Product Market Strategy and Corporate Policies*

Job Market Paper

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Abstract

Corporate finance has related corporate policies to cash flow risk. I show that corporate valuation and policies are better understood when taking into account the dynamics of products, which microfound firms' cash flows. I demonstrate empirically that product portfolio age is negatively related to firm value, investment and leverage, consistent with the product life cycle channel. I quantify its importance by estimating a model of financing, investment, and product portfolio decisions. The model rationalizes the stylized facts by showing that capital investment and product introductions act as complements and that product dynamics induce stronger precautionary savings motives. The results indicate that product dynamics are important, as they explain 25% of variation in investment and leverage. The estimates imply that product life cycle effects are large and stronger among firms supplying fewer products and competing more intensely. Alleviating these effects can increase firm value by up to 4.5%.

JEL Classification: G31, G32.

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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 the products in their portfolios every year (Argente et al., 2018).[1] Thus, the large product-level variation is bound to influence cash flow dynamics, and, as such, to impact firms' policies. Moreover, as firms choose not only the product market strategy but also the way in which it is financed and implemented in their real activities, product market strategy must be related to investment and financing decisions.

The importance of product portfolio dynamics, resulting from firms' product market strategies, raises a number of novel questions for financial economists. First, how do firms differ in their product market strategies? Second, through which channels do firms' product decisions influence corporate policies? Third, to what extent do firms' product portfolio choices translate to their investment and financing decisions? Finally, how quantitatively important are product portfolio dynamics for corporate policies?

In this paper, I demonstrate both empirically and quantitatively that corporate valuations and policies are better understood when taking into account product dynamics. First, I describe the empirical relation between firms' product portfolio characteristics and their investment and financing decisions. Second, I develop and estimate a dynamic model to understand the economic mechanisms underpinning the empirical results. By doing so, I document that product dynamics have significant and economically meaningful implications for corporate policies.

I analyze firms' product market strategies by using detailed data on product portfolios of US nondurable consumer goods manufacturers. I focus on three product portfolio characteristics: size, adjustments, and age, which are measured by the number of products, the extent of net product creation, and the share of old products in the portfolio, i.e. those exceeding

[1] Product dynamics contribute much more to macroeconomic fluctuations than the effects of labor markets or establishment entry and exit (Broda and Weinstein, 2010). The large extent of product creation and destruction can be attributed to product life cycle, which results in firms having to constantly introduce new products and withdraw old ones, as firms' growth crucially depends on either developing current product lines or introducing novel products (e.g. Levitt, 1965, Argente et al., 2019).

half of their lifespan. Product portfolio age is particularly important, given its relation to product life cycle, that is the fact that product revenue declines as it ages (e.g. Argente et al., 2019).

I document that product portfolio age has a sizeable effect on firms' profitability, implying that product life cycle effects translate to the product portfolio level. Crucially, the effect of product portfolio age on revenue is markedly different from that of *firm* age. I also show that the product life cycle channel results in a negative relationship between the market-to-book ratio and product portfolio age. This result implies that managing product portfolios has direct implications for firm value. Thus, 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.

I 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. Importantly, 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 a fixed introduction cost. The fact that the firm can adjust the product portfolio's composition has direct implications for cash flow dynamics, and thus connects the firm's real, financial, and product decisions.[2]

The model provides economic rationale to the empirical stylized facts. First, it shows that capital investment and product introductions are complements rather than substitutes, indicating 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 and durability of revenues associated with a younger product portfolio increases its

[2]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, products age affects their revenue as well. However, product introductions are different from capital investment.

incentives to invest in physical capital. However, the firm tends to invest less as its product portfolio ages, because its revenues decline, become more risky, and 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 firm's product portfolio ages, it has stronger motives to preserve its debt capacity. This happens as the firm wants to avoid issuing costly external financing to fill the revenue gap created by old products becoming obsolete. However, the firm 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 dynamics on corporate policies, I 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. I find that the estimated model quantitatively matches key features of the data, particularly firms' product portfolio characteristics. 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 study how the relevance of the product life cycle channel changes along dimensions not explicitly captured by the model, I provide a number of cross-sectional predictions about product life cycle and firms' product market environment. I do so by estimating the model on subsamples of firms varying in the size of their product portfolio and the degree of competitive pressure. I also split firms according to the sensitivity of their products to product life cycle. Thus, I can examine whether the model successfully captures differences across firms' product-level characteristics that are not directly represented in the aggregated firm-level data.

First, I document that firms with smaller product portfolios are more exposed to the product life cycle channel, as they face higher product introduction costs and more pronounced revenue discount associated with old products. Because their profits are 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.

Second, I show that competition can reinforce 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 corporate policies. Thus, the empirical evidence shows that both between- and within-firm product market forces are an important determinant of investment and financing decisions.

Third, I 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 product introductions are complemented 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 settings, despite using data aggregated to firm-level. Overall, the evidence from all the sample splits highlights that the estimated model can provide insights concerning how the interactions of different dimensions of firms' product market strategies affect corporate policies.

Finally, I provide evidence that product dynamics have quantitatively important implications for investment and financing policy. By means of variance decomposition, I show that product decisions explain as much as 25% of the variation in leverage and investment in the model. Product-level economic forces also affect firm value. Counterfactual experiments related to the severity of the product life cycle channel indicate that eliminating the revenue gap between new and old product would increase 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 counterfactuals indicate that managing the life cycle of products, by means of introduction cost or sensitivity to ageing, yields material benefits to firms. I also 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. 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 dynamics are sizeable.

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 et al. (2011), Nikolov and Whited (2014), or Nikolov, Schmid, et al. (2018). I contribute to this literature by explicitly considering firms' product portfolio decisions. In particular, I 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 (2007), Gourio and Rudanko (2014), Clayton (2017), D'Acunto, Liu, Pflueger, and Weber (2018) or Hoberg and Maksimovic (2019). I differ from this literature by focusing explicitly on firms' product market strategy and showing that firms' product portfolio characteristics matter for cash flow dynamics and corporate policies. In that respect, this paper is most closely related to Hoberg and Maksimovic (2019), who infer firms' life cycle stage from its product life cycle and study its implications for investment, and D'Acunto, Liu, Pflueger, and Weber (2018), who show that pricing policy, i.e. one of the dimensions of product market strategy, affects how firms make capital structure decisions.

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, I focus on *within-firm* product market characteristics, that is the product market strategy, rather than *between-firm* effects such as competition and I argue that internal product market setting is an important determinant of corporate investment and financing policy.

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, Hanley, Baslandze, and Moreira (2019) and Argente, Lee, and Moreira (2018, 2019), who study the reasons why firms choose to supply multiple goods. In contrast to these papers, I analyze the corporate finance implications of product portfolio choice.

I. Data and Stylized Facts

In this section, I analyze the empirical relation between characteristics describing firms' product market strategies and corporate policies. I focus on three such characteristics: product portfolio size, frequency of product portfolio adjustments and product portfolio age. I first describe how these are measured, show that they exhibit a large degree of heterogeneity, and document that they are related to firms' investment and financing policies as well as firm value. Next, I focus on product portfolio age, that is closely linked to the notion of product life cycle, which will play the key role in the structural model. The empirical evidence suggests that the product portfolio age dimension has important valuation effects, and that managing product portfolio structure matters for firm value. Finally, I document that both corporate investment and financing policy are negatively related to product portfolio age when controlling for firm characteristics.

A. *Data sources*

I use the data from AC Nielsen Homescan to reconstruct product portfolios of firms supplying the products. The dataset contains information on prices and quantities of retail consumer goods sold in the US over the period of 2004 to 2017. The product data is comprehensive, covering about 66% of CPI expenditures (Broda and Weinstein, 2010), and detailed, as it contains information not only on individual product's prices and quantities sold, but also on product introductions and withdrawals. This allows me to compute the product's exact lifespan, which will be used extensively to compute a measure of product portfolio age. I merge the AC 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.

Defining a product

I focus primarily on the UPC-level definition of a product, as it allows me to investigate the life cycle of each individual product, and thus of product portfolio, that will be the key ingredient in the structural estimation. 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 I study in this paper.[3]

[Table 1 about here.]

Table 1 presents the summary statistics of product characteristics across three different samples: the Nielsen Homescan, the sample of all public firms, and the final sample of firms used in the paper.[4] The table shows that firms vary substantially in the number of supplied products, with an average public firm supplying roughly 11 times more products than an average

[3]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 I revisit the issue of product definition in more detail.

[4]In particular, I remove a number of firms that have been matched but are nonetheless unlikely to be affected by the product channel, as they are not exposed to selling own products. An example of such firm is Amazon, which oftentimes sell own products in retail stores, but these do not constitute the *main* source of revenues for Amazon. Appendix A provides all the details about data processing.

firm in the sample. However, their average net product entry and net product creation rates are lower than those of private firms, given the size of their product portfolios. Table 1 also documents that while public firms account for a much smaller share of all products ($\approx 17\%$), their sales constitute $\approx 48\%$ of total product revenue. This result highlights that analyzing product market strategies of public firms remains of great importance, even though they may not supply the majority of products in the economy.[5]

B. *Product portfolio characteristics*

I focus on three characteristics of firms' product portfolios: size, adjustments and age, that provide information about the scope of product market strategies pursued by firms. In particular, I put special emphasis on product portfolio age, given that it is tightly linked to the notion of product life cycle, which implies a negative relationship between product-specific revenue and age (e.g. Levitt, 1965 or more recently Argente et al., 2019). I show that these product-level dynamics naturally translates to the product portfolio level.

[Table 2 about here.]

Product portfolio size

I consider the number of products supplied by firms as the measure of their product portfolio size. Rather than only using the raw number of products supplied by firms, I 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:

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

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 supplied by the firm assuming all of its products generate the same revenue. As such, it

[5] 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. However, this is no longer true when looking at particular markets, in which often as little as 5 firms enjoy a combined market share of roughly 60%.

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.[6]

The data suggests that firms differ greatly in the number of products they supply: as shown in Table 2, the average number of products is 58. Comparing the definition of product portfolio size to the raw number of products in Table 1 suggests that not all products are equally important, 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. However, the effective number of products also varies substantially across- and within firms, which is documented by its distribution in the top panel of Figure 1. 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 ($\rho \approx 0.45$).

[Figure 1 about here.]

The first column of Figure 1 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).

Product portfolio adjustments

I 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 et al. (2019). Each quarter, I 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,

[6] The stylized facts are robust to using the raw number of products as a measure of product portfolio size.

i.e. that are never supplied again in the future (relative to the total number of products):[7]

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

The histogram of product portfolio adjustments in the top panel of Figure 1 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 I 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 dynamics.

The second column of Figure 1 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.

Product portfolio age

To obtain the proxy for product portfolio age, I follow Melser and Syed (2015) and Argente et al. (2018, 2019). Given that I observe both the entry and exit of each product, I define a product as 'old' if its age *exceeds* half of its lifespan. I define the proxy for product portfolio age as the weighted share of old products in the portfolio, where the weights correspond to

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

product-specific revenue:

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

As such, this measure captures the effective age of firms' product portfolios. I proxy product portfolio age in this way, rather than by e.g. computing it directly, as it allows me to directly link the data to the model and thus will be the key input in the structural estimation.[8]

Table 2 indicates that the average product portfolio age is 0.445, suggesting that firms have on average 44.5% of old products. Product portfolio age varies substantially as its standard deviation is 0.33 and variance decomposition into within- and between-firm effects indicates that as much as 79% of the variance can be attributed to within-firm variation.[9] The large variation in product portfolio age is noticeable in the top panel of Figure 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, Panel B of Table 2 suggests that product portfolio size and product portfolio adjustments are negatively related to product portfolio age. This means that, intuitively, firms with older product portfolios have on average fewer products and introduce new products less often.[10]

The third column of Figure 1 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

[8]Argente et al. (2019) 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. The empirical evidence replicated using alternative breakpoints is qualitatively and quantitatively similar. So does using an unweighted measure of product portfolio age. In Appendix B I document that these different measures produce qualitatively similar relationships with corporate policies.

[9]The value is slightly higher if products are defined at the brand-module rather than UPC level (0.519), and is slightly higher when products are not weighted by their revenues (0.512). Taking a higher threshold for the proxy results in a smaller share of older products (0.315 for 75% treshold and 0.202 for 90% treshold), but the variation remains fairly high.

[10]In untabulated analysis, I find that firm age and product portfolio age are weakly correlated, with correlation coefficient $\rho \approx 0.0299$. In fact, firms with share of old products close to 0 and 1 have, on average, similar age. This suggests that product portfolio characteristics can provide additional information above and beyond standard firm characteristics such as firm age.

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 I 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.

C. Implications of product portfolio age

I first document that product portfolio age is connected in a natural way to the notion of product life cycle of Levitt (1965) and Abernathy and Utterback (1978). The top left graph in Figure 2 shows that firms with older product portfolios have lower profitability. This means that the proxy passes the natural 'sanity check' of matching the findings of Argente et al. (2019) 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. Moreover, these findings highlight the fact that product portfolio structure not only influences current, but also future profitability.

[Figure 2 about here.]

Next, I analyze how product portfolio characteristics vary with product portfolio age. The top right graph in Figure 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. The bottom left graph documents that firms with youngest and oldest product portfolios have on average higher cash flow volatility. This result indicates 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).

[Figure 3 about here.]

Having documented that product portfolio structure affects profitability and product-related variables, the natural question that arises is: do product portfolio characteristics also have implications for firm value? Or, in other words, do value-maximizing firms care about actively managing their product portfolios? The relationship between product portfolio age and profitability in Figure 2 already indicates that managing product portfolios can generate value for firms. Figure 1 documents that there exists an interplay between firm value and product portfolio age, but it could be influenced by other variables correlated with this characteristic. To alleviate this concern, the top graph in Figure 3 shows the *unexplained* part of market-to-book, in line with Loderer et al. (2017). The figure further confirms that intuition by showing that product life cycle matters for firm value as proxied by the market-to-book ratio, as it declines with the share of old products, except for firms with very old products.[11] 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 again highlights the incremental information conveyed by product portfolio characteristics.

Having established that product market strategy should influence the behavior of value-maximizing firms, product portfolio structure should also have an effect on firms' investment and financing policy. The middle and bottom graphs in Figure 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 indicate that product portfolio age provides additional explanatory power in standard leverage or investment regressions. For example, in the sample, the within-R^2 in the leverage regression, with specification identical to the one employed in Figure 4, increases from 0.0487 to 0.0547, that is by roughly 11%. For

[11] This finding is largely explained by riskiness. For example, Figure **??** indicates cash flow volatility is a u-shaped function of product portfolio age.

investment regression it increases by 6%.

The empirical relations are also intuitive. The decline in the investment rate is consistent with the intuitive notion that product and capital investment are complements, that will be later formally confirmed by the model. The rationale behind the results for 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 preserve their debt capacity to finance their activities when their revenues vanish. Second, it also makes firms more risky. These effects result in a substitution between debt and cash financing, and hence net leverage declines.[12]

[Figure 4 about here.]

One remaining issue that should be addressed is whether the magnitude of the reduced-form relationships in Panel B of Figure 3 is economically meaningful. To comment on its significance, I compare how other firm characteristics, that are considered as standard determinants of investment and capital structure, fare in explaining residualized investment or leverage, when controlling for all other variables. For each policy, I 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 Figure 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 can provide economically significant additional explanatory power to the standard investment or leverage regressions.

In summary, the stylized facts presented in this section showcase a non-trivial relationship between product market strategy, 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, as isolating product-level

[12] In Figure B.1 in Appendix B I investigate the robustness of these results by using other definitions of product portfolio age using the investment policy as an example. The results imply that all different measures produce qualitatively similar relationship between product portfolio age and investment.

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 I examine the quantitative implication of product dynamics 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.

II. The Model

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

A. 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 ex ante identical products are different ex post to the extent that they are in a different stage of their life cycle. 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 (2019). As such, given capital stock K and profitability shock Z, the firm generates revenue equal to:

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

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. Note that the model specification implies that the firm's maximum capacity is ZK^{θ}. Moreover, absent product life cycle (i.e. when $\xi = 1$), the model would collapse to the standard neoclassical benchmark.[13] The profitability shock Z follows an AR(1) process in logs,

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

Given gross investment I, the firm's next-period physical capital stock evolves according to $K' = I + (1-\delta)K$ with capital depreciation rate $\delta \in [0,1]$. Depreciation expense is tax deductible. When the firm adjusts its capital stock, it incurs capital adjustment costs that are convex and defined as

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

B. 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 revenues. The graphical illustration of an individual product's life cycle is presented in Figure 5.

[Figure 5 about here.]

A product that is introduced immediately becomes new, which corresponds to t_n in Figure 5. Every period, each 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 each 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

[13] Note that 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 revenues, but rather its product portfolio structure.

characterized by a transition matrix:

$$
\begin{array}{c c}
 & \begin{array}{cccc} \text{intr.} & \text{new} & \text{old} & \text{exit} \end{array} \\
\begin{array}{c} \text{intr.} \\ \text{new} \\ \text{old} \\ \text{exit} \end{array} &
\begin{bmatrix}
0 & 0 & 0 & 0 \\
1 & p_{n\to n} & 0 & 0 \\
0 & p_{n\to o} & q_{o\to o} & 0 \\
0 & 0 & q_{o\to e} & 1
\end{bmatrix}
\end{array}
$$

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 revenues and higher durability of revenues, versus product introduction costs equal to $\eta K \cdot \Delta_P$. The product introduction costs are meant to 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 aging of new products and because old products can exit. Thus, 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 Appendix C.

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

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

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,

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

Formally, Equation (1) 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 $1/(1-p_0)$ periods and 'old' for $1/(1-q_0)$ periods. Given that we can observe the left-hand side of Equation (1) in the data, and given the breakpoint 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.

C. 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, I 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:

$$D \leq \omega(1-\delta)K,$$

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):

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

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.

D. *The firm's cash flow*

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

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

This formulation implies that the firm issues external equity if its cash flow is negative or pays out a dividend otherwise.[14]

E. *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 $\Lambda(\cdot)$. The Bellman equation for the problem is:

$$\begin{aligned} V(K, D, \Phi, Z) = & \max_{\Delta_P, K', D'} \left\{ E(\cdot) + \Lambda(E(\cdot)) + \beta \mathbb{E}\left[V(K', D', \Phi', Z') \right] \right\}, \\ & \text{s.t. } D \leq \omega(1-\delta)K. \end{aligned} \tag{2}$$

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

[14] I 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.

for capital, while the lower end is half of the upper end, with a reversed sign.

F. Optimal policies

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

Product portfolio

As evident in the empirical evidence, the product-level dynamics implied by the endogenous product portfolio dynamics have important implications for firm dynamics. To understand how firms choose their product portfolios, I derive the approximate first-order condition for product choice Δ_P, assuming for simplicity that the firm does not issue equity:[15]

$$\underbrace{\eta K}_{\substack{\text{product}\\\text{introduction}\\\text{cost}}} \approx \underbrace{ZK^{\theta}(1-\xi)\frac{\Delta(\phi)}{\Delta(\Delta_P)}}_{\substack{\text{profit increase}\\\text{today}}} + \underbrace{\beta\mathbb{E}\left[\frac{\Delta(V(K',D',\Phi'(\Delta_P),Z'))}{\Delta(\Delta_P)}\right]}_{\substack{\text{profit increase}\\\text{tomorrow}}}. \tag{3}$$

Firms will introduce new products as long as the marginal cost on the left-hand side of Equation (3) is smaller than the marginal benefit of introducing a new product on the right-hand side of Equation (3). The marginal cost is composed of a product introduction cost which does not depend on the product stock. The marginal benefit depends on the discount of old products relative to new products. Furthermore, it also changes with product portfolio composition Φ and the profitability shock Z. For example, when the firm's profitability shock is more persistent (higher ρ), it has more incentives to introduce new products to reap the benefits associated with the profitability shock whose effects last longer. Finally, the marginal value of having an additional new product tomorrow on the firm value also enters the marginal benefit, because the choice of today's product portfolio affects its potential future evolution. Thus, Equation (3) shows that investment and debt decisions of the firm indirectly affect how it chooses its product portfolio structure.[16]

[15] In Equation 3, $\Delta(\cdot)$ indicates the discrete derivative, defined as $\Delta(f(n)) = f(n+1) - f(n)$.

[16] More specifically, Equation (3) shows that the next period stock of new products P'_n and old products

Investment

Equation (3) shows that the firm's choice of product portfolio is intertwined with other corporate policies through the marginal value of future new products. To see how exactly this happens, I derive the investment Euler equation, which sets the discounted expected return on capital investment equal to the value of a dollar payout today:[17]

$$1 = \beta \mathbb{E}\left[\frac{(1+\Lambda'(E(\cdot))}{(1+\Lambda(E(\cdot))}\left(\frac{MB_i}{MC_i} + \frac{MB_i^{\Phi}(K', Z', \Delta_P', \Phi')}{MC_i}\right)\right], \tag{4}$$

where

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

To interpret Equation (4), let us first note that the return on capital investment consists of two parts. The first part is common to e.g. the neoclassical investment model, in which the return on capital investment is the ratio of the marginal benefit of investing 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 the effect on the marginal benefit of investment due to the product portfolio structure, captured by $MB_i^{\Phi}(\cdot)$, to the marginal cost. Note that if $\xi = 1$ and $\Delta_P = 0$ the function $MB_i^{\Phi}(\cdot)$ vanishes and we are back in the neoclassical benchmark. When the firm has more old products, it negatively affects its revenues, and the marginal benefit of investment is lower. Introducing more new products will thus increase the marginal benefit of investment. This illustrates that the relationship between product introductions and investment is positive, that is product and capital investment act as complements, because lower revenue discount due to product portfolio age and higher durability of revenues increases the firm's incentives to invest in physical capital. Therefore, the Euler equation shows that the firm's incentive to invest can vary with the structure of its product portfolio as well as its product adjustment

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 $\partial P_o/\partial \Delta_P$.

[17]Details of the computation are provided in Appendix C.

decisions. 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.

Net debt

To examine how financing and product decisions are interrelated, I combine the first-order condition

$$(1 + \Lambda(E(\cdot))) + \beta\mathbb{E}\left[V_{D'}(K', D', \Phi', Z')\right] = 0 \tag{6}$$

and the envelope condition associated with differentiating Eq. (2) with respect to D, which yields

$$1 = \beta\mathbb{E}\left[\frac{(1 + \Lambda'(E(\cdot)))}{(1 + \Lambda(E(\cdot)))}\left(1 + r(1-\tau) + \lambda'\right)\right], \tag{7}$$

where λ is the Lagrange multiplier associated with the collateral constraint. The right-hand side of Equation (7) 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 λ 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. Absent positive product investment opportunities the firm will preserve its debt capacity, resulting in a negative relationship between product portfolio age and leverage, consistent with the stylized facts. Thus, as Equation (6) shows, even though product choice does not *directly* affect the firm's debt policy, it will have an indirect effect because it affects the firm value as well as the probability that the firm has to incur the equity issuance cost $\Lambda(E)$.[18]

[18]While the emphasis in the model is put on the fact that product dynamics affect firms' financing decisions only through the 'quantitative rationing' effects of the collateral constraint, the negative association between leverage is also consistent with firms issuing debt for tax reasons. Indeed, since younger product portfolios

III. Estimation and Identification

I structurally estimate the model to examine its quantitative implications for the relationship between product market strategy and corporate policies. In this section, I describe the estimation procedure, discuss the identification strategy, present the baseline results and the cross-sectional implications.

A. Estimation

Throughout the paper, I set the tax rate τ to 20% as an approximation of the corporate tax rate relative to personal taxes. I estimate the majority of the structural parameters of the model using simulated method of moments (SMM). The remaining parameters are estimated separately, but the sampling variation induced by the two-stage approach is taken into account in the estimation procedure, which is described in detail in Appendix D. The risk-free interest rate r is estimated at 1.4%, which is the average 3 month T-bill rate over the sample period. I 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 Equation (1), 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

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

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, I directly estimate the proportional external equity financing cost by regressing issuance proceeds on the underwriting fees, which implies a value of 0.0223.[19]

I estimate the remaining 8 parameters $(\theta, \sigma, \rho, \delta, \psi, \omega, \eta, \xi)$ using SMM, where θ is the

increase firms' 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.

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

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 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, I first solve the model numerically, given the parameters, and generate simulated data from the model. Then, I 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. 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. Appendix D provides further details on the estimation procedure.

B. Identification

Before proceeding with estimation, I 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 easily identified from the serial correlation of operating profits, which is estimated using the technique of Han and Phillips (2010).

I select 12 moments related to firms' operating profits, investment, net leverage and product portfolio characteristics. I 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, I 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 I 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, I focus primarily on the product portfolio age and product portfolio adjustments, which, as I 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 its product portfolio share today.

C. Estimation results

I summarize the results of the structural estimation in Table 3. Panel A contains simulated and actual moments. Panel B reports the structural parameter estimates and their standard errors.

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

[Table 3 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.

The estimate of the product introduction cost η is equal to 0.75%, which implies that 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 Figure 1. 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.

Concerning the estimate of the old-product specific discount ξ, it is equal to 0.5282, meaning that firms act as if each old product in their portfolio only contributed 52.82% of a new product's revenue. The discount is thus fairly large, but consistent with the notion of product life cycle. To gauge whether the magnitude of the estimate is sensible, I 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.[20]

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

[20]Moreover, products in the model do not differ with regard to their expected lifetime, whereas this is the case in the data, the effective revenue of old but long-lasting products could be higher than that of old but short-lasting products. I verify that this is the case by splitting the sample into two groups of firms with long- and short-lived products and re-estimating the model. The results indicate that ξ is indeed higher in the sample of firms with long-lived products.

to the existing literature is the convex investment adjustment cost ψ, estimated at 0.8786, which results in a fairly sticky investment policy.[21]

D. Sample splits

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, I 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, I focus on three specific sample splits. First, I investigate whether the estimated model can reconcile differences between firms varying in the sensitivity of their products to product life cycle. This analysis serves as a 'sanity check' as to 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, I focus on sample splits based on the size of product portfolio and on the degree of product market competition. This exercise can in turn provide 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.

Sensitivity to product life cycle

[Table 4 about here.]

I first analyze whether the model can reproduce differences across firms whose products vary in their sensitivity to product life cycle. To this end, for each firm in the sample I estimate a product-level regression of the form

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

where i and t indicate the product and the quarter, and c indicates the product's correspond-

[21] In a different model, Warusawitharana and Whited (2016) also obtain a much higher investment adjustment cost for the food manufacturing industry.

ing cohort.[22] I then split the firms into two groups based on the estimates of β. The firms with the below-median (above-median) sensitivity of product-specific revenue to product age 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 4 presents the estimation results in the two subsamples. Panel A documents that the model-implied and data moments are relatively close, implying that the model captures well policies of firms in both subsamples. The results also suggest that firms whose products are less exposed to product life cycle have higher average profitability and share of old products. The fact that these firms also adopt higher average net leverage speaks to the precautionary savings motive of product life cycle, that should be less pronounced when firms are less exposed to product life cycle. 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 entry rate of these firms is approximately 3 times higher 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 simple check for 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 data to firm-level. The fact that 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, the results imply that 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

[22]Thus, I control for the cohort-specific fixed effects using the Deaton (1997) adjustment as in Argente et al. (2019).

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.

Product portfolio size

[Table 5 about here.]

I now turn to investigating the differences in estimates along dimensions not explicitly captured by the model. Table 5 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. Panel A shows that the model provides a reasonably good fit for both samples, as the simulated and data moments are largely economically indistinguishable. The results imply that firms with large product portfolios also tend to supply younger products, and thus have higher operating profits. Interestingly, the size of product portfolio appears to serve as a way for firms to diversify their revenues, as firms with large product portfolios exhibit lower variance and higher autocorrelation of operating profits.

The corresponding parameter estimates in Panel B 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 these firms managing product portfolios is even more important, as they are more exposed to the product life cycle frictions. Additionally, it is interesting to note that for firms with small product portfolios the fraction of capital that can be collateralized ω is much lower 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). However, the fact that the estimate of ω varies substantially across the two samples 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 or Xu, 2019).

Product market competition

[Table 6 about here.]

Table 6 presents the estimation results based on two subsamples differing in the degree of product market competition.[23] Investigating this dimension 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 A 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. Panel B shows that each of their old products provides about 63% of a new product's revenue; compared to 43% for firms subject to higher 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

[23] 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 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.

portfolios.

IV. Analysis and Counterfactuals

In this section, I study further the implications of the estimated model. I first analyze the numerical policy functions implied by the model and the quantitative importance of product dynamics for variation in investment and financing policy. I then consider a number of counterfactuals to better understand how product market strategy interacts with corporate policies and how important its effects are for firm value.

A. Numerical policy functions

I now examine the implications of the estimated parameters for the firm's optimal policies. To do so, I compute the numerical policy functions $\{I/K, D/K, \Delta_P\} = h(K, D, \Phi, Z)$ for investment rate I/K, leverage D/K, and product introductions Δ_P. In the discussion that follows, I focus on two sets of policy functions. First, I fix K and D at their average values in the simulated sample and set $Z = 1$ as I want to focus on the economic forces driven by product portfolio setting. Panel A of Figure 6 plots the policy functions $\{I/K, D/K, \Delta_P\} = \tilde{h}(P_o|\Phi_i)$ for a firm with a low and high number of new products, i.e. $i \in \{l, h\}$. Second, I fix K, D and Φ at their average values in the simulated sample and in Panel B of Figure 6 I plot the policy functions for the profitability shocks Z: $\{I/K, D/K, \Delta_P\} = \tilde{h}(Z|\Phi_i)$, again in the two cases.

[Figure 6 about here.]

The numerical policy functions in Panel A of Figure 6 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, because the firm has to incur a fixed cost to introduce a new product. That is, the firm only starts introducing new products once its current stock of old products (or, alternatively, current share of old products) is sufficiently large. The threshold at which it happens depends on the stock of new products, as firms will be less sensitive to product portfolio structure as long as they generate sufficiently large revenue, that depends on the share of old products in the portfolio.

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, which is consistent with the intuition behind the investment Euler equation in Equation (4). 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 harvest the benefits of 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, I 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 Figure 6 documents how the firm optimally responds to profitability shock when its optimal product portfolio structure is kept constant. 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 Figure 6 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. Finally, 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 Figure 6, because now the firm finances introducing new products internally, following a high realization of Z.

B. Quantitative importance of product dynamics

I now turn to investigating the quantitative importance of product dynamics for the firm's corporate policies. Given that the model presents a laboratory in which, unlike in the data, one can observe *all* the forces affecting investment and debt policies, we can exactly gauge the importance of product dynamics.

[Table 7 about here.]

In Table 7, I perform a variance decomposition of the firm's investment and leverage policy. The results highlight that product dynamics account for as much as 20% of variation in investment and leverage, independently of how they are measured in the model (by share of old products or stock of new and old products separately). Moreover, most of the variation is due to the dynamics of the stock of old products, which is intuitive given their importance in generating the product life cycle pattern. Overall, the results suggest that product dynamics can contribute substantially to the observed variation in corporate policies.

C. *Counterfactuals*

This subsection describes three counterfactual exercises. In the first exercise, I consider how product-level economic forces affect firm value, firms' precautionary savings incentives and the relationship between product characteristics and corporate policies. In the second exercise, I examine the impact of changing parameter values related to the product market dimension on investment and leverage policies. I 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. In the third exercise, I investigate whether allowing for within-firm product cannibalization alters the conclusions obtained in the baseline model.

Firm value implications

I first investigate firm value effects resulting from altering product market characteristics. In Table 8, I 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 values given in Section III.

[Table 8 about here.]

The results in the second panel of Table 8 indicate 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 important 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.

I now investigate the implications of the estimate of the old product-specific revenue discount ξ. In the second panel of Table 8, I 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.

Finally, I analyze how changing product durability affects firm value. The results in the third panel of Table 8 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.

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, I can examine how the magnitude of these incentives is affected by product-level economic forces. The last column of Table 8 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 severity of product life cycle frictions, via altering the old-product specific discount, are even stronger and indicate that more severe product life cycle effects result in stronger precautionary savings motives, as 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 these precautionary savings motives induces by product life cycle would be absent in standard dynamic models of the firm that do not account for product-level dynamics (e.g. the AK framework).

Comparative statics: product portfolio characteristics

I now consider a different type of a counterfactual exercise by examining the effect of changing product-level characteristics on average firm policies. Figure 7 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 expected benefits and the expected longevity of each product, respectively. In each panel, I 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, I solve a model in which the values of each parameter deviate from its baseline estimated value, and simulate using the resulting optimal policies.

[Figure 7 about here.]

Panel A of Figure 7 documents that 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. 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. As such, 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 implies that 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. Note that these channels are consistent with the policy functions in Figure 6.

Panel B of Figure 7 analyzes the effects of changing the probability than an old product exits $q_{o\to e}$. Essentially, this parameter determines the expected longevity of the firm's products. When this 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.

D. 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, I examine how quantitatively important the effects of cannibalization are on financing and investment.

To this end, I 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

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

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, I effectively assume that product cannibalization acts through ageing the firm's products, which is reasonable given that, as argued by Argente et al. (2019), product life cycle is largely due to changes in customer preferences. In the exercise to follow, I 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]

[Figure 8 about here.]

Figure 8 presents the effects of 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.

V. Conclusion

In this paper, I demonstrate that product market strategy has important implications for corporate policies by developing and estimating a dynamic model of product portfolio de-

[24]The IO 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 I assume a less pronounced effect.

cisions. In line with the product life cycle channel, new products are more profitable, and are expected to last longer than old ones, which can become obsolete. Thus, when deciding whether the introduce new products, the firm trades off the benefits of a younger product portfolio versus product introduction costs. I 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 portfolio adjustments have direct implications for cash flow dynamics, which connects the firm's real, financial, and product decisions.

I document that the model provides economic rationale to the empirical relation between product portfolio age, investment, and leverage. In particular, I find that product-level economic forces have a significant influence on corporate investment and financing policy, as product dynamics explain 25% of variation in investment and leverage in the model. Estimates from the model imply 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. The data suggests that managing the life cycle of products, by means of introduction cost or sensitivity to ageing, yields material benefits to firms.

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	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 1: Comparison of product characteristics in the Nielsen Homescan (NH) sample, the sample of public firms and the sample of firms used in the paper. UPCs, brand-modules and markets are all the different levels of product aggregation. Market shares were 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 the NH. Appendix B provides a more detailed description of all variables. All variables are winsorized at 2.5% and 97.5% percentile.

Panel A: summary statistics

	size	adjustment	age	market-to-book	investment	book leverage	cash	firm size	profitability
mean	58.066	0.002	0.445	1.882	0.021	0.265	0.090	7.601	0.040
median	36.792	0.000	0.405	1.609	0.017	0.272	0.056	7.874	0.038
std. dev.	53.282	0.036	0.324	1.110	0.016	0.169	0.095	2.141	0.024
N	2306	2296	2366	2366	2366	2366	2366	2366	2366

Panel B: pairwise correlations

	size	adjustment	age	market-to-book	investment	book leverage	cash	firm size	profitability
size	1								
adjustments	-0.0189	1							
age	-0.0486	-0.0471	1						
market-to-book	0.0812	0.0607	0.0568	1					
investment	-0.0965	0.0488	-0.0724	0.215	1				
book leverage	0.302	-0.0282	0.0653	-0.146	-0.0667	1			
cash	-0.281	0.0114	0.0127	0.404	0.146	-0.506	1		
firm size	0.375	-0.0211	0.0100	-0.00820	-0.0633	0.364	-0.210	1	
profitability	0.131	0.0358	-0.0372	0.611	0.107	-0.132	0.300	0.111	1

TABLE 2: Summary statistics of variables characterizing firms' product portfolio characteristics and corporate policies. Size is the number of products in product portfolio. Adjustment 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. Age is the share of old products in product portfolio, that is those exceeding half of their lifespan. 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. Profitability is operating profits over total assets. Appendix B provides a more detailed description of all variables. All variables are winsorized at 2.5% and 97.5% percentile.

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	(0.0099)	(0.0272)	(0.0038)	(0.0055)	(0.0845)	(0.0222)	(0.0014)	(0.0124)

Table 3: Structural estimates and 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. Appendix D provides the details about the estimation procedure. 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.

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	(0.0148)	(0.0344)	(0.0092)	(0.0032)	(0.2262)	(0.0270)	(0.0032)	(0.0225)
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	(0.0839)	(0.0389)	(0.0281)	(0.0039)	(2.4328)	(0.0186)	(0.0015)	(0.0407)

Table 4: Structural estimates and model-implied moments: firms whose products have low and high sensitivity to product life cycle. This 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. Appendix D provides the details about the estimation procedure. 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.

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	0.1970	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	0.1738	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	0.6322	0.6961
Mean old product share	0.4427	0.4611	0.4292	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	0.3927	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	(0.0346)	(0.0343)	(0.0045)	(0.0085)	(0.4234)	(0.0232)	(0.0009)	(0.0371)
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	(0.0295)	(0.0148)	(0.0048)	(0.0023)	(0.0943)	(0.0166)	(0.0003)	(0.0195)

TABLE 5: Structural estimates and model-implied moments: firms with small and large product portfolios. This 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. Appendix D provides the details about the estimation procedure. 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.

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	(0.0324)	(0.0460)	(0.0041)	(0.0059)	(0.1860)	(0.0376)	(0.0019)	(0.0181)
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	(0.0248)	(0.0295)	(0.0124)	(0.0050)	(0.1041)	(0.0130)	(0.0009)	(0.0093)

TABLE 6: Structural estimates and model-implied moments: firms exposed to more and less competitive product markets. This 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. Appendix D provides the details about the estimation procedure. 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.

	Investment	Net leverage
Product portfolio age ϕ	0.236	0.256
Stock of new products P_n	0.032	0.030
Stock of old products P_o	0.140	0.161

Table 7: Variance decomposition of the firm's investment and leverage policy. I compute the Type III partial sum of squares for each variable in the model and then normalize each estimate by the total variance. That is, each number represents the % of total variance explained by the variable.

	%Δ firm value	mtb	Corr(·, age) inv	lev	%Δ debt capacity
Baseline	0.00%	-0.208	-0.088	-0.060	0.00%
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%
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%
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%

TABLE 8: The table reports outcomes corresponding to alternative model parametrizations by 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.

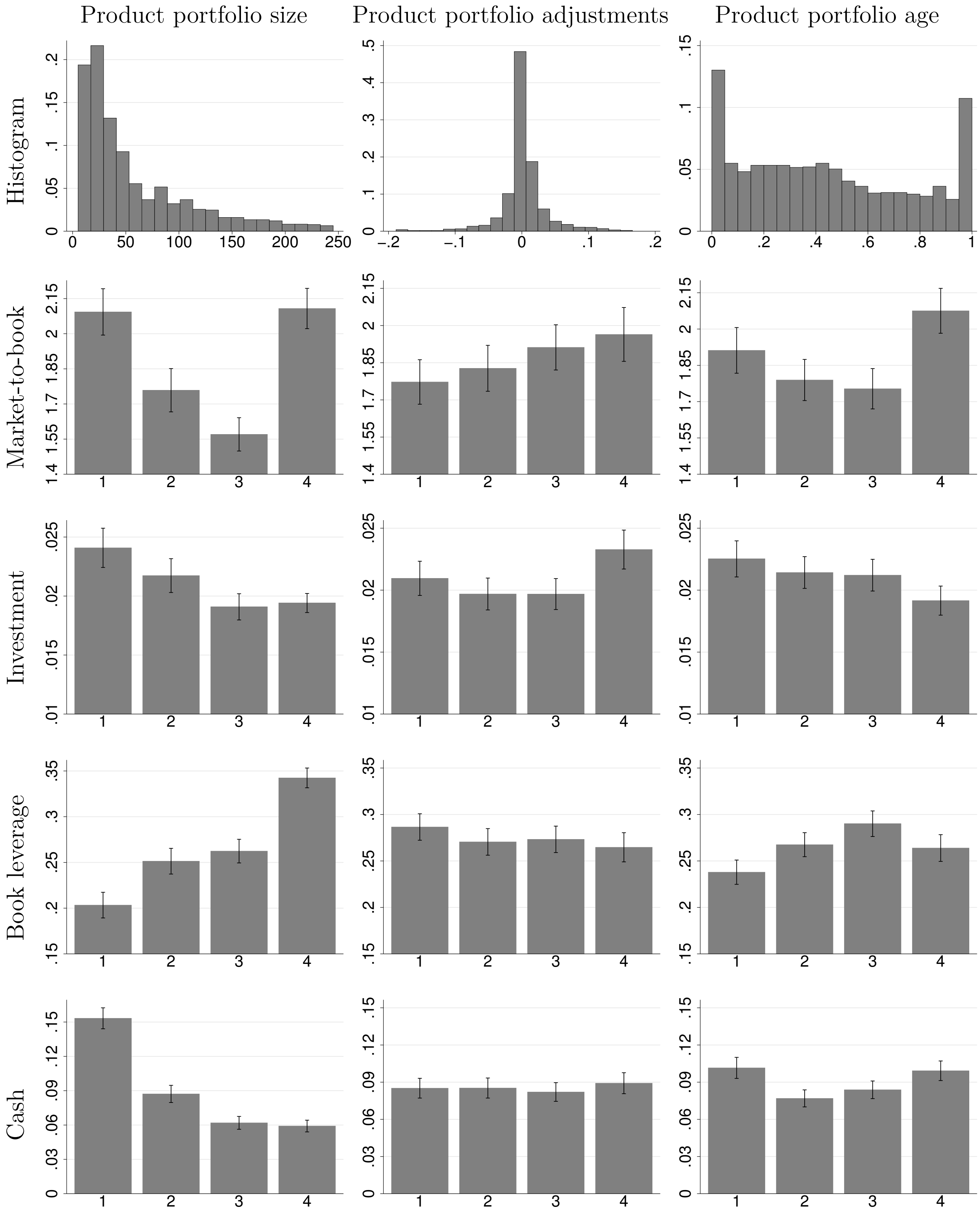

FIGURE 1: The graphs summarize the firms' product portfolio structure and illustrate the relationships between firms' corporate policies and product characteristics. The first row contains the histograms of product portfolio size, adjustments, and age. Rows two to 5 contain the relationship between each 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. Appendix B provides a description of all variables.

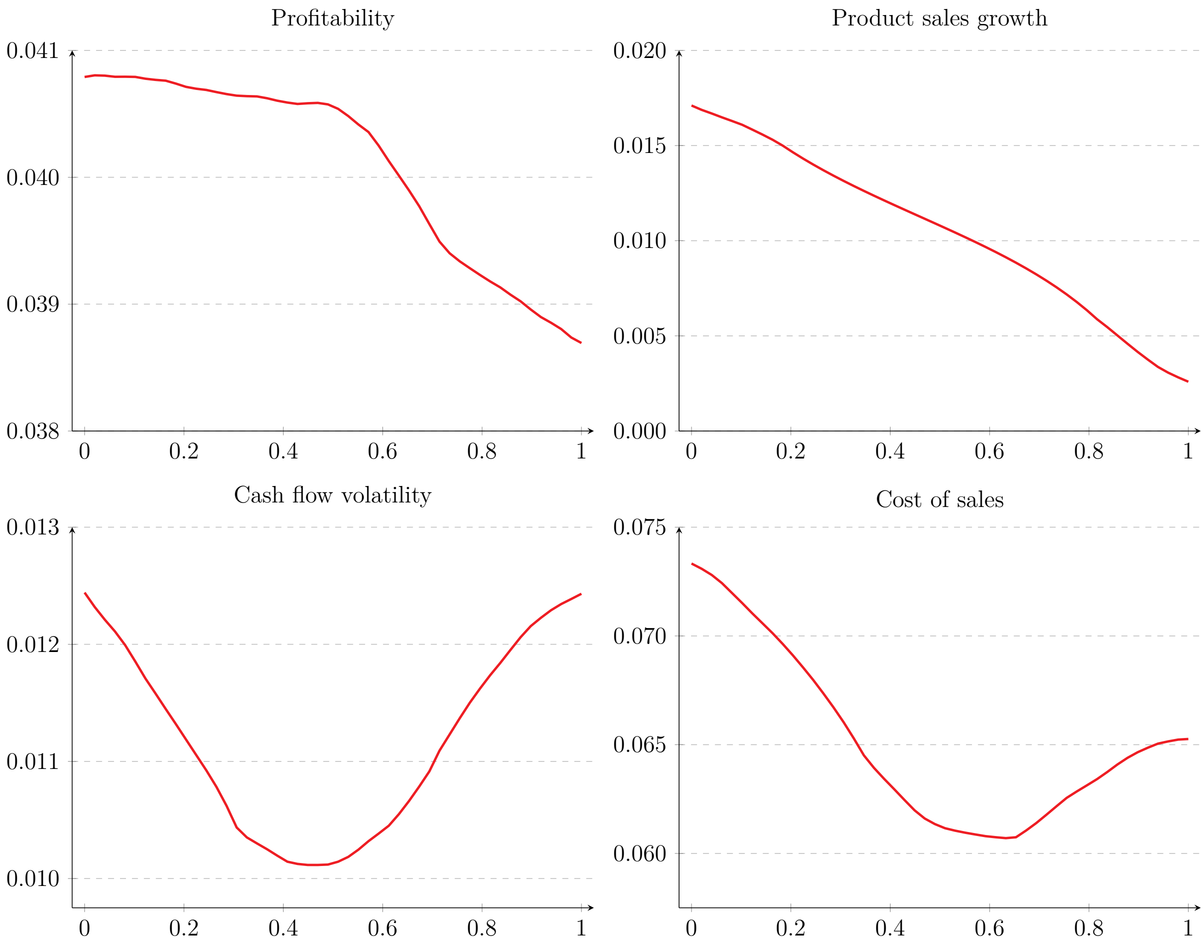

FIGURE 2: The figure shows how profitability, product revenue growth, cash flow volatility, and cost of sales change with product portfolio age. The solid lines are obtained from local polynomial regressions of each variable on the product portfolio age proxy using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. Appendix B provides a description of all variables.

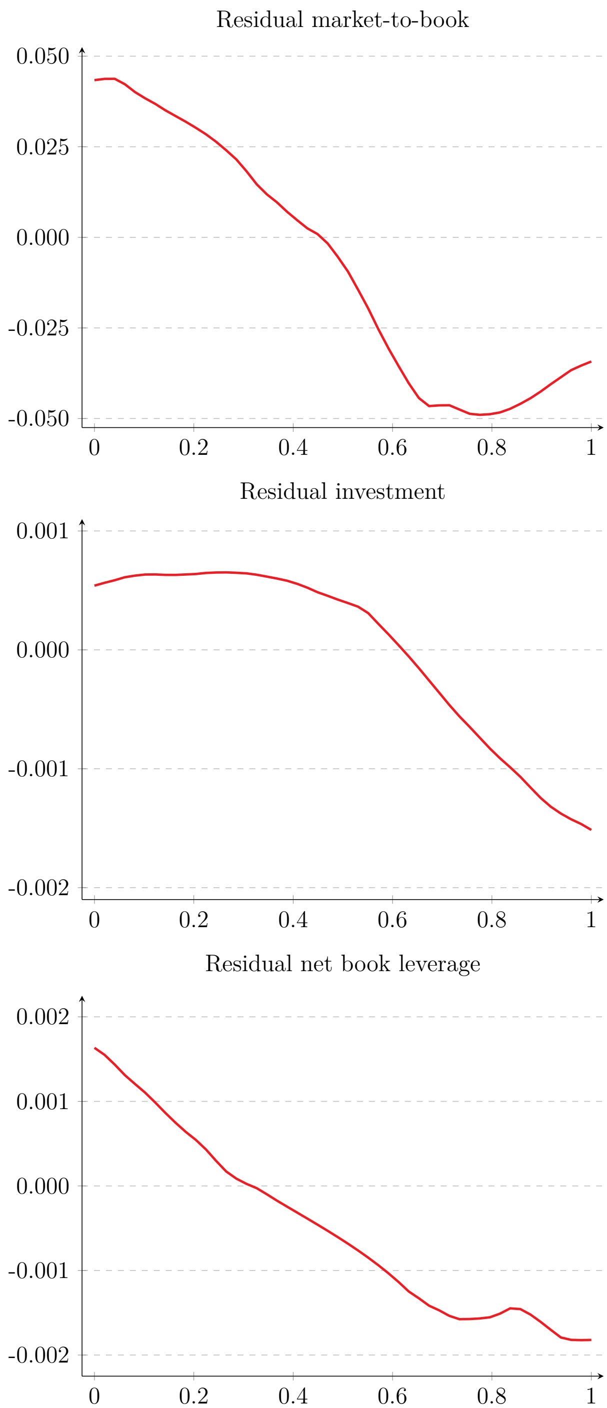

FIGURE 3: The figure shows the relationship between product portfolio age and firms' *unexplained* market-to-book, investment and leverage. The solid lines are obtained from local polynomial regressions of each variable on the product portfolio age proxy using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean smoothing. The controls used to compute the predicted values 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. All models control for firm and time fixed effects. Appendix B provides a description of all variables.

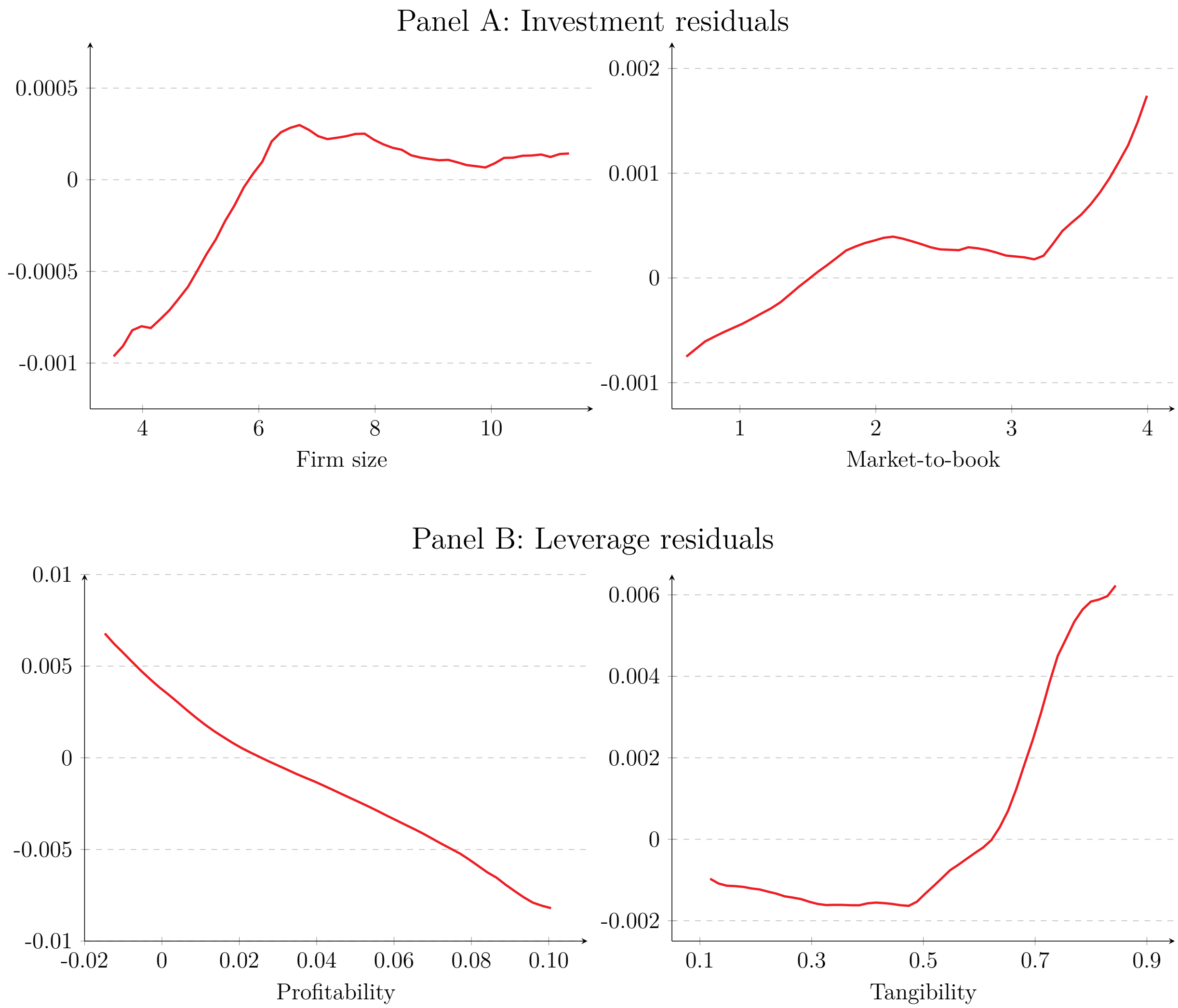

FIGURE 4: Assessing the significance of product portfolio age for corporate policies. All graphs are obtained from local polynomial regressions of the residuals from an investment (or leverage) regression on a given variable, using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator 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. Appendix B provides a description of all variables.

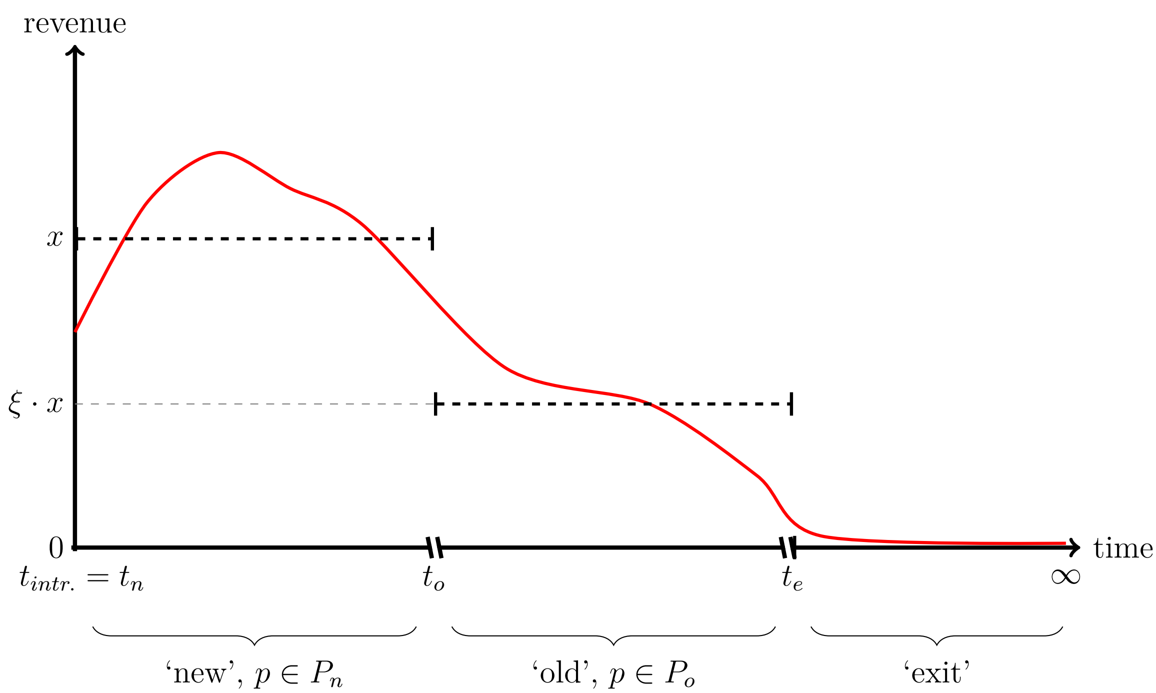

FIGURE 5: Graphical representation of each product's evolution in the model.

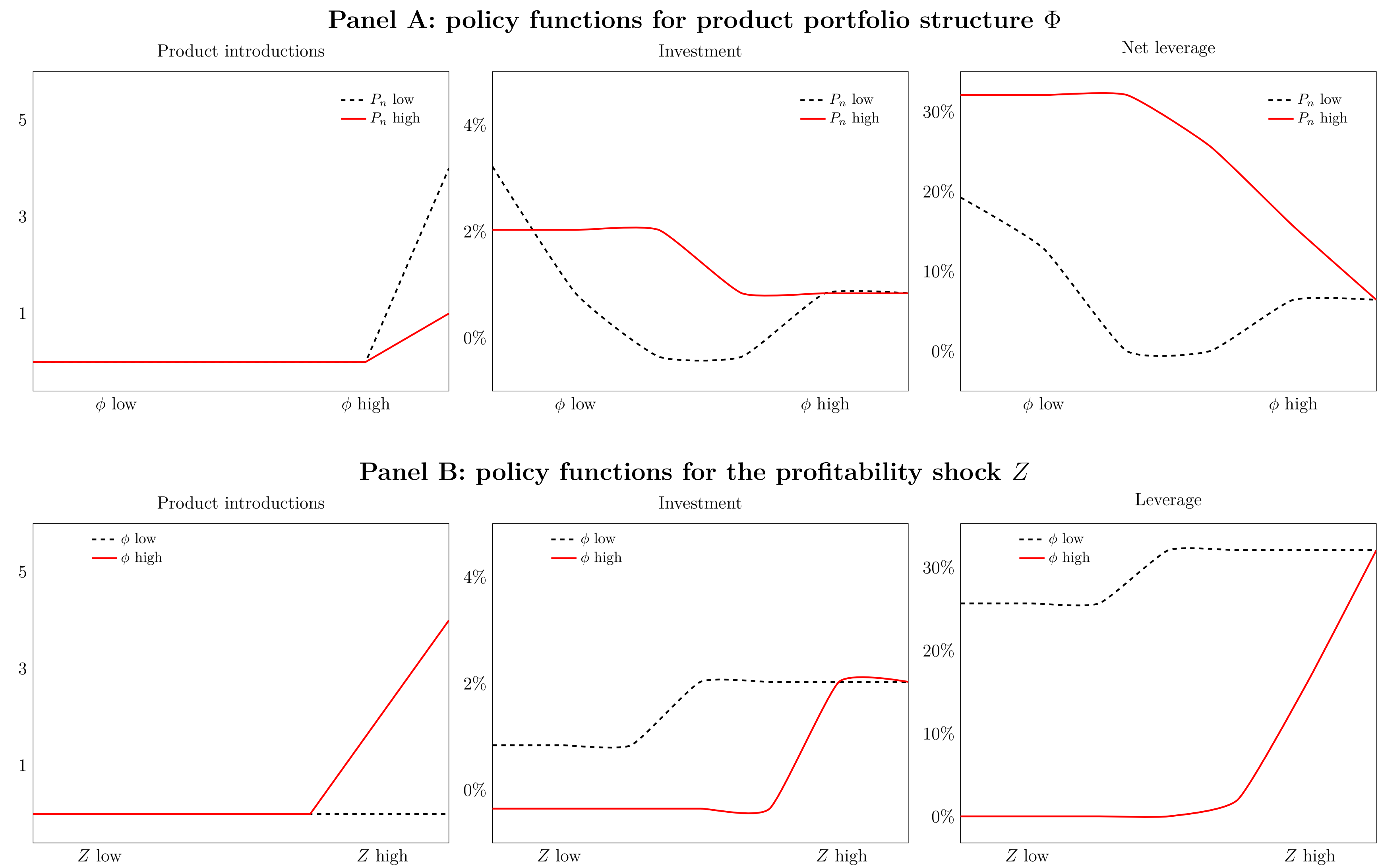

FIGURE 6: Numerical policy functions for the product portfolio structure Φ and for the profitability shock Z. In Panel A, the policy functions are computed for the baseline parameter estimates and average values of capital, debt, and profitability shock. In Panel B, the policy functions are computed for the baseline parameter estimates and average values of capital, debt, and product portfolio structure.

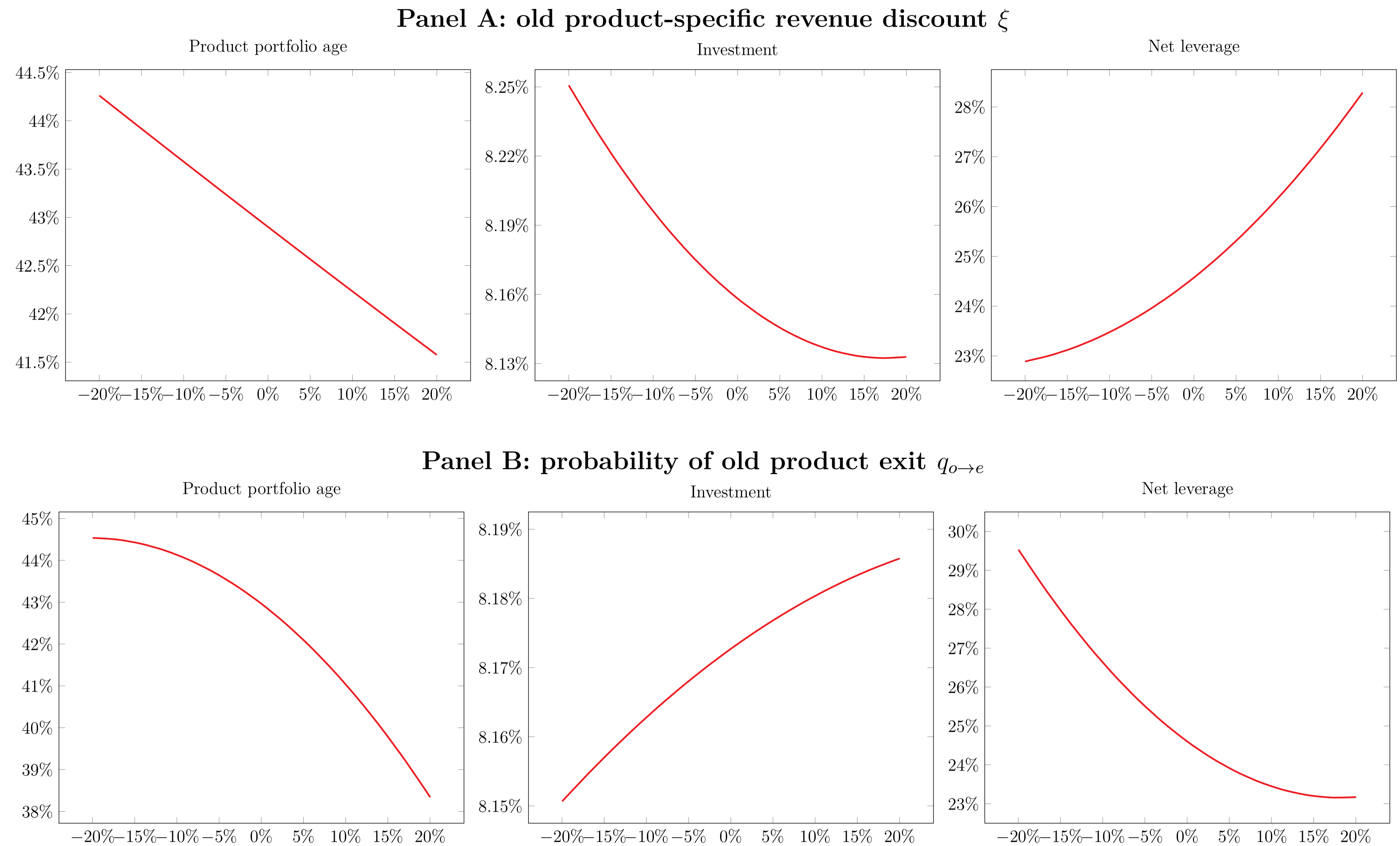

Figure 7: Comparative statics of product-related parameters. Each point on the curve corresponds to moments from a counterfactual experiment, starting from the baseline estimates of structural parameters and changing only the respective parameter by 20% up and 20% down. Each curve is a polynomial interpolation of moments from a discrete set of counterfactual experiments.

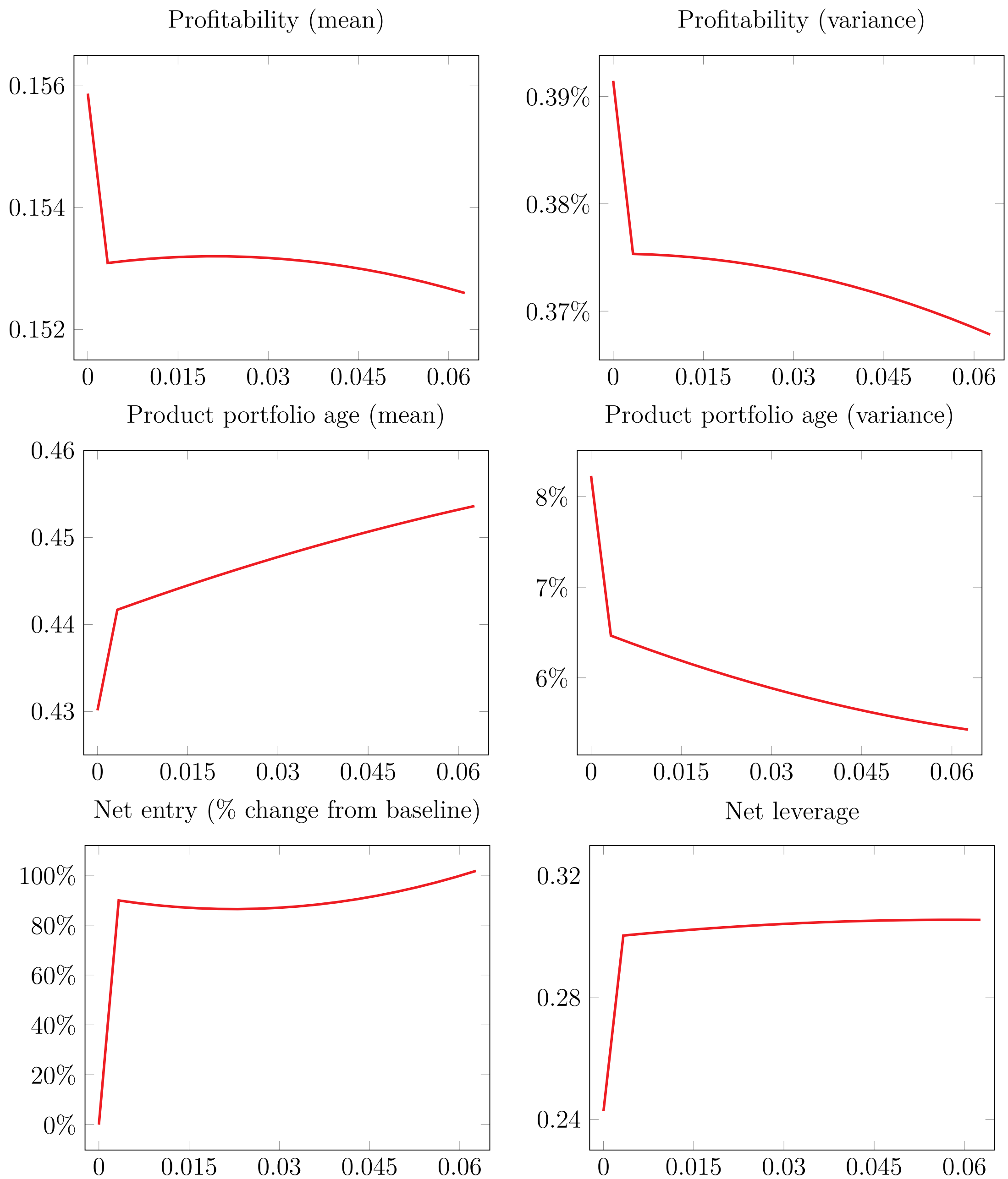

FIGURE 8: The effects of cannibalization–comparative statics of the cannibalization parameter ϵ. Each point on the curve corresponds to moments from a counterfactual experiment, starting from the baseline estimates of structural parameters and changing only the respective parameter. Except for the point corresponding to $\epsilon = 0$, each curve is a polynomial interpolation of moments from a discrete set of counterfactual experiments.

Appendix

A. Product market data

A. Data description

I use the AC 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 14 years (2004–2017).[25]

A.1 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.

TABLE A.1: 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

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

[25]It should be noted that Nielsen Homescan database by construction focuses on nondurable consumer goods, so most apparel, electronics and home furnishing purchases may not be recorded.

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 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.

	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

Table A.2: Summary statistics of different product classifications of 37,492 firms.

A.2 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, I 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, I 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, I 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, I 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. I 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.

	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: Sales' shares of matched firms. All variables are winsorized at 2.5% and 97.5% percentile.

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.

B. Sample selection

To refine the data for further empirical analysis, I first apply the standard Compustat data filters: I 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, I remove all financial conglomerates (SIC$\geq$ 6000). I 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, I only keep firms in industries in which the average projected sales share is at least 10%. I also remove all firms which have on average less than 20 UPC codes. Even though I 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. I 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.

B. Data and stylized facts

A. Definitions of variables

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

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

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

where rx_x is the revenue concentration at level x:

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

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 $eff\_no\_prod = 1/rc$.

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

$$ne_{it} = (\text{\# product introductions}(it) - \text{\# product withdrawals}(it))/\text{total \# products}(it),$$

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. I also consider net product creation:

$$nc_{it} = (\text{revenue of entering products}(it) - \text{revenue of exiting products}(it))/\text{total revenue}(it),$$

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.

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

$$\text{age(x)} = \frac{\text{weighted \# of products with age exceeding x\% of lifespan}}{\text{total \# of products}},$$

where the weights correspond to product-specific revenues.

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 plant, property and

equipment.

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**:
$$ihhi_{it} = \sum_{m=1}^{M} s_{mit} HHI_{mt},$$
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. Cash flow volatility: the rolling standard deviations of profitability, computed over the past 8 quarters.

C. Model solution

A. Product transition matrix

To get the product transition matrix T_Φ, I 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 I also allow old products to transition to being new (which in the main specification is not allowed) hence I need to know both $q_{o\to o}$ and $q_{o\to e}$:

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

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

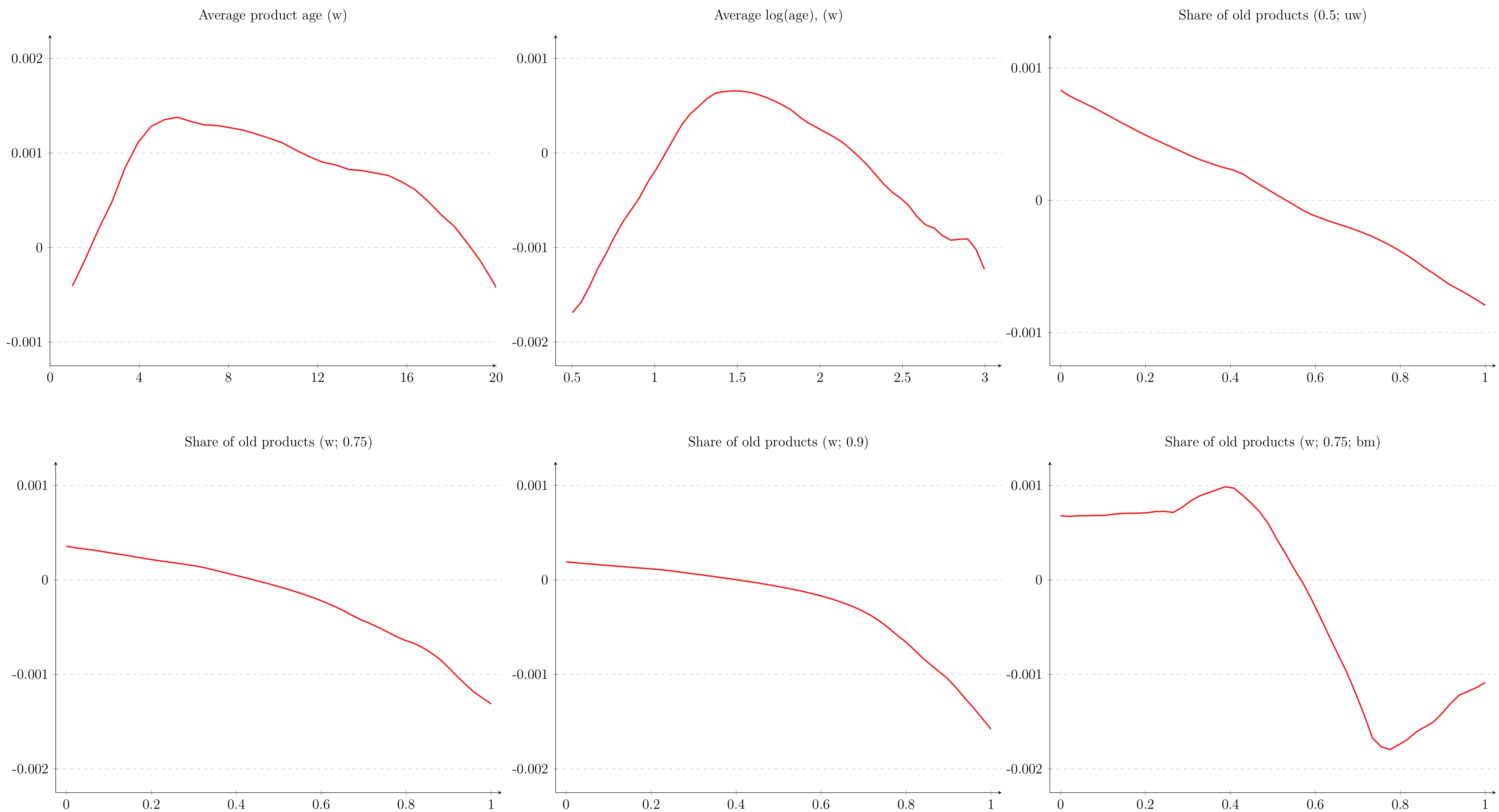

Figure B.1: Robustness check: defining product portfolio age. Each graph is obtained from local polynomial regression of the residuals from an investment regression on a given product portfolio age variable, using an Epanechnikov kernel function with a rule-of-thumb bandwidth estimator and local-mean 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.

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

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

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, I 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 robust to considering alternative normalization schemes, e.g. attributing the residual probability to current state.

B. *Further details on computing the investment Euler equation*

To compute the investment Euler equation, I first take the first-oder condition of (2) with respect to K', which yields

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

as well as the envelope condition that gives

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

Combining them both yields the investment Euler equation

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

where

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

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

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

where $i = I/K$. Thus, we derived Equation (4):

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

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

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

D. Structural estimation

I follow Lee and Ingram (1991) when estimating the model using structural method of moments. As in Hennessy and Whited (2007), I extract as much of observed heterogeneity from data as possible to make the model- and data-implied moments comparable, that is I 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, I compute a set of moments $h(x_i)$.

I 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. I 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

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

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. I use the optimal clustered weight matrix constructed as in Bazdresch et al. (2017). I use simulated annealing to find the optimum to the minimization problem.

Under mild regularity conditions, the SMM estimator is asymptotically normal

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

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).