external equity issuance cost $\Lambda(\cdot)$ and the collateral constraint. The Bellman equation for the problem is

$$
\begin{aligned}
V(K, D, \Phi, Z) = & \max_{\Delta_P, K', D'} \left\{ E(\cdot) + \Lambda(E(\cdot)) + \beta \mathbb{E}\left[V(K', D', \Phi', Z')\right] \right\}, \\
& \text{s.t. } D \leq \omega(1-\delta)K.
\end{aligned}
\tag{12}
$$

The model is solved numerically using value function iteration. It should be noted that we only have to keep track of two out of four possible product states, given that entering products are translated into new products and exiting products produce revenue of zero. The grid for the productivity shock Z and transition matrix T_Z, are created following Tauchen (1986). The grid for capital is formed around the approximated steady-state capital. The grid for debt is formed such that its upper end point is equal to the upper end of the grid for capital, while the lower end is half of the upper end, with a reversed sign.

[13] We assume that the product introduction costs are considered as part of operating expenses, so that they can be deduced from taxes. Hence, firm's operating profits can be consequently interpreted as gross profits minus operating expenses.

3.6. *Optimal policies*

In this section, we analyze the optimal product, investment and financing policies implied by the model. We derive the first-order conditions and investigate how product portfolio decisions interact with the firm's choice of investment and debt. We focus on highlighting insights that are inherently different from those stemming from standard dynamic models of the firm.

3.6.1. *Product portfolio*

To understand how firms optimally adjust their product portfolios, we derive the approximate first-order condition for product choice Δ_P, assuming for simplicity that the firm does not issue equity:[14]

$$\underbrace{\eta K}_{\substack{\text{product}\\ \text{introduction}\\ \text{cost}}} \approx \underbrace{Z K^{\theta}(1-\xi)\frac{\Delta(\phi)}{\Delta(\Delta_P)}}_{\substack{\text{profit increase}\\ \text{today}}} + \underbrace{\beta \mathbb{E}\left[\frac{\Delta(V(K', D', \Phi'(\Delta_P), Z'))}{\Delta(\Delta_P)}\right]}_{\substack{\text{profit increase}\\ \text{tomorrow}}}. \tag{13}$$

Firms will introduce new products as long as the marginal cost on the left-hand side of Eq. (13) is smaller than the marginal benefit of introducing a new product on the right-hand side of Eq. (13). The marginal cost consists of a product introduction cost. The marginal benefit depends on the old-product specific revenue discount ξ. Furthermore, the marginal benefit also changes with product portfolio structure Φ and the profitability shock Z. For example, when the profitability shock is more persistent (higher ρ), the firm has more incentives to introduce new products to reap the benefits associated with the profitability shock whose effects last longer. Finally, the marginal benefit of a new product today also contains the expected marginal change in firm value, because today's product portfolio adjustment affects its potential future evolution. Thus, Eq. (13) shows that investment and debt decisions of the firm indirectly affect how it chooses its product portfolio structure.[15]

[14] In Eq. (13), $\Delta(\cdot)$ indicates the discrete derivative, defined as $\Delta(f(n)) = f(n+1) - f(n)$.

[15] More specifically, Equation (13) shows that the next period stock of new products P_n' and old products P_o' both depend on how many new products were introduced in the current period, as it affects the transition matrix T_Φ. Thus, $\partial V'/\partial \Delta_P$ is a non-trivial quantity that depends on $\partial P_n/\partial \Delta_P$ and $\partial P_o/\partial \Delta_P$.

3.6.2. Investment

Eq. (13) suggests that the firm's product portfolio adjustment is intertwined with other corporate policies through the effect on the expected marginal change in firm value. To see the exact link between investment and product decisions, we derive the investment Euler equation, which sets the discounted expected return on capital investment equal to the value of a dollar payout today:[16]

$$1 = \beta \mathbb{E}\left[\frac{(1+\Lambda'(E(\cdot))}{(1+\Lambda(E(\cdot))}\left(\frac{MB_i}{MC_i} + \frac{MB_i^{\Phi}(K', Z', \Delta'_P, \Phi')}{MC_i}\right)\right], \tag{14}$$

where

$$MB_i^{\Phi}(K', Z', \Delta'_P, \Phi') = -\theta(1-\tau)(1-\xi)\phi' K'^{\theta-1} Z' - \eta\Delta'_P. \tag{15}$$

Eq. (14) shows that the return on capital investment consists of two parts. The first part, common to e.g. the neoclassical investment model, is the ratio of the marginal benefit of investment MB_i, which comprises the marginal increase in output, the value of additional depreciated capital, and lower adjustment costs in the future, to the marginal cost MC_i, equal to a dollar spent on investment and the corresponding investment adjustment costs. The second part is the ratio of the marginal benefit of investment due to the product portfolio structure, captured by $MB_i^{\Phi}(\cdot)$, to the marginal cost.

Product and investment policies are related, because older product portfolio negatively affects the firm's revenue, resulting in a lower marginal benefit of investment. Introducing more new products increases the marginal benefit of investment, because lower revenue discount associated with younger product portfolios and higher durability of revenue increase the firm's incentives to invest in physical capital. Intuitively, the firm can now benefit from its physical capital for a longer period of time. This suggests that product introductions and capital investment act as complements. Finally, a direct computation shows that $\partial MB_i^{\Phi}(\cdot)/\partial\phi' < 0$, documenting that the model is able to reconcile the stylized fact that product portfolio age and investment are negatively related. Overall, the Euler equation shows that incentive to

[16] Details of the computation are provided in the Internet Appendix.

invest in physical capital can vary with the firm's product portfolio structure.

3.6.3. Net debt

To examine how financing and product decisions are interrelated, we combine the first-order condition for the debt choice D' and the corresponding envelope condition, which yields

$$1 = \beta \mathbb{E} \left[\frac{(1+\Lambda'(E(\cdot)))}{(1+\Lambda(E(\cdot)))} \left(1 + r(1-\tau) + \mu'\right) \right], \tag{16}$$

where μ is the Lagrange multiplier associated with the collateral constraint. The right-hand side of Eq. (16) is the expected discounted value of debt, which is equal to the interest payments less the tax shield and the shadow value of relaxing the constraint on issuing debt. The Lagrange multiplier μ indicates that debt is more valuable when the collateral constraint is expected to bind, highlighting that the firm may have incentives to preserve its debt capacity today to avoid reaching the collateral constraint tomorrow and having to issue costly external equity. This result, standard in dynamic investment models such as e.g. Gamba and Triantis (2008) or DeAngelo et al. (2011), shows that debt capacity has value as it grants the firm more financial flexibility. One implication of this notion is the fact that financial, investment and product policies will be intertwined: if the firm is more likely to introduce new products tomorrow, it will follow a conservative debt policy today.

Eq. (16) suggests that the model can reconcile the stylized facts: absent positive product introduction opportunities, the firm will preserve its debt capacity, resulting in a negative relation between product portfolio age and leverage. Thus, even though product choice does not *directly* affect the firm's debt policy, it has an indirect effect, because it affects the firm value as well as the probability of incurring the equity issuance cost.[17]

[17] While the model puts emphasis on the fact that product introduction decisions affect firms' financing decisions only through the 'quantitative rationing' effects of the collateral constraint, the negative association between leverage and product portfolio age is also consistent with firms issuing debt for tax reasons. Indeed, since younger product portfolios are associated with higher profits, their incentives to shield these profits from taxation are also higher and thus they will issue more debt. This channel is also present in the model.

4. Estimation and Identification

We structurally estimate the model to examine the quantitative implications of product decisions on corporate policies. In this section, we describe the estimation procedure, discuss the identification strategy, present the baseline results and the cross-sectional implications of the model.

4.1. Estimation

Throughout the paper, we set the tax rate τ to 20% as an approximation of the corporate tax rate relative to personal taxes. While the majority of the structural parameters of the model are estimated using simulated method of moments (SMM), several parameters are estimated separately. The risk-free interest rate r is estimated at 1.4%, which is the average 3 month T-bill rate over the sample period. We also estimate separately the probability of a 'new' product remaining 'new' $p_{n\to n}$ and the probability of an 'old' product exiting $p_{o\to e}$. These probabilities can be inferred directly using the expected lifetime of a product implied by the model, shown in Eq. (8), and the definition of the empirical proxy. In particular, in the data a product is considered 'old' if it exceeds half of its lifetime. This means that each product spends half of its lifespan being 'new' and the other half being 'old.' In terms of the model, this implies that

$$m^{(\text{intr.,exit})} = \frac{1}{2}\frac{1}{1-p_{n\to n}} + \frac{1}{2}\frac{1}{1-q_{o\to o}}, \;\; \frac{1}{1-p_{n\to n}} = \frac{1}{1-q_{o\to o}}. \tag{17}$$

In the data, the average lifespan of a product (weighted by revenue) is 15.94 quarters. This implies that $p_{n\to n} = 0.8746$ and $q_{o\to e} = 1 - q_{o\to o} = 0.1254$. Finally, we directly estimate the proportional external equity financing cost by regressing issuance proceeds on the underwriting fees, which implies a value of 0.0223.[18]

We estimate the remaining 8 parameters $(\theta, \sigma, \rho, \delta, \psi, \omega, \eta, \xi)$ using SMM, where θ is the production function curvature, σ is the standard deviation and ρ the autocorrelation of the profitability process; δ is the physical capital depreciation rate; ψ is the capital adjustment

[18]By doing so, we only control for direct costs of equity issuance, as in e.g. Warusawitharana and Whited (2016) or Michaels, Page, and Whited (2018).

cost parameter; ω is the parameter governing the collateral constraint; η is the product introduction cost and ξ is the old-product specific revenue discount. To do so, we first solve the model numerically, given the parameters, and generate simulated data from the model. Then, we compute a set of moments of interest using both the simulated and actual data. The SMM estimation procedure determines the parameter values that minimize the weighted distance between the model-implied moments and their empirical counterparts. Appendix C provides further details on the estimation procedure.

It is important to note that the fact that the sample of firms in the data is fairly homogeneous speaks in favor of using SMM, because SMM estimates the parameters of an average firm, the concept of which is more appropriately defined in subsamples of similar firms.

4.2. Identification

Before proceeding with estimation, we discuss the identification of the structural parameters. SMM estimators are identified when the selected empirical moments equal the simulated moments if and only if the structural parameters are at their true value. A sufficient condition for this is a one-to-one mapping between a subset of structural parameters and the selected moments, that is the moments have to vary when the structural parameters vary. Because the firm's investment, financing, and payout decisions are intertwined, all of the moments are to some extent sensitive to all the parameters. However, some relationships are strongly monotonic in the underlying parameters and as such more informative of the relationship, thus useful for identifying the corresponding parameter. For example, the mean and variance of operating profits are informative of μ and σ while ρ is identified from the serial correlation of operating profits, which is estimated using the technique of Han and Phillips (2010).

We select 12 moments related to firms' operating profits, investment, net leverage and product portfolio characteristics. We do not choose the moments arbitrarily but rather include a wide selection of moments to understand which features of the data the model can and cannot explain. Therefore, we examine all means, variances and serial correlations of all main variables of interest that can be computed in the model. Notably, in the estimation procedure we refrain from using moments related to the size of the product portfolio (i.e. the number of products), given that the model is unlikely to match the data on this margin, as firms introduce products for variety of reasons that are not captured by this model (see e.g. Hottman et al., 2016). Instead, we focus primarily on the product portfolio age and product portfolio adjustments, which, as we argue, help identify parameters related to the product space characteristics.

The remaining parameters are identified as follows. The physical capital depreciation rate δ is strongly linked to the mean of investment. The capital adjustment cost parameter ψ is identified by the variance and autocorrelation of investment, as higher adjustment costs result in the firm smoothing its investment. The collateral constraint parameter ω is identified by the mean of net leverage. The product introduction cost η is identified by the variance and autocorrelation of old product share, as higher cost results in more lumpy product introduction policy. The old-product specific discount ξ, on the other hand, is tightly linked to the mean of old product share, as it determines the trade off the firm faces when deciding on product introductions today.

4.3. Estimation results

We summarize the results of the structural estimation in Table 4. Panel A contains simulated and actual moments. Panel B reports the parameter estimates and their standard errors.

The estimated model fits the data fairly well on financial, real and product dimensions, which is justified by the low values of t-statistics in Panel A testing the difference between the model- and data-implied moments. The only exceptions are the mean and serial correlation of net leverage and the variances of investment and product portfolio age. Nevertheless, even if the difference between simulated and actual moments is statistically significant, the economic difference is negligible, especially for the variances and autocorrelations.

[Table 4 about here.]

Panel B documents that all model parameters are economically meaningful and statistically significant. It is worth noting that the structural parameters have been estimated precisely, as their standard errors are low, indicating that the model is well identified.[19]

The estimate of the product introduction cost η is equal to 0.75%, which implies that

[19] In the Internet Appendix we show that the model parameters are locally identified by the underlying moments by computing the diagnostic measure of Andrews, Gentzkow, and Shapiro (2017).

a typical sample firm behaves as if it had to incur a cost of approximately \$7.64m when introducing a new product. While this cost appears substantial, it is required to square the fact that firms do not continuously adjust product portfolios in the data, as the distribution of product entry is fairly lumpy (see also Fig. A.2 in the Internet Appendix). Moreover, the estimated cost is fixed and as such can be interpreted as if it comprised both the direct costs of introduction (such as marketing, R&D expenditures, etc.) as well as indirect ones, such as the present value of costs related to supplying the product.

The old-product specific discount ξ is estimated at 0.5282, meaning that firms act as if each old product in their portfolio only contributed 52.82% of a new product's revenue. As such, the discount is fairly large, which is consistent with the notion of product life cycle. In particular, the fact that the estimate of ξ is strictly larger than 0 implies that product life cycle effects are present and important. On the other hand, the fact that it is not equal to 1 suggests firms still benefit from old products, which is indeed the case as their profitability does not drop to 0, as per Fig. 2. To gauge whether the magnitude of the estimate is sensible, we consider a back-of-the-envelope calculation and compute the average revenue of 'old' and 'new' products in the data. The obtained value of 59.1% suggests that the estimated value of ξ is in a reasonable range. Barring potential measurement error, the fact that it is lower than its data 'counterpart' could be explained by the fact that firms in the model do not withdraw products by themselves, which makes the old products relatively 'worse' compared to the new ones.

The structural estimates of the remaining parameters are in range of those in extant studies of firms' financing and investment policy. For example, the standard deviation of the profitability shock σ and the collateral constraint parameter ω that determines the firm's debt capacity are close to the ones obtained in Nikolov, Schmid, and Steri (2018) and the persistence of the profitability process ρ is similar to the one reported in Warusawitharana and Whited (2016) for the food manufacturing industry, which comprise the majority of the sample firms. The only parameter that may seem on the higher end of the range compared to the existing literature is the convex investment adjustment cost ψ, estimated at 0.8786, which results in a fairly sticky investment policy.[20]

[20]In a different model, Warusawitharana and Whited (2016) also obtain a much higher investment adjust-

4.4. Cross-sectional implications of the model

The results discussed until now show that the model is able to jointly explain the corporate investment, financing and product portfolio policies of an average sample firm. In this section, we provide further empirical evidence of the importance of the product life cycle channel by estimating the model on subsamples of firms that vary along key firm characteristics. In particular, we focus on two specific sets of sample splits. First, we investigate whether the estimated model can reconcile differences between firms varying in their products' sensitivity to product life cycle. This analysis serves as a 'sanity check' whether the product life cycle effects in the model correspond to the ones observed in the data, despite using firm-level rather than product-level data in the estimation procedure. Second, we analyze whether other important product market characteristics matter for the product life cycle channel. To this end, we focus on sample splits based on the size of product portfolio, the degree of product market competition, the durability of the products and product uniqueness. This exercise, in turn, provides further insight as to how the economic forces behind product life cycle affect corporate policies of firms differing in dimensions not explicitly captured in the model. It also shows which features of the data explain the magnitude of the product introduction cost.

4.4.1. Sensitivity to product life cycle

[Table 5 about here.]

To analyze whether the model can reflect differences across firms whose products vary in their sensitivity to product life cycle, for each firm in the sample we estimate a product-level regression of the form

$$\log(\text{rev})_{it} = \alpha + \beta \times \log(\text{age})_{it} + \eta_i + \gamma_c + \varepsilon_{it}, \tag{18}$$

where i and t indicate the product and the quarter, and c indicates the product's corresponding cohort.[21] We then split the firms into two groups based on the estimates of β. The firms

ment cost for the food manufacturing industry.

[21] We control for the cohort-specific fixed effects using the Deaton (1997) adjustment as in Argente et al. (2019b).

with the below-median (above-median) sensitivity of product-specific revenue to product age β should be less (more) exposed to product life cycle effects, for example due to the fact that their products are more (less) durable or are less (more) susceptible to ageing.

Table 5 presents the estimation results for the two subsamples. Panel A documents that the model-implied and data moments are relatively close, implying that the model captures well the policies of firms in both subsamples. The results also suggest that firms whose products are less exposed to product life cycle have on average higher profitability and older product portfolios. The fact that these firms also adopt higher net leverage speaks to the importance of the precautionary savings motive of product life cycle, that should be less pronounced when firms are less exposed to product life cycle. On the other hand, firms with higher sensitivity to product life cycle invest more on average, which is related to the fact that they tend to introduce more products and complement it with capital investment. This is also true in the data, as the net product entry rate of these firms is approximately 3 times higher as compared to the one of firms with low product life cycle sensitivity (0.4% vs 1.2% per year, on average). The fact that this moment is not used in the estimation procedure serves as a test for the external validity of the subsample analysis.

The parameter estimates in Panel B indicate that products of firms with high product life cycle sensitivity lose about 49.79% of revenue when they become old, as compared to 38.55% for products of firms with low product life cycle sensitivity. This result shows that the model successfully captures the intuition underlying the relationship between product revenue and age, and as such the product-level information is not lost when aggregating product-level data to firm-level. The fact that the average net leverage across the two subsamples is different while the estimate of the collateral constraint parameter ω is nearly the same further reinforces the importance of product dynamics on firms' precautionary savings incentives. Finally, firms with higher product life cycle sensitivity are also more sensitive to firm-wide productivity shocks, as the estimate of production function curvature θ is higher for these firms, as is the standard deviation of the profitability shock. This finding suggests that there can be some differences in the underlying economic environment across the two subsamples of firms, for example they may supply products in industries that may be subject to different kinds of customer demand dynamics.

4.4.2. Product characteristics

We now turn to investigating the differences in estimates along product dimensions not explicitly captured by the model. We focus on four sample splits, based on the size of product portfolio, the degree of product market competition, the durability of the products and product uniqueness. Table 6 contains the parameter estimates for each subsample. To keep the presentation of the results concise, the corresponding data- and model-implied moments are relegated to the Internet Appendix.

[Table 6 about here.]

Product portfolio size Panel A of Table 6 shows the estimation results for firms with small and large product portfolios, that is those with below- and above-median effective number of products, respectively. The parameter estimates indicate that firms with small product portfolios face a higher costs of introducing new products and a more pronounced old-product specific revenue discount. These results reinforce the notion that for managing product portfolios is even more important for small firms, as they are more exposed to product life cycle. Additionally, the fraction of capital that can be collateralized ω is much lower for firms with small product portfolios than for firms with large product portfolios. This result has two explanations. First, since the correlation between product portfolio size and firms size is positive, a part of the result is simply due to small firms having less capital (in terms of total assets) that can be pledged as collateral, consistent with e.g. Nikolov, Schmid, and Steri (2018). The fact that the estimate of ω varies substantially across the two samples, however, suggests that the number of products also plays a critical role, which can be consistent with firms behaving as if their intangible assets (e.g. patents or trademarks) can be pledged as collateral as well (see e.g. Mann, 2018; Suh, 2019; Xu, 2019). Finally, the size of product portfolio also appears to serve as a way for firms to diversify their revenues, as firms with large product portfolios have lower estimated variance of profitability shock and higher estimated profitability shock autocorrelation.

Product market competition Panel B of Table 6 presents the estimates from two subsamples differing in the degree of product market competition.[22] Investigating this dimension

[22]This is done by first computing the HHI of each 'market' in which firms operate, which are defined by product groups (see Appendix A), and then computing the firm-specific exposure to the markets, by

of the data is important for two reasons. First, the degree of competition could affect the trade-offs determining product life cycle, for example firms operating in more competitive markets could be forced to introduce more new products to be able to keep up with their competitors or gain market share. Second, the empirical literature on product markets has largely focused on this dimension of the data, that is on how the between-firm effects affect firms' investment and financing policy. It is therefore instructive to examine how *within*-firm product market forces, such as product life cycle, are related to corporate policies. Importantly, the measure of competition adopted in this paper is better suited to characterize the competitive environment faced by firms as it incorporates complete information about the product markets they operate in.

The results in Panel B suggest that each old product of firms operating in more concentrated markets provides about 63% of a new product's revenue; compared to 43% for firms subject to more competitive pressure. Firms in less competitive product markets also face lower costs of introducing new products. Given that higher competition may result in products become obsolete quicker, that is ξ being lower, the results show that product life cycle is related to product market competition, highlighting that both between- and within-firm product market forces play an important role in shaping corporate policies. The product market competition dimension also appears to affect the extent of product life cycle more product portfolio size does, given that the difference in ξ across the two samples is larger than for firms differing in the size of product portfolios. Finally, model- and data-implied moments (available in the Internet Appendix) suggest that firms operating in less competitive product markets have higher operating profits, consistent with less intensive competition. Importantly, while these firms have similar level of old product share to firms operating in competitive environment, the effect on profitability is mitigated as these firms are less exposed to product life cycle channel.

Product durability In the model, each product is ex ante homogeneous and is expected to last for the same amount of time. However, in reality firm can influence the expected durability of their products, e.g. by expanding to more lasting product categories or investing

computing the average HHI weighted by the firm's share of sales in a given market. In particular, the HHI of each market is computed using all available data on private and public firms. More details about how the competition proxy is computed are provided in Appendix B.

in consumer retention. To this end, we investigate how product durability interacts with the product-level forces in the model. Panel C of Table 6 presents the estimation results from two subsamples split according to the expected durability of firms' products, measured by the products' average calendar age at exit.

The estimates suggest that firms with higher product durability face higher product introduction costs (0.913% vs. 0.667%) *and* are more exposed to product life cycle, as their old products provide only 42% of their revenue, as compared to 60% for firms that introduce less durable products. While the first result is intuitive, the second one might appear contrary to the notion of product durability. However, product durability should, by definition, have a large effect on the product transition probabilities. This is indeed the case, as the implied $p_{n \to n}$ changes from 81.74% to 90.55% across the two subsamples, which suggests that products of firms with higher product durability are expected to last twice as long than those of firms with lower product durability. This means that the net effect of having product durability can still be positive, despite products of these firms losing a larger chunk of revenue when they age. Finally, the other parameter estimates remain similar for both subsamples, indicating that product durability remains a fairly distinctive product feature that does may reveal itself in other firm characteristics.

Product uniqueness – cost of sales The last sample split that we investigate is related to cost of sales, which captures all costs not directly related to goods sold, such as advertisement or corporate expenses (Compustat item `xsga`). This sample split is important, for several reasons. First, it speaks to the notion of selling more or less specialized products, thus following different strategies (e.g. product uniqueness of Titman and Wessels, 1988). Second, since cost of sales contains marketing expenses, it should be related to product life cycle, to the extent that firms try to influence the lifetime of their products by e.g. advertising. Finally, it measures a cost of selling the product, which should be closely related to the product introduction cost η, and as such the sample split serves as a sanity check of whether the model can correctly recover this feature of the data. To this end, we split the firms into two samples based on their cost of sales as a fraction of total assets and re-estimate the model.

The results of this exercise are presented in Panel D of Table 6 and indicate that firms with higher cost of sales have higher product introduction costs (0.797% vs. 0.872%), which is intuitive. Their products are, however, less exposed to product life cycle, as new products only lose 44% of their revenue when becoming old, as compared to 59% for firms with lower cost of sales. Interestingly, higher cost of sales do not translate to higher durability. In fact, firms with higher cost of sales have *lower* average lifespan of their products (85.98% vs. 88.78%), indicating that lower product durability could be the underlying reason why firms spend more on selling-related activities. It also highlights that product durability is markedly different from product uniqueness, plausibly proxied by the cost of sales: more specialized firms are not necessarily those that also supply more durable products.

5. Analysis and Counterfactuals

In this section, we study the implcations of product-level economic forces for corporate policies. First, we analyze the numerical policy functions implied by the model. Second, we consider a number of counterfactuals to better understand how product market strategy interacts with corporate policies and how quantitatively important its effects are. Finally, we analyze the role of product cannibalization in shaping corporate policies.

5.1. Numerical policy functions

To examine the implications of the estimated parameters for the firm's optimal policies, we compute the numerical policy functions $\{I/K, D/K, \Delta_P\} = h(K, D, \Phi, Z)$ for investment rate I/K, net leverage D/K, and product introductions Δ_P. In the discussion that follows, we focus on two sets of policy functions. First, we fix K and D at their average values in the simulated sample and set $Z = 1$ as we want to focus on the economic forces driven by product portfolio setting. Panel A of Fig. 7 plots the policy functions $\{I/K, D/K, \Delta_P\} = \tilde{h}(P_o|P_n^i)$ for a firm with a low and high number of new products, i.e. $i \in \{l, h\}$. Second, in Panel B of Fig. 7 we fix K and D at their average values in the simulated sample and plot the policy functions for the profitability shocks Z: $\{I/K, D/K, \Delta_P\} = \tilde{h}(Z|\Phi^i)$, while varying Φ from a low to a high value, i.e. $i \in \{l, h\}$.

[Fig. 6 about here.]

The numerical policy functions in Panel A of Fig. 7 show how the firm optimally responds to changing the product portfolio structure. In particular, the left graph in Panel A shows that the policy function for product introductions Δ_P can be characterized by an inaction region due to a fixed cost of product introduction. That is, the firm only starts introducing new products once its current stock of old products is sufficiently large. The threshold at which it happens depends on the stock of new products, as firms with more new products are less exposed to product life cycle than firms with less new products.

The policy function for product introductions Δ_P has natural implications for investment and financing policy. The middle graph in Panel A illustrates that investment decreases in the number of old products, consistent with the investment Euler equation. The Euler equation also reveals the intuition behind the spike in investment that is visible for a large number of old products, which coincides with the firm introducing new products. That is, if the product introduction cost is sufficiently small, the firm's marginal benefit of investment increases in Δ_P. In other words, capital and product investment are *complements*: the firm wants to invest more in physical capital as its product portfolio becomes younger to benefit from higher and more durable operating revenue.

The right graph in Panel A documents the precautionary savings motive induced by product dynamics, as it indicates that the firm's leverage policy depends on its product portfolio structure. Importantly, the firms appears to finance product introductions to a large extent with debt, given how the increase in the policy function coincides with Δ_P. It should also be mentioned that when the share of old products in the portfolio is low, leverage tends to decrease with P_o. This happens largely because the firm has higher precautionary savings incentives and thus values preserving debt capacity more, because it would have to tap external financing when the old products exit and its revenue drops. Thus, given the costly nature of external equity it is optimal for the firm to act conservatively and adopt lower leverage. In the counterfactual experiments below, we show that this effect largely depends on the product-level characteristics. Finally, the firm also adopts lower leverage as it benefits less from tax shields due to lower operating income.

Panel B of Fig. 7 documents how the firm optimally responds to profitability shock when varying its product portfolio structure. The left graph in Panel B suggests that the firm with a high share of old products may choose not to introduce net products when it experiences a low realization of Z, because introducing new products is costly. The result in the middle graph in Panel B is fairly standard in the dynamic investment models, as investment increases with Z, but it also confirms the intuition conveyed in Panel A of Fig. 7 that the firm invests less when it has an older product portfolio. That is, the product dimension changes the firm's sensitivity of investment to the profitability shock.

The right graph in Panel B illustrates that the firm's choice of leverage varies differently with Z, depending on its product portfolio structure. When hit by a low shock realization, the firms tend to disinvest and use the proceeds to pay down debt, resulting in lower leverage. Similarly, when the realization of the shock is high, the firms prefer to preserve their debt capacity to fund future profitable investment opportunities, and thus adopt lower leverage ratios. The only exception is the firm with a low share of old products, which also issues debt to fund investment for a very high shock realization. It is also worth noting that for high Z realizations, the firm with a high share of old products focuses on introducing new products, that is renewing its product portfolio, rather than investing in capital. This coincides with no apparent spike in leverage, unlike in Fig. 7, because now the firm finances introducing new products internally, following a high realization of Z.

To conclude the discussion of the policy functions, we investigate whether the dynamics induced by the product-level economic forces are economically important. To this end, we perform a variance decomposition of the firm's investment and leverage policy. The results highlight that product dynamics account for roughly 20% of the total investment and leverage variance, independently of how they are measured in the model (by share of old products or stock of new and old products separately).[23] Moreover, most of the variation is due to the dynamics of the stock of old products, which is intuitive given their importance in the product life cycle channel. Overall, the results suggest that product dynamics can contribute substantially to the observed variation in corporate policies.

[23] To get these numbers, we compute the Type III partial sum of squares for each variable in the model and then compute its share in the total variance. That is, the number represents the % of total variance explained by the variable.

5.2. Counterfactuals

We now turn to investigating the quantitative importance of product dynamics for the firm's corporate policies by means of several counterfactual exercises. First, we consider how product-level economic forces affect firm value, firms' precautionary savings incentives and the relationship between product characteristics and corporate policies. Second, we examine the impact of changing parameter values related to the product market dimension on investment and leverage policies. We do so by varying the old-product specific discount ξ and the probability of product exit $q_{o\to e}$ that govern the expected benefit per product and expected product lifetime.

5.2.1. Firm value implications

We first investigate how important product market characteristics are in shaping firm value. In Table 7, we consider the effects of changing the cost of introducing new products η, the old product-specific discount ξ and the individual-product transition probabilities $p_{n\to o}$ and $q_{o\to e}$ from their baseline estimates.

[Table 7 about here.]

In the first panel of Table 7, we conduct counterfactual experiments related to the severity of product life cycle. When setting $\xi = 0$, product life cycle is very severe, as old products generate zero revenue. In contrast, $\xi = 1$ implies that new and old products contribute the same amount to the firm's cash flow. Comparing the baseline results and those for $\xi = 0$ indicates that firm value is 3.55% higher due to the fact that each of their old products generates 58% of a new product's revenue rather than 0%. However, the firms still lose from the product life cycle effects, as changing ξ from its baseline estimate of $\xi = 0.5282$ to $\xi = 1$ would increase firm value by 4.48%. All in all, this evidence suggests that introducing products that age slower over their life cycle can bring material benefits to the firm.

It is also interesting to investigate how the correlations between corporate policies and product portfolio age vary in these different cases from their baseline value. Not surprisingly, making the distinction between old and new products irrelevant by setting $\xi = 1$ dampens the correlations to essentially 0, as product portfolio age loses any impact. In the second case, the relationships remain the same or become stronger. This shows that the channel between product portfolio structure and corporate policies described in the paper is sensitive to product characteristics.

The second panel of Table 7 indicates that lower values of η result in higher firm value, as product introductions become cheaper, and thus firms have more flexibility in adjusting their product portfolio. The effects are quantitatively large as well: increasing η by 50% results in 5.72% lower firm value. Increasing the product introduction cost also changes the correlations between corporate policies and product portfolio age, because the firm's product policy becomes more lumpy and product introductions are less frequent.

Finally, we analyze how changing product durability affects firm value. The results in the third panel of Table 7 show that changing the probability of a new product becoming old to $p_{n \to o} = 1$ lowers firm value by 10.71%, and is much lower than increasing the probability of an old product exiting to $q_{o \to e} = 1$ that results in 3.03% lower firm value. However, these can be reconciled by the fact that the estimated old-product specific discount implies that old products are approximately two times worse than new ones in terms of their contribution to the firm's revenues. Overall, the results indicate that managing product durability can also be beneficial for firms.

5.2.2. Quantifying the effects on precautionary savings incentives

As argued before, the product life cycle effects induce particular precautionary savings incentives for firms. In the counterfactual exercise, we examine how the magnitude of these incentives is affected by product-level economic forces. The last column of Table 7 presents the percentage change in firms' debt capacity, measured as the difference between the maximum debt capacity ωK and net debt D (both scaled by capital K), relative to the values implied by the estimated model.

The results suggest that product characteristics can largely magnify firms' incentives to preserve debt capacity. For example, changing product introduction costs affects how often firms' decide to introduce new products. Less frequent product introductions lower their incentives to preserve debt capacity, because they require less funding for product introductions. The effects of varying the exposure to the product life cycle channel, by altering the old-product specific discount, are even stronger: more severe product life cycle effects result in stronger precautionary savings motives. This happens because the firm can lose a larger fraction of revenue due to product exit, which makes it value spare debt capacity more. This is the reason why removing the difference between new and old products results in the firm preserving its debt capacity less, as then the influence of the product life cycle channel is non-existent. This finding also highlights that the financing behavior induced by the product life cycle channel would be absent in standard dynamic models of the firm that do not account for product-level dynamics (e.g. the AK framework). In other words, product life cycle magnifies the precautionary savings effects.

5.2.3. Comparative statics: product portfolio characteristics

We now consider a different type of a counterfactual exercise by examining the effect of changing product-level characteristics on average firm policies. Fig. 8 presents the resulting comparative statics for the old product-specific revenue discount ξ in Panel A and for the probability of old product exit $q_{o \to e}$ in Panel B, which govern the firm's exposure to the product life cycle channel and the durability of each product, respectively. In each panel, we examine the effect of a 20% upward or downward change in each parameter on average investment, net leverage, and product portfolio age. To construct these figures, we solve a model in which the values of each parameter deviate from its baseline estimated value, and simulate using the resulting optimal policies.

[Fig. 7 about here.]

Higher values of ξ imply that each product provides the firm with more benefits over the same expected lifetime. As such, the firm has more incentives to introduce new products and its product portfolio age declines, see the leftmost graph of Panel A of Fig. 8. This, in turn, results in the firm substituting capital for product investment, as the latter becomes relatively cheaper for the same level of total output and average investment decreases with ξ. As for leverage, there are three main reasons why it increases in ξ. First, the firm finances product introductions by issuing debt, especially when it has an old product portfolio. Second, smaller old product discount ξ results in higher profits, which incentivizes the firm to issue debt to benefit from tax shields. Finally, higher ξ means that the firm is less exposed to the product life cycle channel and thus having many old products is less risky for the firm, as they differ less from new products, which means that the firm values preserving debt capacity less. These channels are consistent with the policy functions in Fig. 7.

Panel B of Fig. 8 presents the effects of changing the probability that an old product exits $q_{o\to e}$. Essentially, this parameter determines the expected longevity of the firm's products. When the probability is lower, the firm needs to introduce less new products to achieve the same level of product portfolio longevity firm, as the existing products are expected to survive for a longer period of time. This results in a higher average product portfolio age, see the rightmost graph in Panel B. Thus, when the firm's products become less durable, it invests more in physical capital to make up for the revenue lost due to shorter lifetime of its products. However, the effect is quantitatively smaller than in case of ξ. The firm also adopts lower leverage to ensure that it has enough debt capacity to fund investment and introduce new products using debt rather than resorting to costly external financing.

All in all, the results of the comparative statics further reinforce the notion that product portfolio characteristics play a major role in shaping corporate policies.

5.3. The effects of cannibalization

Arguably, the product setting in the model is silent on many aspects of real-world product portfolio management, for example the fact that introducing new products usually results in negative externalities for firms' existing product lines, which is known as 'cannibalization.' Thus, one could argue that these effects could play a major role in shaping firms' product market strategies. To study whether this is indeed the case, we examine how quantitatively important the effects of cannibalization are on financing and investment.

To this end, we extend the model by explicitly allowing for a dependence between the number of introduced products and the probability of a existing products becoming old $p_{n\to o}$. In the extended model, it is parametrized as

$$\tilde{p}_{n\to o} = p_{n\to o} + \sum_{p=1}^{\Delta_P} \epsilon^p, \tag{19}$$

where Δ_P is the number of products introduced by the firm and ϵ can be considered as a parameter related to the firm's elasticity of substitution between existing and new products' revenues. Since in the model old products generate lower revenue than new ones, we effectively assume that product cannibalization acts through ageing the firm's products, which is reasonable given that, as argued by Argente et al. (2019b), product life cycle is largely due to changes in customer preferences. In the exercise to follow, we assume that ϵ varies from 0 (the baseline case) to 0.0627, that is a half of $p_{n \to o}$. This implies that the product-specific revenue is expected to lower by 21.9% when introducing one new product, as compared to the "no cannibalization" benchmark.[24]

[Fig. 8 about here.]

Fig. 9 presents the effects of the cannibalization parameter ϵ on the firm's profitability, product portfolio age, net product entry and net leverage. The figures indicate that controlling for potential cannibalization has intuitive implications for corporate policies: average profitability decreases, as new product now have shorter lifespan, which translates to higher product portfolio age, and much higher new product entry, that nearly doubles. Finally, leverage increases for two reasons. First, as firms finance product introductions by issuing debt, they also adopt higher leverage. Second, higher cannibalization rate results in a more stable product portfolio structure, and thus profitability, as both variances decrease. This lowers the firm's precautionary savings incentives and thus results in higher leverage.

Overall, the effect of cannibalization can magnify the effects of product life cycle, but does not appear to alter the main mechanisms through which product dynamics interact with corporate policies.

6. Conclusion

In this paper, we demonstrate that product life cycle has important implications for corporate policies by developing and estimating a dynamic model of product portfolio decisions. In line with the product life cycle channel, new products are more profitable, and are expected to last longer than old ones. Thus, when deciding whether the introduce new products, the firm

[24]The industrial organizations and marketing literature do not specify a clear-cut candidate for the value of this parameter. For example, Hottman et al. (2016) estimate the product elasticity of substitution due to *price* increases, which implies a cannibalization rate of 0.5 for the median firm in their sample. This means that about half of the sales of a new product introduced by a firm comes from the sales of existing products and half from the new ones. That is, in this analysis we assume a less pronounced effect.

trades off the benefits of a younger product portfolio versus product introduction costs.

We embed the product life cycle channel into a flexible model of financing and investment that can be taken to the data by means of structural estimation. The firm's product introduction decisions have direct implications for cash flow dynamics. As a result, investment, financing and product decisions are intertwined at firm level. In particular, the model implies that product introductions and capital investment act as complements and that product life cycle induces stronger precautionary savings motives for firms. These predictions are in line with empirical stylized facts about product portfolio age, investment and leverage.

Using detailed data on firms' product portfolios, we structurally estimate the model to quantify the effects of the product life cycle channel. By doing so, the paper delivers three novel results. First, the structural estimates imply that the product-level forces are quantitatively important, as products lose 48% of their revenue when they become old and firms spend $7.64m per product introduction. Second, the estimated model provides important cross-sectional predictions, as the estimates suggest that firms supplying fewer products, competing more intensely, and supplying products more sensitive to ageing are also more exposed to the product life cycle channel. Third, by means of counterfactual experiments, we find that product life cycle substantially affects firm value as well as corporate investment and financing decisions. Overall, the data suggests that managing the life cycle of products, by means of introduction cost or sensitivity to ageing, yields material benefits to firms.

Appendix

The Appendix consists of three sections. Section A provides more details about the product data and sample selection. Section B contains the definitions of variables. Section C describes the structural estimation procedure.

Appendix A. Product market data

1. *Data description*

We use the Nielsen Homescan (NH) data to obtain information about firms' product market strategies. An extensive description of the database can also be found in e.g. Broda and Weinstein (2010) or Hottman, Redding, and Weinstein (2016). The data contains three dimensions: household, product and time. Each household in the sample reports the prices and quantities of items purchased during each shopping trip and any potential discounts or deals associated with the purchases. Overall, the data contains a representative sample of approximately 40,000-60,000 households stratified into 61 geographic areas in the US. The sample is designed so that it can be projected to the total US population (projection factors are available). In total, the data spans over the period of 15 years (2004–2018).[25]

2. *Product classification in NH*

Each product in the data belongs to specific categories, varying in their granularity. There are categories such as Departments (10), Product Groups (≈125), Modules (≈1,075) and UPC codes (≈4.3 million out of which ≈2.3 million are present in the consumer panel files). Most products also have a specific brand. An example of product classification can be found in Table A.1.

The most granular level of product categories is the UPC code. Each UPC code is 12-digit long and the first 6 to 11 digits are a unique identifier of the firm to which the product belongs ('GCP code'). However, firms can have many GCP codes. To obtain all possible combinations, all GCP codes are collected using the GLN code, issued by GS1 (which also

[25] By construction, Nielsen Homescan focuses on nondurable consumer goods, so most apparel, electronics and home furnishing purchases may not be recorded.

Table A.1
Example of a product in the data.
Details of 'NESTLE USA 8.47 OZ (240g) Nescafe Frothe Latte Coffee Drink'.

Compustat identifier	GS1 identifier	product identifier	product department	product group	product module	product brand
(6 digits)	(13 digits)	(12 digits)	DRY GROCERY	CANDY	CANDY – CHOCOLATE	HERSHEY'S KISSES

manages the issuance of the UPC codes). The GLN code is used to identify physical locations or legal entities of the firms. The key is 12 digits long and comprises a GS1 Company Prefix, Location Reference, and Check Digit. Both the GCP code as well as the GLN codes are obtained from the GEPIR database provided by POD, which additionally contains the full name and the address of each firm. Overall, the POD database is able to match 3.4 millions UPCs ($\approx$ 78% of all available products and $\approx$ 96% of product data available in the consumer panel files) which belong to 51,592 firms (37,492 firms in the panel data).

Table A.2 contains the summary statistics of firm-level number of products per category. It indicates the large degree of heterogeneity in the data: while an average firm owns roughly 8.82 products, a typical (median) firm owns only 2. Similar conclusions can be drawn from looking at other classifications of products.

Table A.2
Summary statistics of different product classifications.
Each classification contains data from 37,492 uniquely identified firms in Nielsen Homescan.

	mean	sd	q1	med	q3	min	max
# UPCs	63.8	493.43	2	5	17	1	36352
# brand-modules	8.82	37.28	1	2	5	1	1738
# brands	4.67	17.69	1	1	3	1	1126
# product modules	4.83	22.62	1	2	3	1	795
# product groups	2.44	5.12	1	1	2	1	111
# departments	1.37	0.89	1	1	1	1	11

3. Merging with Compustat

The matched firm-product data can be merged with accounting data from Compustat by using text matching of firm names. However, many public firms own multiple subsidiaries and the firm-product data could thus contain their name rather the one of the ultimate parent. For example, in the data P&G directly 'owns' most if not all of the products while Newell Brands only owns its products through some of the 121 subsidiaries. As such, we obtain the names of subsidiaries of each firm in Compustat from Capital IQ.

The text matching procedure is conducted using fuzzy merging based on several 'similarity' functions and the matches were manually verified. The matching scores are based on GEDSCORE, SPEDIS and % of the same 3-character combinations of one company name in the other. All punctuation, special characters and common words are removed before conducting the comparison. After the merge, we manually add firms with at least 200 UPC codes to the data (out of all unmatched firms with more than 800 UPC codes – 477 firms – 15% turned out to be public or subsidiaries of public firms). In total, we was able to merge 1376 GLN-level firms (or subsidiaries) from the firm-product data, which correspond to 720 US-headquartered Compustat firms.

To verify that the matching procedure is reasonable, we analyze the 'sales share', i.e. the ratio of the projected sales (to the whole US; computed using the projection factors in the data) of each matched Compustat firm-quarter to its actual sales in that quarter, which are available in the data. We only focus on 2-digit SIC industries with at least two matched firms. Table A.3 contains the summary statistics on sales share for the whole sample as well as for 2-digit SIC industries.

Table A.3
Sales' shares of matched firms.
The table presents summary statistics concerning the sales' shares of matched firms, computed as the ratio of the projected sales of each matched Compustat firm-quarter to its actual sales in that quarter. All variables are winsorized at 2.5% and 97.5% percentile.

	mean	sd	p25	median	p75	N
Agricultural Production - Crops	0.530	0.221	0.316	0.529	0.723	110
Food & Kindred Products	0.580	0.469	0.221	0.487	0.797	2573
Tobacco Products	0.181	0.093	0.099	0.141	0.264	118
Chemical & Allied Products	0.503	0.564	0.103	0.263	0.861	616
Rubber & Miscellaneous Plastics Products	0.608	0.632	0.076	0.419	1.106	123
Electronic & Other Electric Equipment	0.369	0.339	0.098	0.264	0.469	206
Total	0.542	0.481	0.173	0.404	0.784	3746

Table A.3 suggests that not all industries are equally well-represented in the data. For example, Agriculture and Food industries are relatively well matched. Other industries, such as Electronic and Chemicals, are characterized by large degree of within-industry dispersion in sales share. This is partially related to the fact that AC Nielsen data focuses on particular product categories, which are only partially present in some industries (e.g. one could think about Procter and Gamble, whose product portfolio is relatively well-captured in the data, but which is primarily in the Chemicals sector also containing other firms with low sales share). However, the matched sample contains primarily firms from the 'food' industry, which comprises two SIC2 codes: 01 and 20, and these firms rely heavily on the retail channel in generating sales.

4. Sample selection

To refine the data for further empirical analysis, we first apply the standard Compustat data filters: we remove firms with missing data on any variables used in structural estimation, market-to-book larger than 15 or negative book equity. Based on the matched sample, we remove all financial conglomerates (SIC$\geq$ 6000). We require that firm's projected sales share (that is, the ratio of Homescan-based sales to accounting measures of sales reported in Compustat) be at least 5% and no more than 150% of its total sales on average. Moreover, we only keep firms in industries in which the average projected sales share is at least 10%. We also remove all firms which have on average less than 20 UPC codes. Even though we control for the sales share in the empirical analysis, this filter is important as it disposes of firms that do no rely on retail channel (so the main mechanism is unlikely to matter) or that were plausibly mismatched. As an example, this filter removes firms such as American Crystal Sugar Co or Archer-Daniels-Midland Co. for whom the retail channel is clearly of secondary if not tertiary importance. Another example of such a firm would be Amazon, which oftentimes sell own products in retail stores, but these do not constitute the main source of revenues for Amazon. Finally, we winsorize the remaining data at 2.5% and 97.5% level. The final sample spans 2004Q1 to 2017Q4 and contains 2,366 firm-quarter observations.

Appendix B. Data and stylized facts

1. *Definitions of variables*

This section presents the definitions of variables used throughout the paper.

1. **Product portfolio age** – weighted share of old products in the portfolio:

$$\text{age}_{it} = \frac{\text{weighted \# of products with age exceeding 50\% of lifespan}(it)}{\text{total \# of products}(it)}, \tag{20}$$

   where the weights correspond to product-specific revenues.

2. **Product portfolio size** – effective number of products at level x, $x \in [\text{upc}, \text{bm}]$:

$$eff\_no\_prod_{it} = 1/rc\_x_{it}, \tag{21}$$

   where rx_x is the revenue concentration at level x:

$$rc\_x_{it} = \frac{H_{it} - 1/N_{it}}{1 - 1/N_{it}}, \text{ with } H_{it} = \sum_{x=1}^{N_{it}} \left(\frac{r\_sale_{xt}}{\sum_{x=1}^{N_{it}} r\_sale_{xt}} \right)^2, \tag{22}$$

   where r_sale_{xt} are the estimated aggregate retail sales for each $x \in \{\text{upc}, \text{bm}\}$ product at time t. To see where the measure for the effective number of products stems from, suppose that a firm supplies N products. Then its revenue concentration is $rc = \sum_{i=1}^{N} s_i^2$, where s_i is the share of product i in the firm's sales. Assuming all products provide equal revenue, their revenue share is $s_i = s = 1/N$, thus the HHI is now $rc = \sum_{i=1}^{N} 1/N^2 = N/N^2 = 1/N$, which implies that we can back out the 'effective' number of products as $eff\_no\_prod = 1/rc$.

3. **Product portfolio adjustments** – net product entry:

$$ne_{it} = (\text{\# prod. introductions}(it) - \text{\# prod. withdrawals}(it))/\text{total \# prod.}(it), \tag{23}$$

   where an 'introduction' indicates a new product that has never been offered by firm i before time t and a 'withdrawal' indicates that a product was no longer supplied by firm i after time t. We also consider net product creation:

$$nc_{it} = (\text{rev. of entering prod.}(it) - \text{rev. of exiting prod.}(it))/\text{total rev.}(it), \tag{24}$$

where an 'entry' indicates an introductions of a new product that has never been offered by firm i before time t and an 'exit' indicates a product that was no longer supplied by firm i after time t.

4. **Market-to-book**: book value of debt plus market value of equity over total assets.
5. **Investment**: capital expenditure minus asset sales over gross PPE.
6. **Net book leverage**: book debt minus cash and short-term investments over book debt plus book equity.
7. **Cash**: cash and short-term investments over total assets.
8. **Firm size**: natural logarithm of real total assets.
9. **Profitability**: operating income over total assets.
10. **Cost of sales**: general and administrative expense over total assets.
11. **Implied competition**:

$$ihhi_{it} = \sum_{m=1}^{M} s_{mit} HHI_{mt}, \tag{25}$$

where $s_{m,i,t}$ is the share of firm's i sales in market m at time t, and $HHI_{m,t}$ is the Herfindahl of market m at time t, computed using *all* firms available in the sample, both public and private.

12. **Firm age**:

$$\text{firm age}_{it} = -\frac{1}{1 + \text{listing age}_{it}}, \text{ where listing age}_{it} = t - t_{i0}, \tag{26}$$

with t_{i0} being the first appearance of firm i in CRSP, as in Pástor and Veronesi (2003) or Loderer et al. (2017).

13. **Cash flow volatility**: the rolling standard deviations of profitability, computed over the past 8 quarters.
14. **Log sales**: natural logarithm of real sales.
15. **Log product sales**: natural logarithm of the real estimated product sales.

16. **Product durability**: average calendar age of products at exit.

Appendix C. Structural estimation

We follow Lee and Ingram (1991) when estimating the model using structural method of moments. As in Hennessy and Whited (2007), we extract as much of observed heterogeneity from data as possible to make the model- and data-implied moments comparable, that is we use within-transformed variables to compute all moments except for means, which are computed using the raw data. Let the pooled time series of all firms be $x_i = x_1, \ldots, x_N$, where $N = n \times T$ is the total number of firm-year observations. Using the transformed data, we compute a set of moments $h(x_i)$.

We create the simulated moments by first solving solving the model given a vector of parameters $\beta = (\theta, \sigma, \rho, \psi, \eta, \omega, \xi)$ and then generating simulated data y from the model. We simulate $S = 10$ datasets of $N = 2,000$ firm-quarters, following Michaelides and Ng (2000), who find that a simulation estimator behaves well in finite samples if the simulated sample is approximately ten times as large as the actual data sample. The resulting moments in a given simulated sample are given by the vector $h(y_s, \beta)$.

The simulated methods of moments estimator $\widehat{\beta}$ is then the solution to

$$\widehat{\beta} = \arg\min_{\beta} \left[g(x) - g(y, \beta)\right]' W \left[g(x) - g(y, \beta)\right], \tag{27}$$

where $g(x) = \frac{1}{N}\sum_{i=1}^{N} h(x_i)$ and $g(y, \beta) = \frac{1}{S}\sum_{s=1}^{S} h(y_s, \beta)$ are the sample means of the actual and model-implied data, and W a positive definite weight matrix. We use the optimal clustered weight matrix constructed as in Bazdresch, Kahn, and Whited (2017). We use simulated annealing to find the optimum to the minimization problem.

Under mild regularity conditions, the SMM estimator is asymptotically normal

$$\sqrt{N}(\widehat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0, V), \tag{28}$$

where V is the covariance matrix adjusted for sampling variation induced by estimating a number of parameters outside of the model, see Newey and McFadden (1994).

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Table 1
Comparison of product characteristics across different samples.

The table compares product characteristics in the Nielsen Homescan (NH) sample, the sample of public firms and the sample of firms used in the paper. Market shares are computed at the market level. Net product entry is the difference between the share of entering products in a firm's product portfolio and the share of exiting products. Net product creation is the difference between the share of the revenues of the entering products in a firm's product revenue and the share of the revenue of the exiting products. Share of aggregate revenue (all UPCs) is the portion of aggregate product revenue (aggregate number of UPCs) that can be attributed to each subsample. Establishments are firms identified in NH. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

	NH	Public	Sample
Average # of UPCs	63.8	707.5	441.1
Average # of brand-modules	8.8	49.1	49.0
Average # of markets	2.4	7.4	6.9
Average market share (all markets)	0.4%	1.4%	2.3%
Average net product entry	0.7%	0.4%	0.2%
Average net product creation	0.5%	0.2%	0.1%
Share of aggregate revenue	100%	47.9%	22.5%
Share of all UPCs	100%	16.7%	7.3%
# establishments	37492	1376	403
# public firms		720	108

Table 2

Summary statistics of product portfolio and firm characteristics.

Age is the share of old products in product portfolio, that is those exceeding half of their lifespan. Size is the number of products in product portfolio. Adjustments is the net product entry, that is the difference between the share of entering products in a firm's product portfolio and the share of exiting products. Market-to-book is the market value of equity plus book value of debt over total assets. Investment is capital investment over gross plant, property and equipment. Book leverage is book debt over total assets. Cash is cash and short-term investments over total assets. Firm size is the log of deflated total assets. Firm age is defined as in Loderer et al. (2017). Profitability is operating profits over total assets. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

Panel A: summary statistics

	age	size	adjustments	market-to-book	investment	book lev.	cash	firm size	profitability	firm age
mean	0.445	62.822	0.002	1.882	0.021	0.265	0.090	7.601	0.040	-0.067
median	0.405	37.726	0.000	1.609	0.017	0.272	0.056	7.874	0.038	-0.036
std. dev.	0.324	60.306	0.071	1.110	0.016	0.169	0.095	2.141	0.024	0.076
N	2366	2366	2366	2366	2366	2366	2366	2366	2316	2360

Panel B: pairwise correlations

	age	size	adjustments	market-to-book	investment	book lev.	cash	firm size	profitability	firm age
age	1									
size	-0.063	1								
adjustments	-0.022	-0.028	1							
market-to-book	0.057	0.074	0.061	1						
investment	-0.072	-0.081	0.043	0.215	1					
book leverage	0.065	0.287	-0.062	-0.146	-0.067	1				
cash	0.013	-0.281	0.045	0.404	0.146	-0.506	1			
firm size	0.010	0.430	-0.0161	-0.008	-0.063	0.364	-0.210	1		
profitability	-0.037	0.120	0.068	0.611	0.107	-0.132	0.300	0.111	1	
firm age	0.030	0.131	-0.019	0.035	-0.123	-0.105	-0.011	0.191	0.118	1

Table 3
The effect of product introductions on cash flow.

The table shows the change in average profitability, log sales, and log product sales when introducing new products today relative to no product introductions, while controlling for firm and time fixed effects. Product introductions are measured by increases in the number of UPC codes. The 'dummy$^+$' row treats all product introductions equally. The below/ above median$^+$ rows split product introductions into two equally-sized groups. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

Panel A: Log sales			
	t	$t+4$	$t+8$
dummy	4.2%	3.7%	3.3%
below median$^+$	2.6%	2.6%	2.6%
above median$^+$	5.9%	5.1%	4.0%

Panel B: Log product sales			
	t	$t+4$	$t+8$
dummy	12.5%	11.3%	10.3%
below median$^+$	7.6%	5.8%	4.5%
above median$^+$	18.0%	17.4%	16.5%

Panel C: Profitability			
	t	$t+4$	$t+8$
dummy	4.0%	2.5%	3.8%
below median$^+$	2.7%	0.9%	3.3%
above median$^+$	5.5%	5.2%	3.4%

Table 4

Structural estimates and model-implied moments.

The table reports the structural estimates and the model-implied moments. The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. Panel A reports the simulated and actual moments, while Panel B the the estimated parameters and their standard errors. Standard errors are clustered at firm-level. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Moments

	Simulated	Actual	t-stat
Mean operating profits	0.0390	0.0401	0.5259
Variance of operating profits	0.0010	0.0009	-0.3700
Serial correlation of operating profits	0.2401	0.2093	-0.2749
Mean investment	0.0204	0.0212	0.5619
Variance of investment	0.0004	0.0006	2.1910
Serial correlation of investment	0.1740	0.1742	0.0024
Mean net leverage	0.2428	0.1716	-2.7116
Variance of net leverage	0.0087	0.0093	0.4914
Serial correlation of net leverage	0.6424	0.7848	3.0527
Mean old product share	0.4301	0.4444	1.3965
Variance of old product share	0.0823	0.0946	2.4429
Serial correlation of old product share	0.4113	0.4392	0.3108

Panel B: Parameters

Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.6593	0.3457	0.3392	0.0810	0.8786	0.3591	0.0075	0.5282
Std. error	(0.0354)	(0.0284)	(0.0453)	(0.0038)	(0.2613)	(0.0332)	(0.0017)	(0.0518)

Table 5
Structural estimates and model-implied moments: sensitivity to product life cycle.

The table reports the estimation results for subsamples of firms more and less exposed to product life cycle, classified using the firm-specific regression coefficient of product-level revenue on age, while controlling for product-level and cohort-level fixed effects. The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. Panel A reports the simulated and actual moments, while Panel B the estimated parameters and their standard errors, clustered at firm-level. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Moments

	Low sensitivity to PLC		High sensitivity to PLC	
	Simulated	Actual	Simulated	Actual
Mean operating profits	0.0395	0.0428	0.0328	0.0376
Variance of operating profits	0.0008	0.0008	0.0009	0.0011
Serial correlation of operating profits	0.1543	0.1455	0.2067	0.3123
Mean investment	0.0178	0.0190	0.0183	0.0240
Variance of investment	0.0002	0.0003	0.0006	0.0012
Serial correlation of investment	0.0653	-0.0030	0.2805	0.3189
Mean net leverage	0.2096	0.1863	0.1848	0.1565
Variance of net leverage	0.0070	0.0073	0.0039	0.0112
Serial correlation of net leverage	0.6546	0.8056	0.6958	0.7673
Mean old product share	0.4250	0.4248	0.4349	0.4647
Variance of old product share	0.0839	0.0860	0.0842	0.1034
Serial correlation of old product share	0.3832	0.4420	0.4141	0.4367

Panel B: Parameters

Low sensitivity to product life cycle								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.5641	0.3253	0.2167	0.0707	0.5657	0.3140	0.0066	0.6145
Std. error	(0.0469)	(0.0305)	(0.0259)	(0.0033)	(0.1147)	(0.0308)	(0.0005)	(0.0213)
High sensitivity to product life cycle								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.7002	0.3951	0.3197	0.0719	0.4775	0.3173	0.0079	0.5021
Std. error	(0.0547)	(0.0570)	(0.0550)	(0.0077)	(0.3556)	(0.0313)	(0.0016)	(0.1031)

Table 6

Cross-sectional evidence from sample splits.

The table reports the estimation results for subsamples of firms varying according to specific firm characteristics. Panel A presents the results for firms with with small and large product portfolios, classified using the median breakpoint of the effective number of products. Panel B presents the results for firms exposed to more and less competitive product markets, computed using the exposure of each firm's sales to the HHI of each market. Panel C presents the results for firms supplying more and less durable products, computed using the products' average calendar age at exit. Panel D presents the results for firms with higher and lower selling-related expenses, computed using Compustat item `xsga` scaled by total assets. The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. The table reports the estimated parameters, standard errors clustered at firm-level are in parentheses. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Product portfolio size

	θ	σ	ρ	δ	ψ	ω	η	ξ
Smaller	0.7062	0.3294	0.1070	0.1041	0.5509	0.2385	0.0096	0.4334
	(0.0383)	(0.0452)	(0.0196)	(0.0086)	(0.1087)	(0.0428)	(0.0017)	(0.0547)
Larger	0.6636	0.2610	0.2799	0.0773	0.5967	0.3043	0.0053	0.6141
	(0.0520)	(0.0237)	(0.0620)	(0.0028)	(0.1996)	(0.0291)	(0.0007)	(0.0213)

Panel B: Product market competition

	θ	σ	ρ	δ	ψ	ω	η	ξ
Competitive	0.7457	0.3558	0.3802	0.0810	0.6455	0.3429	0.0064	0.4484
	(0.0452)	(0.0404)	(0.0997)	(0.0056)	(0.1711)	(0.0397)	(0.0010)	(0.0535)
Concentrated	0.5873	0.1878	0.2813	0.0865	0.5315	0.2720	0.0063	0.6310
	(0.0347)	(0.0237)	(0.0614)	(0.0056)	(0.0953)	(0.0269)	(0.0012)	(0.0575)

Panel C: Product durability

	θ	σ	ρ	δ	ψ	ω	η	ξ
Lower	0.6473	0.2238	0.2905	0.0904	0.4003	0.3757	0.0067	0.6004
	(0.0429)	(0.0423)	(0.0846)	(0.0031)	(0.1271)	(0.0368)	(0.0011)	(0.0705)
Higher	0.7113	0.2299	0.3270	0.0926	0.6709	0.3104	0.0091	0.4208
	(0.0434)	(0.0373)	(0.1130)	(0.0069)	(0.0990)	(0.0367)	(0.0010)	(0.0277)

Panel D: Cost of sales

	θ	σ	ρ	δ	ψ	ω	η	ξ
Lower	0.7203	0.1283	0.1897	0.0708	0.8094	0.4248	0.0080	0.4114
	(0.0743)	(0.0556)	(0.0356)	(0.0056)	(0.2971)	(0.0355)	(0.0012)	(0.0588)
Higher	0.6050	0.3756	0.1294	0.0822	0.3190	0.3330	0.0087	0.5586
	(0.0390)	(0.0334)	(0.0542)	(0.0086)	(0.2499)	(0.0334)	(0.0026)	(0.1030)

Table 7

Counterfactual experiments.

The table reports the outcomes of alternative model parametrizations, resulting from varying the product introduction cost η (first panel), the old-product specific revenue discount ξ (second panel), and the individual-product transition probabilities p and q (third panel). The first column reports the % change in the average market-to-book relative to baseline estimation results, the three following columns the correlation between product portfolio age and market-to-book, investment, and leverage, respectively, and the last column the % change in the average debt capacity (measured as the difference between maximum debt capacity ωK and current net debt, both as a fraction of capital) relative to baseline estimation results.

	%Δ firm		Corr(·, age)		%Δ debt
	value	mtb	inv	lev	capacity
Baseline	0.00%	-0.208	-0.088	-0.060	0.00%
Old product generates no revenue $\xi = 0$	-3.55%	-0.045	-0.044	-0.201	117.54%
Old and new products are the same $\xi = 1$	4.48%	0.000	0.000	-0.009	-61.41%
50% lower product introduction cost η	9.14%	-0.113	-0.090	0.000	11.38%
50% higher product introduction cost η	-5.72%	-0.231	0.004	-0.171	-43.59%
New product immediately becomes old $p_{n\to o} = 1$	-10.71%	-0.203	0.081	0.090	-59.40%
Old product immediately exits $q_{o\to e} = 1$	-3.03%	0.009	-0.019	-0.154	-62.73%

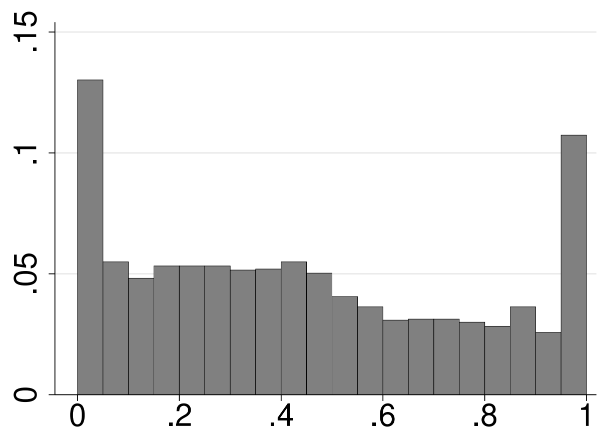


Fig. 1. Histogram of product portfolio age. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

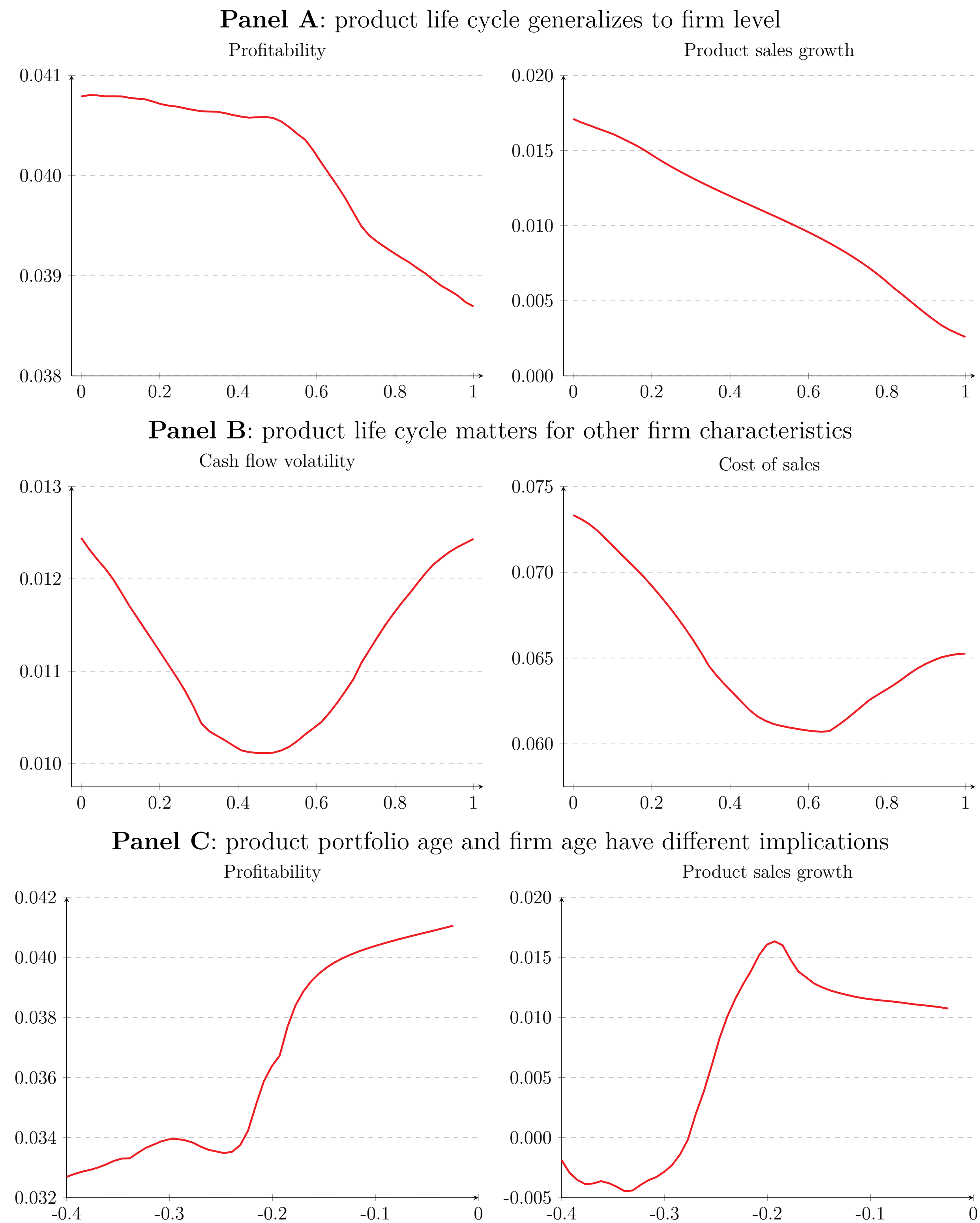


Fig. 2. Product portfolio age, firm age and firm characteristics. The figure shows how profitability and product revenue growth change with product portfolio age (Panel A) and firm age (Panel C) and how cash flow volatility and cost of sales relate to product portfolio age (Panel B). The solid lines are obtained from local polynomial regressions of each variable on the product portfolio age or firm age proxy using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

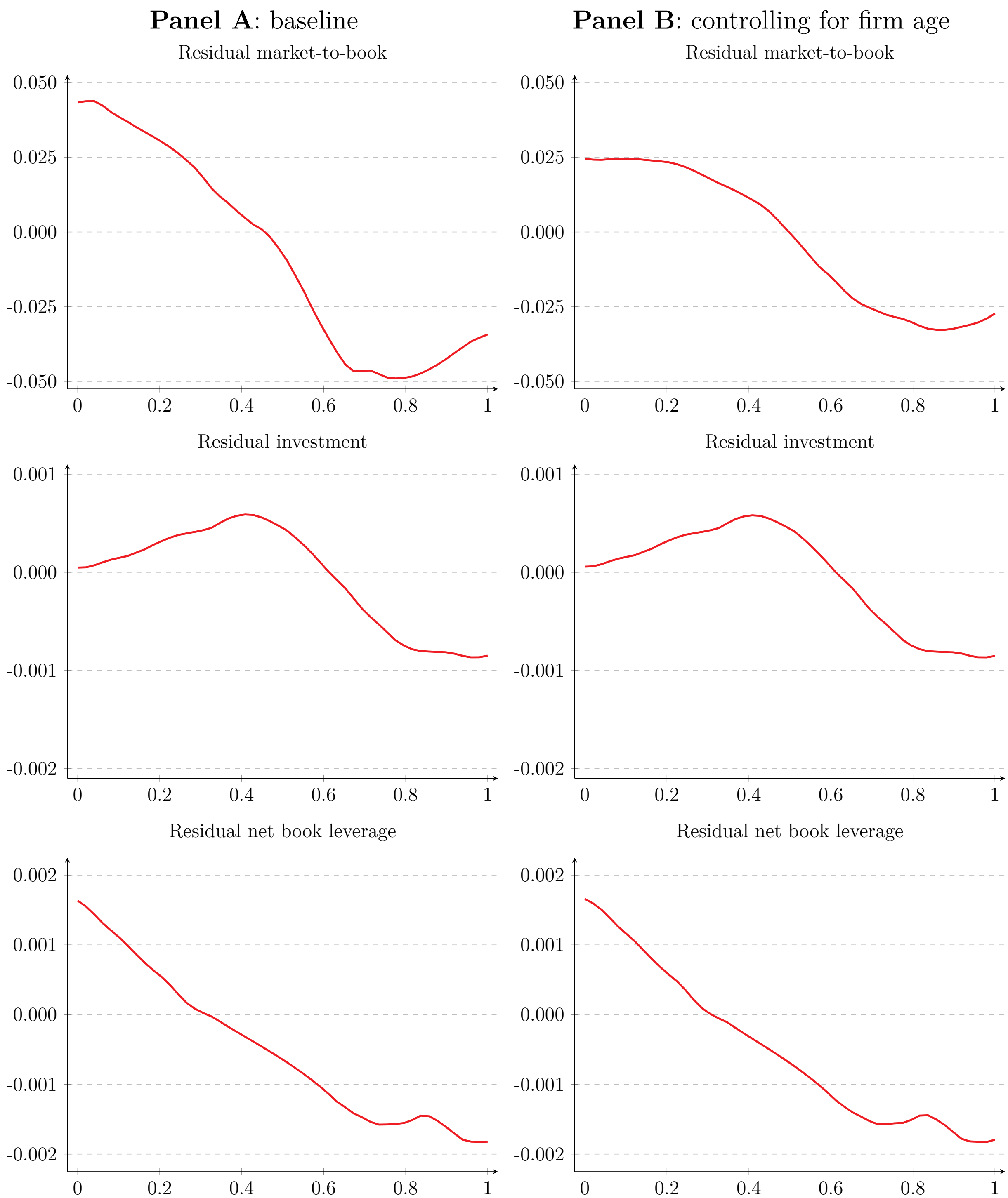
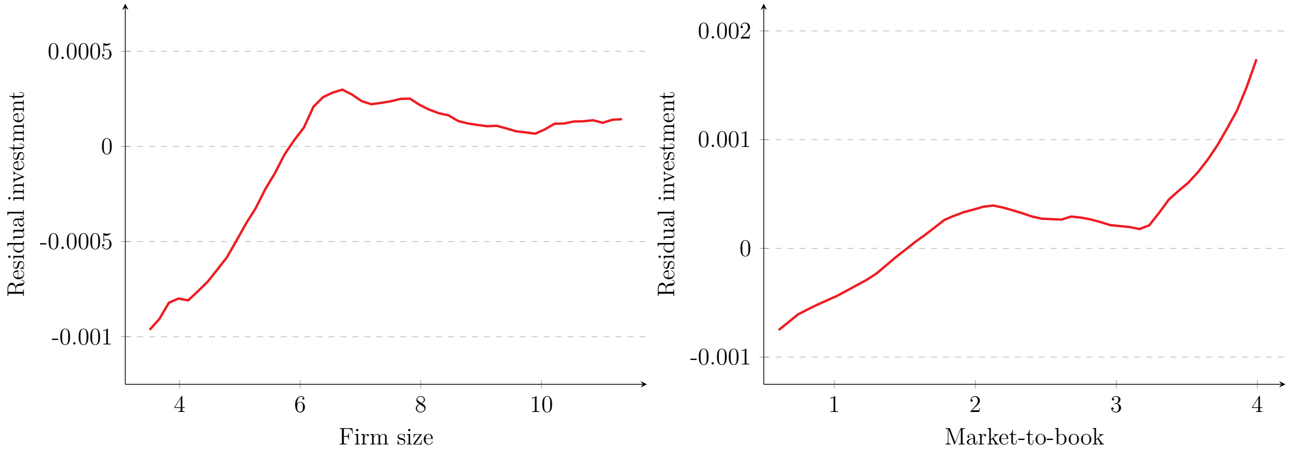


Fig. 3. The relationship between product portfolio age and firms' unexplained market-to-book, investment and leverage. The solid lines are obtained from local polynomial regressions of each variable on the product portfolio age proxy using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. The controls used to compute the predicted values in Panel A include profitability, investment, leverage, size, cash flow volatility for market-to-book, profitability, size, cash flow volatility, market-to-book and tangibility for leverage, and size, cash flow, and market-to-book for investment. The controls in Panel B also include firm age. All models control for firm and time fixed effects. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

Panel A: Investment residuals



Panel B: Leverage residuals

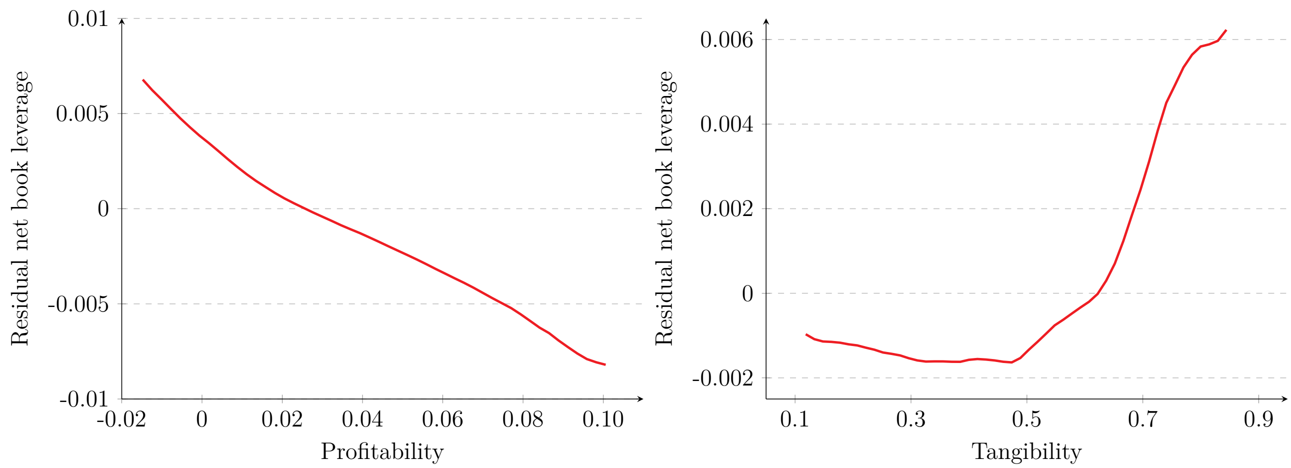


Fig. 4. Assessing the significance of product portfolio age for corporate policies. All graphs are obtained from local polynomial regressions of the residuals from an investment (or leverage) regression on a given variable, using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. The controls used to compute the investment residuals include size, cash flow, and market-to-book. The controls used to compute the leverage residuals include profitability, size, cash flow volatility, market-to-book, share of old products, and tangibility for profitability and profitability, size, cash flow volatility, market-to-book, and share of old products for tangibility. All regression models control for firm and time fixed effects. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

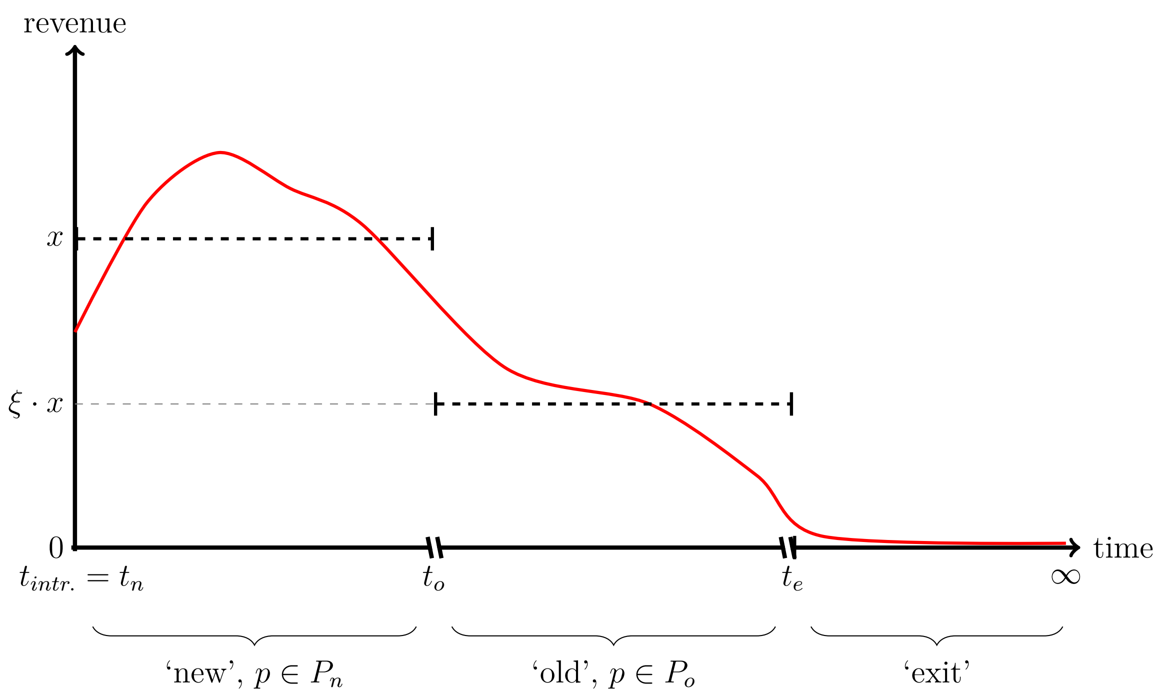


Fig. 5. Graphical representation of each product's evolution in the model.

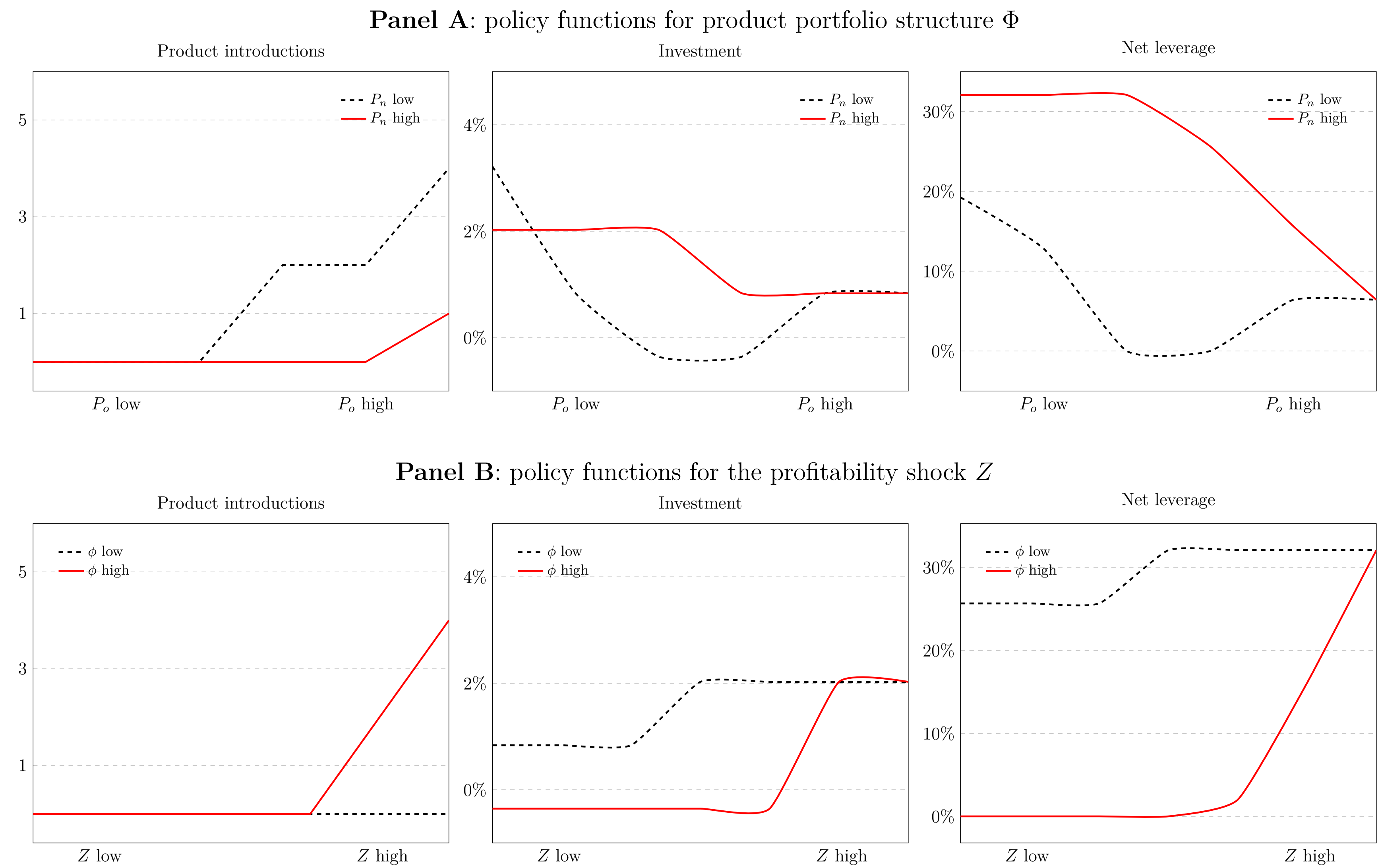
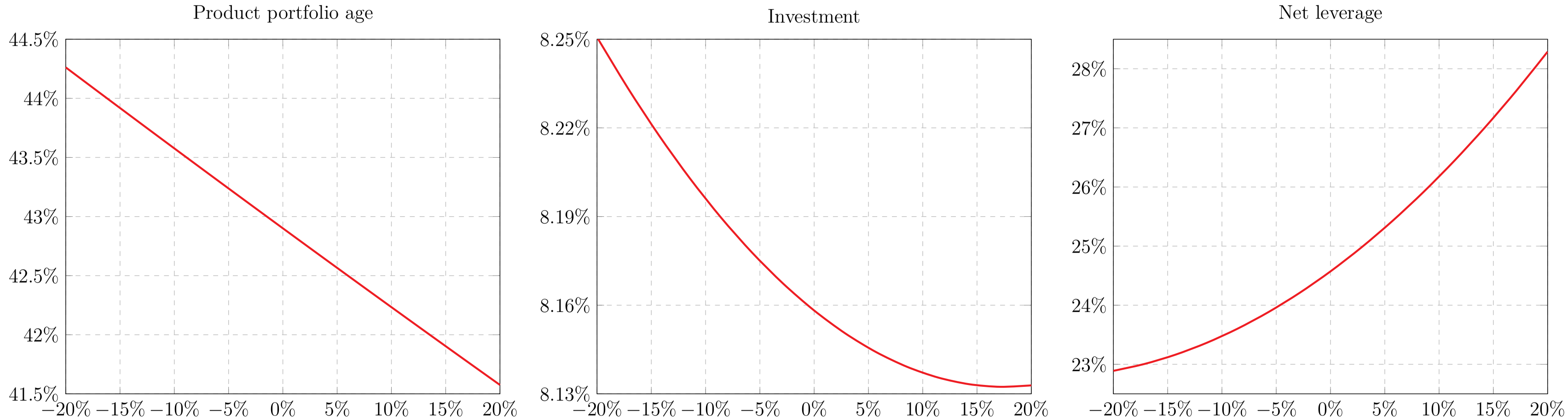


Fig. 7. Numerical policy functions for the product portfolio structure Φ and the profitability shock Z. In Panel A, the policy functions are computed for the baseline parameter estimates and average values of capital, debt, and profitability shock. In Panel B, the policy functions are computed for the baseline parameter estimates and average values of capital and debt.

Panel A: old product-specific revenue discount ξ



Panel B: probability of old product exit $q_{o \to e}$

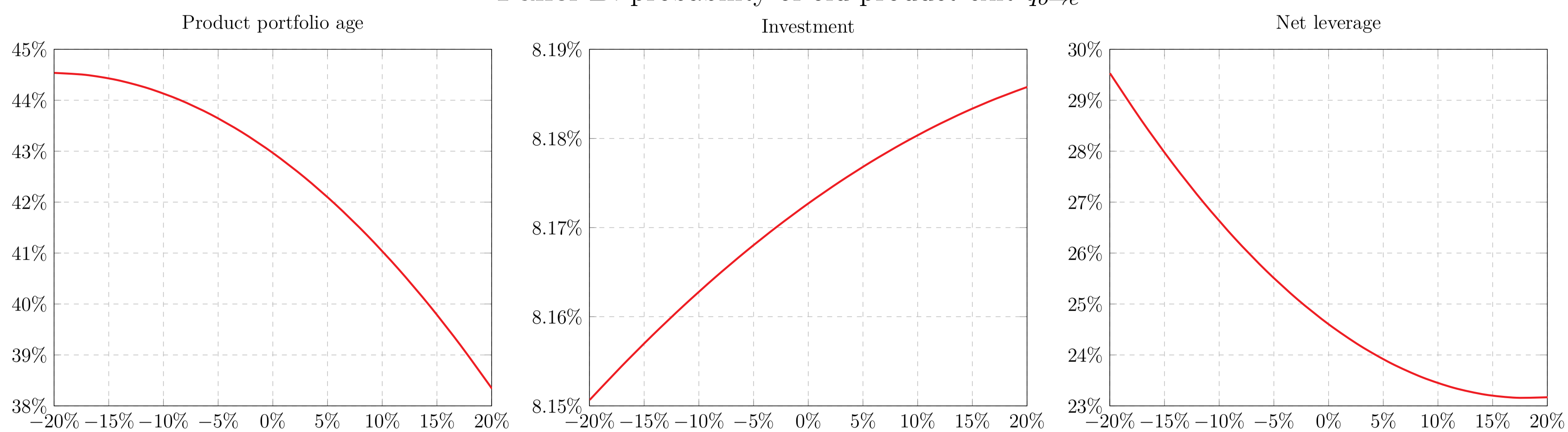


Fig. 8. Comparative statics of product-related parameters. Each point on the curve corresponds to the value of a given moment from a counterfactual experiment, starting from the baseline estimates of structural parameters and changing only the respective parameter by 20% up and 20% down. Each curve is a polynomial interpolation of moments from a discrete set of counterfactual experiments.

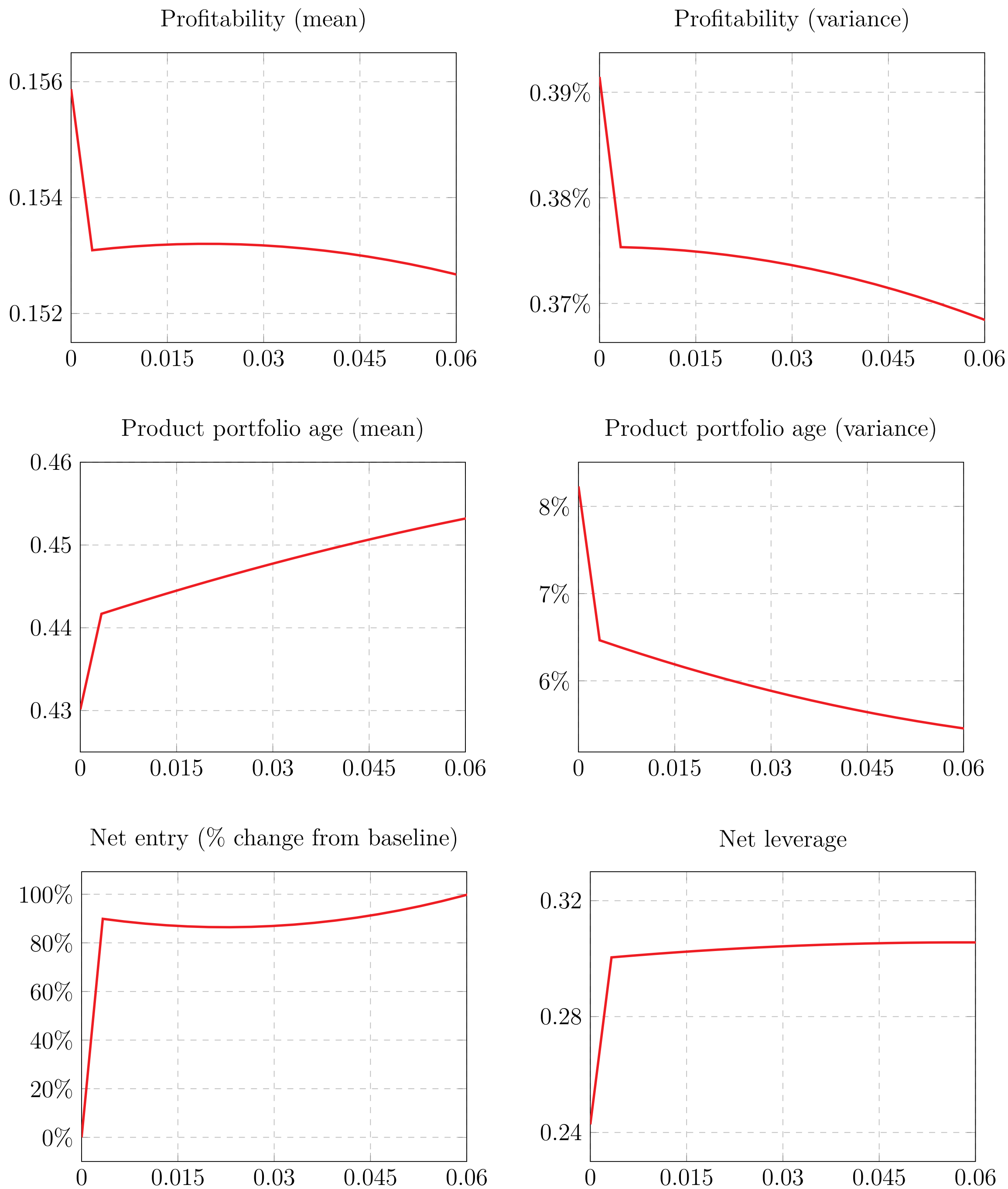


Fig. 9. The effects of cannibalization. Comparative statics of the cannibalization parameter ϵ. Each point on the curve corresponds to the value of a given moment from a counterfactual experiment, in which the baseline estimates of structural parameters are retained while changing only the cannibalization parameter ϵ. Except for the point corresponding to $\epsilon = 0$, each curve is a polynomial interpolation of moments from a discrete set of counterfactual experiments.

Internet Appendix to the paper Product Market Strategy and Corporate Policies*

December 23, 2020

Internet Appendix

The Internet Appendix consists of three sections. Section A contains the analysis of product characteristics other than product portfolio age, additional empirical results, and robustness checks. Section B provides additional details regarding the solution of the model. Section C provides more detail on the estimation procedure and contains in-depth estimation results.

Internet Appendix A. Data and stylized facts

1. Robustness: defining product portfolio age

Table A.1 documents that the stylized fact about investment and product portfolio age is qualitatively robust to adopting a different definition of a product or a different definition of product portfolio age.

*Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at 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 researcher(s) 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.

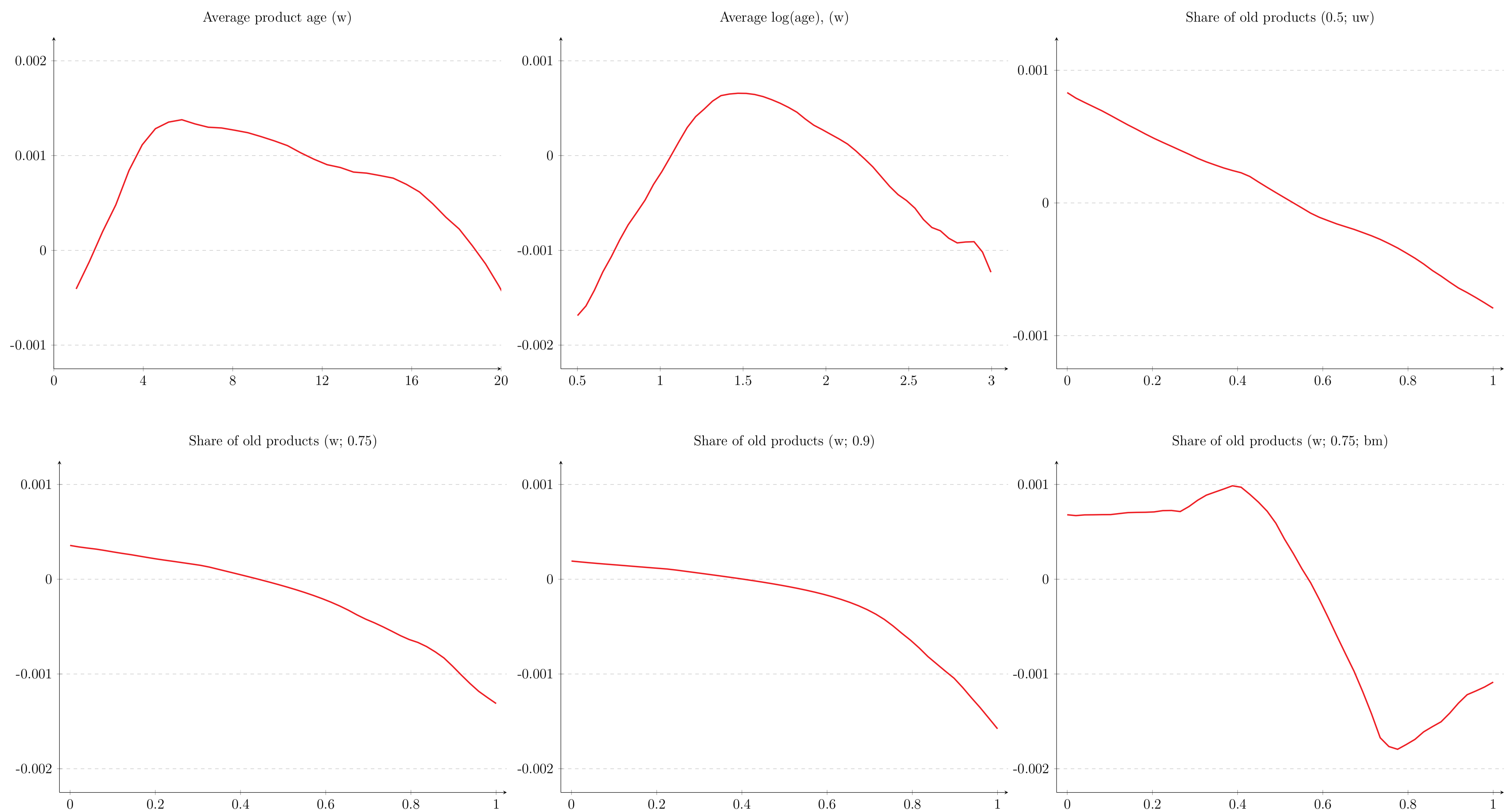


Fig. A.1. Robustness check: defining product portfolio age. Each graph is obtained from local polynomial regression of the residuals from an investment regression on a given product portfolio age variable, using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. The controls used to compute the investment residuals include size, cash flow, and market-to-book. w indicates that product-level revenue weights were used (uw - not used). $0.5, 0.75, 0.9$ are the tresholds used to define an old product, i.e. one that exceeds 50%, 75% and 90% of its lifespan, respectively. bm indicates that brand-module level was used rather than UPC-level. Appendix B provides a description of all variables.

2. Further evidence about product portfolio characteristics

In this part of the appendix we investigate basic empirical relationships between three product portfolio characteristics: age, size, and adjustments, and corporate policies.

The first column of Fig. A.2 documents that product portfolio age is largely negatively related to firm value, except for the firms with oldest product portfolios which are also predominantly riskier. Capital investment tends to decline with product portfolio age, which suggests that investment and product introductions act to a large extent as complements. Finally, leverage is a hump-shaped function of product portfolio age (and cash a u-shaped one), meaning that firms with youngest and oldest product portfolios adopt lower leverage ratios. It should be noted, however, that these relationships are 'contaminated' by other firm characteristics. For example, the fact that leverage initially increases with product portfolio age could be attributed to firm entry and their initial growth, rather than within-firm changes in product portfolio composition. For this reason, in the following subsection we investigate the relationship between product portfolio age and corporate policies in more detail given that this characteristic will be the key ingredient in the model to follow.

We consider the number of products supplied by firms as the measure of their product portfolio size. Firms differ greatly in the number of products they supply: as shown in Table 1, the average number of products is 441. A comparison with Table 2 suggests that not all products are equally important for firms, as the average 'effective' number of products (58) is much lower than the raw one (441). This result indicates that the majority of firms' revenues can be attributed to a small number of products, supporting the notion that product revenues are fairly concentrated. Thus, rather than only using the raw number of products supplied by firms, we focus on the *effective* number of products, equal to the inverse of their product revenue concentration measured using the normalized HHI of each firm's product revenue:

$$\text{portfolio size}_{it} = 1/\tilde{H}_{it}, \text{ with } H_{it} = \sum_{p=1}^{P_{it}} \left(\frac{rev_{pit}}{\sum_{p=1}^{P_{it}} rev_{pit}} \right)^2, \tag{1}$$

where P_{it} is the number of products supplied by firm i in quarter t and rev_{pit} is the revenue of product p. The effective number of products can be interpreted as the number of products

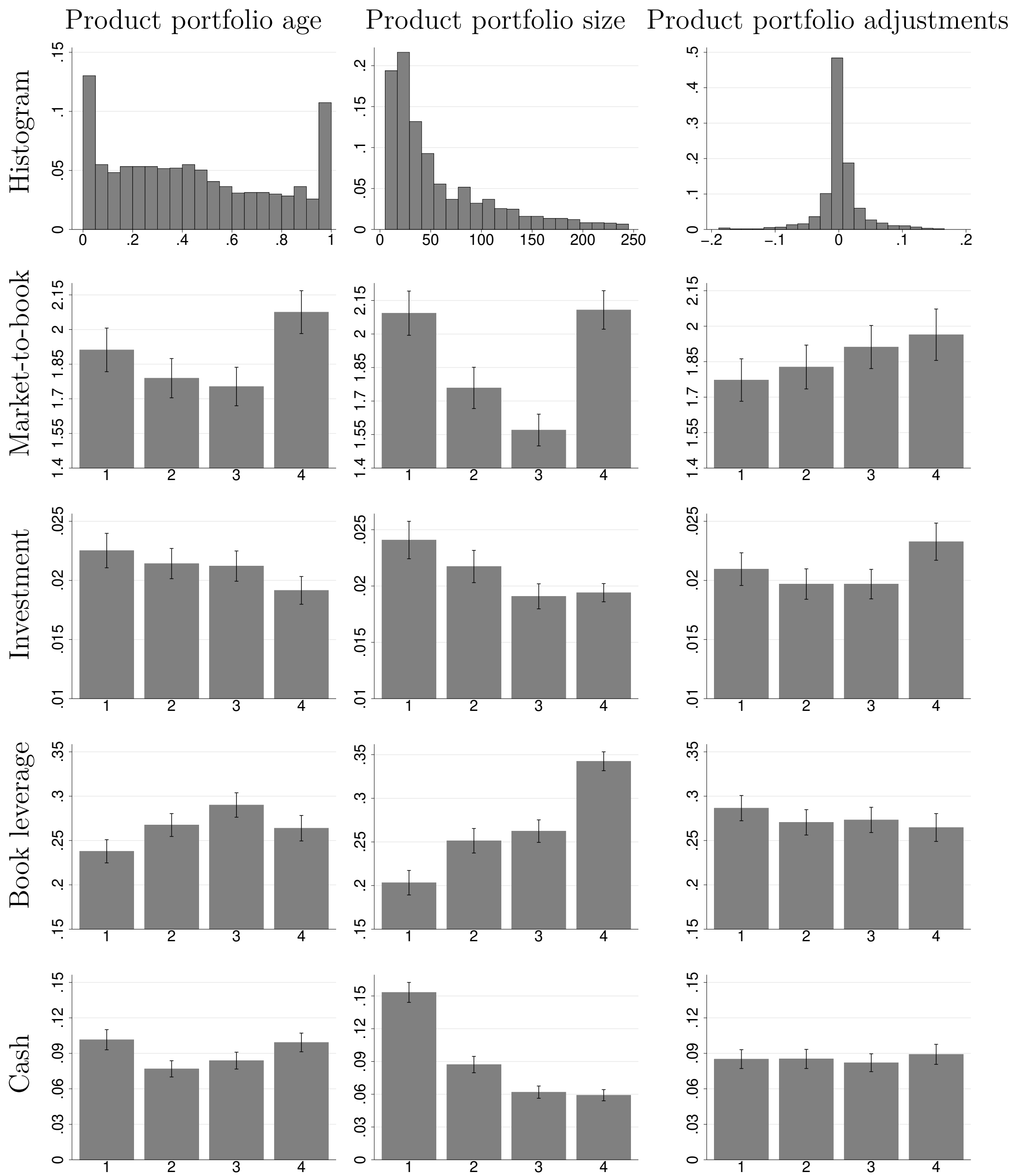


Fig. A.2. Product portfolio structure and the relationship between firms' corporate policies and product characteristics. The first row contains the histograms of product portfolio age, size and adjustments. Rows two to 5 contain the relationship between each product portfolio- and firm characteristic. In each of these graphs, every product portfolio characteristic is divided in four equally-sized bins and the corresponding average firm characteristic in every bin is computed. Each bar contains the 95% confidence interval. Appendix B provides a description of all variables.

supplied by the firm assuming all of its products generate the same revenue. As such, it better reflects the number of products that contribute to the firm's total sales as opposed to the raw number which may contain many small products contributing little. However, the effective number of products also varies substantially across- and within firms, which is documented by its distribution in the top panel of Fig. A.2. Notably, the shape of the distribution of product portfolio size resembles that of firm size, which is intuitive given that firm- and product portfolio size are positively, but not perfectly, correlated ($\rho \approx 0.45$).

We measure the product portfolio adjustments by computing the extent of net product entry, that is the difference between firm-level product entry and exit, similar to to Argente, Lee, and Moreira (2019). Each quarter, we count the share of new products introduced by each firm, that is ones that have never been supplied before, and the share of products that are withdrawn, i.e. that are never supplied again in the future (relative to the total number of products):[1]

$$\text{net entry}_{it} = \frac{\text{weighted \# product introductions}(it) - \text{\# product withdrawals}(it)}{\text{total \# products}(it)}. \qquad (2)$$

The histogram of product portfolio adjustments in the top panel of Fig. A.2 shows that 50% of time firms' product portfolios do not change, which indicates that product portfolio adjustments take place relatively infrequently. This result is 'the other side' of the evidence of Argente et al. (2019), who document that product reallocation is very large in the aggregate: while the average net product entry equals 0.9% per quarter, not all firms adjust their product portfolios all the time. This indicates that a large degree of between- and within-firm variation in product portfolios is necessary to reconcile the two findings. Moreover, in Table 2 we report that the average net entry amounts to 0.26% each quarter, thus more than 3 times lower than the aggregate one, implying that a vast majority of product creation and destruction takes place in private firms. In practice, these numbers correspond to an average sample firm introducing 3.5 products each quarter, which increase its retail sales by roughly 1.2%, suggesting that within-firm product-level dynamics have important implications for cash flow

[1] Given the definition of the proxy, we exclude first- and last year of the data to make sure that product entry and exit are correctly captured.

dynamics.

The second column of Fig. A.2 indicates that firms with smaller product portfolios invest more and adopt lower leverage ratios (or hold more cash) than firms with larger product portfolios. The u-shaped relationship between product portfolio size and market-to-book suggests that firms with many products also have higher valuations. This result is at odds with the standard notion that market-to-book declines with firm size and is consistent with the notion of product portfolio size increasing firms' market power, e.g. through differentiation (e.g. Feenstra and Ma, 2007). The third column of Fig. A.2 shows that firm value increases in the extent of net product entry. This reaffirms the notion that managing product portfolios is important for firms. The graphs also show that firms invest more when withdrawing or introducing new products. This suggests that capital investment could serve as a substitute or a complement for product introductions.

The first column of Fig. A.2 documents that product portfolio age is largely negatively related to firm value, except for the firms with oldest product portfolios which are also predominantly riskier. Capital investment tends to decline with product portfolio age, which suggests that investment and product introductions act to a large extent as complements. Finally, leverage is a hump-shaped function of product portfolio age (and cash a u-shaped one), meaning that firms with youngest and oldest product portfolios adopt lower leverage ratios. It should be noted, however, that these relationships are 'contaminated' by other firm characteristics. For example, the fact that leverage initially increases with product portfolio age could be attributed to firm entry and their initial growth, rather than within-firm changes in product portfolio composition. For this reason, in the following subsection we investigate the relationship between product portfolio age and corporate policies in more detail given that this characteristic will be the key ingredient in the model to follow.

3. A comparison with firm age

Fig. A.3 provides further evidence that product portfolio age and firm age capture different notions of life cycle. While Fig. 3 suggests that both residualized investment and leverage

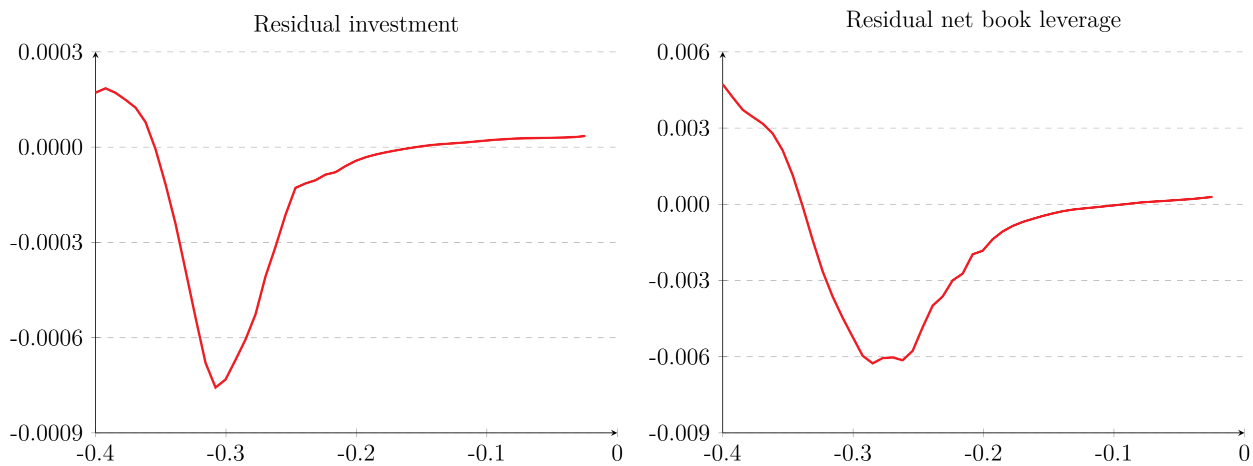


Fig. A.3. Firm age and corporate policies. The figure shows how firms' unexplained investment and leverage change with firm age (defined as in Loderer et al. (2017)). The solid lines are obtained from local polynomial regressions of each variable on the firm age proxy using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. The controls used to compute the predicted values include profitability, size, cash flow volatility, market-to-book and tangibility for leverage, and size, cash flow, and market-to-book for investment. All variables are winsorized at 2.5% and 97.5% percentile. Appendix B provides a description of all variables.

tend to decrease as product portfolio ages, the evidence for firm age is mixed. Whereas for very young firms these policies are also negatively related with age, on average the unexplained parts of investment and leverage tend to increase as firms age. However, only the effect on net leverage is economically meaningful, as the correlation with residual investment is one order of magnitude smaller than that for firm age. This means that product portfolio age provides much more explanatory power in investment regression than firm age does, when controlling for other firm characteristics.

Internet Appendix B. Model solution

1. Product portfolio transition matrix

To get the product portfolio transition matrix T_Φ, we have to consider all possible states of the products in the future $\Phi' = (P'_n, P'_o)$ conditional on $\Phi = (P_n, P_o)$. We know that $P_e = (P'_n + P'_o) - (P_n + P_o)$ products exit. There are 3^2 cases in total to consider. Two examples of how these are computed are as follows, note that for the purpose of computing the transition matrix we also allow old products to transition to being new (which in the main specification is not allowed) hence we need to know both $q_{o\to o}$ and $q_{o\to e}$:

- $P'_n = P_n$ and $P'_o = P_o$:

$$\Pr(\Phi'|\Phi) = \sum_{k=0}^{\min(P_o,P_n)} Bin(\max(P_n-k,0),P_n,p_{n\to n}) \times Trin(k,P_e,P_o,q_{o\to o},q_{o\to e}). \quad (3)$$

- $P'_n = P_n$ and $P'_o < P_o$:

$$\Pr(\Phi'|\Phi) = \sum_{k=0}^{\min(P'_n,P_o-P_e)} Bin(\max(P_n-k,0),P_n,p_{n\to n}) \times Trin(k,P_e,P_o,q_{o\to o},q_{o\to e}). \quad (4)$$

Given that solving the model on the grid means that that the firm can have at most $\bar{P}_n$ new products and $\bar{P}_o$ old products, the transition matrix will be ill-defined in certain states, as the probabilities will not sum to one. To alleviate this issue, we normalize each such state by distributing the residual probability across all states with non-zero probability, with weights proportional to ex ante transition probabilities to these states. The results are qualitatively robust to considering alternative normalization schemes, e.g. attributing the residual probability to current state.

2. Further details on computing the investment Euler equation

To compute the investment Euler equation, we first take the first-order condition of Eq. (12) with respect to K', which yields

$$(1+\Lambda(E(\cdot)))(-1-\Psi_{K'}(K,K')) + \beta\mathbb{E}\left[V_{K'}(K',D',\Phi',Z')\right] = 0 \quad (5)$$

as well as the envelope condition that gives

$$V_K(K,D,\Phi,Z) = (1+\Lambda(E(\cdot)))(1-\tau)[(1-\phi(1-\xi))\theta K^{\theta-1}Z-\eta\Delta_P]+\tau\delta+(1-\delta)-\Psi_K(K,K'). \quad (6)$$

Combining them both yields the investment Euler equation

$$
\begin{aligned}
1 =& \beta \mathbb{E}\left[\mathcal{F}_{\Lambda} \frac{1}{1+\frac{\psi}{2} i}\left((1-\tau) \theta K'^{\theta-1} Z'+1-(1-\tau) \delta+\psi i'\left(\frac{1}{2} i'+1-\delta\right)\right.\right. \\
& \left.\left.-(1-\tau)\left(\phi'(1-\xi) \theta K'^{\theta-1} Z'+\eta \Delta_P'\right)\right)\right],
\end{aligned} \tag{7}
$$

where

$$
\mathcal{F}_{\Lambda}=\frac{(1+\Lambda'(E(\cdot)))}{(1+\Lambda(E(\cdot)))} \tag{8}
$$

is the ‘external financing discount factor,’ see e.g. Eisfeldt and Muir (2016). Thus, the marginal benefit (MB_i) to investment in physical capital and the marginal cost (MC_i) are

$$
\begin{aligned}
MB_i & =(1-\tau) \theta K'^{\theta-1} Z'+1-(1-\tau) \delta+\psi i'\left(\frac{1}{2} i'+1-\delta\right), && (9) \\
MC_i & =1+\psi i, && (10) \\
MB_i^{\Phi}(\cdot) & =-(1-\tau)\left(\phi'(1-\xi) \theta K'^{\theta-1} Z'+\eta \Delta_P'\right), && (11)
\end{aligned}
$$

where $i=I/K$. Thus, we derived Eq. (14).

$$
1=\beta \mathbb{E}\left[\frac{(1+\Lambda'(E(\cdot))}{(1+\Lambda(E(\cdot))}\left(\frac{MB_i}{MC_i}+\frac{MB_i^{\Phi}(K', Z', \Delta_P', \Phi')}{MC_i}\right)\right]. \tag{12}
$$

Verifying that $\partial MB_i^{\Phi}(\cdot)/\partial \phi' < 0$ follows from a direct computation

$$
\frac{\partial MB_i^{\Phi}(\cdot)}{\partial \phi'}=-(1-\tau)(1-\xi) \theta K'^{\theta-1} Z'<0. \tag{13}
$$

Internet Appendix C. Structural estimation

1. Estimation diagnostics

We compute the diagnostic measure of Andrews et al. (2017) to investigate whether the model parameters are locally identified by the underlying moments. The key benefit of the measure is that a reported high sensitivity means not only that the moment is sensitive to the underlying parameter, but also that the parameter is precisely estimated. The results

Table C.1
Local sensitivity of parameters to moments.

The table presents the sensitivities of structural parameters to moments using the normalized diagnostic tool of Andrews et al. (2017). Blank entries indicate sensitivities lower than 0.5 in absolute value. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount.

Moments	θ	σ	ρ	δ	ψ	ω	η	ξ
Mean operating profits	-0.960	-0.542					0.544	
Variance of operating profits		0.650						
Serial correlation of operating profits			0.824				-0.655	
Mean investment	0.805			0.917			-0.686	0.624
Variance of investment	-0.537			-0.512	-0.501			
Serial correlation of investment			-0.591				0.715	
Mean net leverage						0.914		
Variance of net leverage								
Serial correlation of net leverage							0.516	-0.530
Mean old product share			-0.544	0.512				
Variance of old product share			0.521		-0.588			
Serial correlation of old product share								

are presented in Table C.1, in which each column corresponds to a structural parameter and each row to a moment. The sensitivities in the table are trimmed at 0.5 in absolute value to ease the presentation of key relationships, similar to Michaels, Page, and Whited (2018).

The results confirm the intuition behind the identification of the structural parameters. For example, the standard deviation and persistence of the profit shock are sensitive to variance and serial correlation of profitability, the depreciation rate δ is closely linked to the mean of investment and the collateral constraint parameter ω is strongly positively related to the mean of net leverage. More importantly, the product-related moments are sensitive to product characteristics ξ and η. It should be noted, however, that the elasticities are only local and, moreover, highly sensitive to the numerical properties of the gradient. Because of that it might appear that some moments are not informative about the underlying parameter while in reality they do provide substantial identifying information. One example of that are the product introduction cost η and the old-product specific revenue discount ξ: while the Andrews et al. (2017) sensitivities are smaller than 0.5 in absolute value, over a wider range of the parameter values they are substantial. Moreover, the sign and magnitudes of these elasticities for product-related moments are different, in line with the intuition outlined in Section 3.

2. Additional results: sample splits

In this subsection we present additional details concerning the cross-sectional estimates discussed in the main text. In particular, for each sample split we provide the data- and model-implied moments in addition to the structural estimates.

Table C.2

Structural estimates and model-implied moments: product portfolio size.

The table reports the estimation results for subsamples of firms with small and large product portfolios, classified using the median breakpoint of the effective number of products. The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. Panel A reports the simulated and actual moments, while Panel B the estimated parameters and their standard errors. Standard errors are clustered at firm-level. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Moments

	Small product portfolio		Large product portfolio	
	Simulated	Actual	Simulated	Actual
Mean operating profits	0.0441	0.0391	0.0365	0.0415
Variance of operating profits	0.0012	0.0014	0.0005	0.0005
Serial correlation of operating profits	0.1001	0.1005	0.1969	0.4092
Mean investment	0.0265	0.0239	0.0195	0.0190
Variance of investment	0.0009	0.0011	0.0003	0.0003
Serial correlation of investment	0.1904	0.1137	0.1828	0.1573
Mean net leverage	0.1145	0.1022	0.2027	0.2396
Variance of net leverage	0.0080	0.0111	0.0073	0.0062
Serial correlation of net leverage	0.6137	0.7649	0.6327	0.6961
Mean old product share	0.4427	0.4611	0.4310	0.4278
Variance of old product share	0.0825	0.1074	0.0772	0.0736
Serial correlation of old product share	0.4073	0.3897	0.3908	0.6292

Panel B: Parameters

Small product portfolio								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.7062	0.3294	0.1070	0.1041	0.5509	0.2385	0.0096	0.4334
Std. error	(0.0383)	(0.0452)	(0.0196)	(0.0086)	(0.1087)	(0.0428)	(0.0017)	(0.0547)
Large product portfolio								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.6636	0.2610	0.2799	0.0773	0.5967	0.3043	0.0053	0.6141
Std. error	(0.0520)	(0.0237)	(0.0620)	(0.0028)	(0.1996)	(0.0291)	(0.0007)	(0.0213)

Table C.3
Structural estimates and model-implied moments: product market competition.

The table reports the estimation results for subsamples of firms exposed to more and less competitive product markets, computed using the exposure of each firm's sales to the HHI of each market, defined by product groups (see Appendix A). The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. Panel A reports the simulated and actual moments, while Panel B the estimated parameters and their standard errors. Standard errors are clustered at firm-level. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Moments

	More competitive		Less competitive	
	Simulated	Actual	Simulated	Actual
Mean operating profits	0.0335	0.0338	0.0458	0.0469
Variance of operating profits	0.0008	0.0010	0.0004	0.0007
Serial correlation of operating profits	0.2626	0.2141	0.2113	0.2519
Mean investment	0.0208	0.0215	0.0218	0.0210
Variance of investment	0.0007	0.0008	0.0004	0.0004
Serial correlation of investment	0.1882	0.1501	0.1934	0.1634
Mean net leverage	0.2238	0.1820	0.1825	0.1598
Variance of net leverage	0.0084	0.0092	0.0059	0.0077
Serial correlation of net leverage	0.5800	0.8213	0.6076	0.7242
Mean old product share	0.4411	0.4322	0.4312	0.4567
Variance of old product share	0.0789	0.0835	0.0763	0.0848
Serial correlation of old product share	0.3882	0.3198	0.3871	0.3331

Panel B: Parameters

Firms exposed to more competitive product markets								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.7457	0.3558	0.3802	0.0810	0.6455	0.3429	0.0064	0.4484
Std. error	(0.0452)	(0.0404)	(0.0997)	(0.0056)	(0.1711)	(0.0397)	(0.0010)	(0.0535)
Firms exposed to less competitive product markets								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.5873	0.1878	0.2813	0.0865	0.5315	0.2720	0.0063	0.6310
Std. error	(0.0347)	(0.0237)	(0.0614)	(0.0056)	(0.0953)	(0.0269)	(0.0012)	(0.0575)

Table C.4

Structural estimates and model-implied moments: product durability.

The table reports the estimation results for subsamples of firms supplying more and less durable products, computed using the products' average calendar age at exit. The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. Panel A reports the simulated and actual moments, while Panel B the estimated parameters and their standard errors. Standard errors are clustered at firm-level. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Moments

	Less durable		More durable	
	Simulated	Actual	Simulated	Actual
Mean operating profits	0.0422	0.0391	0.0397	0.0412
Variance of operating profits	0.0005	0.0010	0.0006	0.0007
Serial correlation of operating profits	0.2010	0.2224	0.2770	0.0571
Mean investment	0.0230	0.0213	0.0235	0.0212
Variance of investment	0.0006	0.0006	0.0006	0.0006
Serial correlation of investment	0.1480	0.2053	0.2550	0.1980
Mean net leverage	0.2842	0.1574	0.1951	0.1855
Variance of net leverage	0.0047	0.0081	0.0060	0.0086
Serial correlation of net leverage	0.4682	0.8528	0.6066	0.7401
Mean old product share	0.4482	0.4688	0.4188	0.4201
Variance of old product share	0.0948	0.0957	0.0721	0.0742
Serial correlation of old product share	0.3011	0.3026	0.4495	0.8090

Panel B: Parameters

Firms supplying less durable products								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.6473	0.2238	0.2905	0.0904	0.4003	0.3757	0.0067	0.6004
Std. error	(0.0429)	(0.0423)	(0.0846)	(0.0031)	(0.1271)	(0.0368)	(0.0011)	(0.0705)
Firms supplying more durable products								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.7113	0.2299	0.3270	0.0926	0.6709	0.3104	0.0091	0.4208
Std. error	(0.0434)	(0.0373)	(0.1130)	(0.0069)	(0.0990)	(0.0367)	(0.0010)	(0.0277)

Table C.5
Structural estimates and model-implied moments: cost of sales.

The table reports the estimation results for subsamples of firms with higher and lower selling-related expenses, computed using Compustat item `xsga` scaled by total assets. The estimation is done using simulated method of moments, which chooses model parameters by minimizing the distance between the moments from a simulated panel of firms and their data counterparts. Panel A reports the simulated and actual moments, while Panel B the estimated parameters and their standard errors. Standard errors are clustered at firm-level. θ is the production function curvature; σ is the standard deviation of the profitability shock; ρ is the persistence of the profitability process; δ is the capital depreciation rate; ψ is the investment adjustment cost; ω is the parameter governing the collateral constraint; η is the product introduction cost; ξ is the old-product specific revenue discount. Appendix C provides the details about the estimation procedure.

Panel A: Moments

	Lower cost of sales		Higher cost of sales	
	Simulated	Actual	Simulated	Actual
Mean operating profits	0.0307	0.0353	0.0422	0.0447
Variance of operating profits	0.0002	0.0005	0.0012	0.0014
Serial correlation of operating profits	0.3117	0.4049	0.0796	0.1113
Mean investment	0.0178	0.0191	0.0209	0.0233
Variance of investment	0.0003	0.0004	0.0006	0.0009
Serial correlation of investment	0.3123	0.2148	0.2277	0.1962
Mean net leverage	0.2953	0.2179	0.1916	0.1248
Variance of net leverage	0.0044	0.0079	0.0050	0.0091
Serial correlation of net leverage	0.6444	0.7740	0.6749	0.7513
Mean old product share	0.4318	0.4673	0.4381	0.4216
Variance of old product share	0.0780	0.0906	0.0886	0.0867
Serial correlation of old product share	0.4069	0.5927	0.3763	0.3720

Panel B: Parameters

Firms with lower cost of sales								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.7203	0.1283	0.1897	0.0708	0.8094	0.4248	0.0080	0.4114
Std. error	(0.0743)	(0.0556)	(0.0356)	(0.0056)	(0.2971)	(0.0355)	(0.0012)	(0.0588)
Firms with higher cost of sales								
Parameter	θ	σ	ρ	δ	ψ	ω	η	ξ
Estimate	0.6050	0.3756	0.1294	0.0822	0.3190	0.3330	0.0087	0.5586
Std. error	(0.0390)	(0.0334)	(0.0542)	(0.0086)	(0.2499)	(0.0334)	(0.0026)	(0.1030)

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