Product Switching and Young Firm Dynamics*

Seula Kim†
Penn State

Karam Jo‡
Penn State

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Abstract

We study the life-cycle patterns of product-switching of multi-product firms and their aggregate implications. Using firm-product-level administrative data for the U.S. manufacturing sector, we estimate the match quality of firm-product pairs—a time-invariant, product-specific measure of firm performance—and show that young firms face greater challenges in identifying and retaining well-matched products. Young firms are more likely to keep poorly performing products while dropping better ones. Moreover, although young firms actively experiment by adding new products, often distant from their existing portfolio, many of these additions are misaligned with their expertise. These patterns suggest that young firms' limited ability to find and retain the right products hampers their ability to climb the match-quality ladder and impedes performance improvements. To interpret these patterns, we develop a simple model of learning about product match quality over the firm life-cycle.

JEL Code: L11, L21, L25, L60, O31
Keywords: product add and drop, product switching, young firm dynamics, firm growth

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†Email: seulakim@psu.edu. Address: 614 Kern Building, University Park, PA 16802.
‡Email: karamjo@psu.edu. Address: 403 Kern Building, University Park, PA 16802.

1 Introduction

Finding an optimal set of products to produce is important for firms to allocate their resources efficiently. Firms add and drop products throughout their life-cycle, and the literature finds that this product-switching behavior is prevalent and has a profound impact on a firm's scope and performance (Bernard et al., 2010; Argente et al., 2018). When switching products, firms often remain close to their existing ones (e.g., Bernard et al., 2010; Boehm et al., 2022). However, firms also venture into entirely new industries, and such radical product switching can sometimes yield substantial performance gains and contribute to long-term success.[1] Yet some firms fail to successfully introduce new products, suggesting that they may excel in certain areas while struggling in others.[2]

Furthermore, decisions to add or drop products may be particularly important for young firms, as their scope of production and specialty are not yet fully established. As a result, they may need to search more intensively to find the right products to produce. These dynamics also have important implications for the aggregate economy, as the growth of young firms is a main driving force of aggregate productivity and economic growth (Haltiwanger, 2012; Haltiwanger et al., 2013; Decker et al., 2014, 2016; Haltiwanger et al., 2016; Foster et al., 2018). However, relatively little is known about the types of products firms choose to add or drop in optimizing their product portfolio, and especially how these decisions evolve over the firm life-cycle.

In this paper, we study how firms add and drop products over their life-cycle and how product switching contributes to firm growth. In particular, we look into the types of products firms switch by introducing a new concept termed "firm-product match quality," a time-invariant, product-specific measure of firm performance. This mea-

[1] For example, Samsung started as a grocery trading company, but by shifting its core business to electronics and semiconductor manufacturing, it eventually evolved into the globally recognized firm as is today. Similarly, 3M began as a mining venture but became renowned by diversifying into a wide range of products for worker safety, healthcare, and consumer goods.

[2] For instance, Dyson and Apple both attempted to enter the electric car market but ultimately failed. Likewise, McDonald's was unsuccessful in its attempt to sell pizza, despite potential advantages such as leveraging similar inputs or existing distribution networks.

sure controls for time-varying compounding factors such as product life-cycle patterns (e.g., Argente et al., 2024), customer capital accumulation, and transitory product-level shocks (e.g., fluctuations in market conditions), which obscure the firm-specific ability to produce a given product. Thus, the match quality measure reflects how well a firm can produce a specific product and the extent of its expertise in that area.[3,4]

By using the match quality measure, we investigate whether firms climb up the match quality ladder of products by actively reoptimizing their product portfolios—adding products with higher match quality while dropping those with lower match quality. We then analyze how this pattern evolves over the firm life-cycle, particularly among young firms, and its impact on firm growth and performance.

We use a detailed product-firm level dataset for the manufacturing sector from the U.S Census Bureau from 1982 to 2007 for our analysis. In this dataset, we define a "product" as either a five-digit Standard Industrial Classification (SIC) category for the pre-2002 years or a seven-digit North American Industry Classification System (NAICS) category for the years from 2002 onward and identify product-firm pairs in each Census year. Most importantly, we measure product-firm pair match quality by estimating time-invariant characteristics associated with each product-firm pair using the pair fixed effect of the real value of shipments.[5] To our knowledge, this approach represents one of the novel contributions of our paper.

In the data, we observe that firms generally drop products that have poor match quality with them more frequently. Young firms, however, exhibit a distinct pattern: they drop products less frequently on average, but, importantly, they drop products with better match quality more frequently and products with poor match quality less frequently than mature firms.

Next, we examine whether firms climb up the match-quality ladder of products by es-

[3]A firm's expertise in producing a given product includes knowledge of the production process, including where to source material inputs from, as well as knowledge about customer taste and distribution networks.

[4]A product with higher match quality serves as a proxy for the "right" set of products for the firm.

[5]Our approach closely follows Bonhomme et al. (2019), which estimates worker-firm complementarities in earnings.

timating the association between product dropping and the quality of products added. We find that firms that drop products between two consecutive census years are more likely to add new ones simultaneously, with this tendency being more pronounced among young firms. Moreover, the probability of adding products with higher match quality than existing ones increases when at least one product is dropped in the same period. However, young firms are less likely to add higher match quality products relative to mature firms, and this difference is primarily driven by cases in which they simultaneously drop products.

We further test whether the proximity between newly added products and a firm's existing products varies with firm age. Using input-material-based proximity and industry classifications, we find that, on average, firms add products closer to their existing portfolio when they simultaneously drop products. However, compared to mature firms, young firms tend to add products that are more distant from their existing product portfolio when they simultaneously drop products.

Lastly, we show that product switching, and thus, climbing the product match-quality ladder, matters for firm growth and performance. In particular, we find that product churning, the simultaneous addition and dropping of products, is positively associated with various firm performance measures, including growth in value added, employment, total factor productivity, and labor productivity. Combining these findings with the product-switching pattern of young firms suggests that young firms are less likely to climb the match quality ladder as fast as mature firms, potentially slowing their growth.

Taken together, these findings imply that young firms face greater challenges in identifying and retaining the right products. While they actively experiment by adding new products—often distant from their existing portfolios—many of these additions misalign with their underlying specialty. Their limited ability to shed poorly matched products and adopt better-aligned ones early in the life cycle prevents them from climbing up the match-quality ladder and constrains performance improvements.

To account for these patterns, we develop a simple model in which firms draw a product and decide to add or drop the product based on their perceived match quality.

In the model, firms are born with initial prior beliefs about match quality with a new product. They update their priors after observing the realized match output and extracting signals via Bayesian learning process. When firms draw a product, they decide whether to keep or drop it based on their beliefs which can characterize the expected sum of profits. The model predicts that younger firms, with limited information, are more likely to drop a good match quality product and keep a bad match quality product compared to mature counterparts. This suggests that the learning process over the firm life-cycle can explain the observed product-switching patterns.

Literature Review. Our paper is closely related to a line of recent studies on product switching within firms. Bernard et al. (2010) is the closest study to our paper. They use the same dataset as ours (the Census of Manufactures) and study the extent of product switching within firms for the U.S. manufacturing sector. Broda and Weinstein (2010) document the patterns of product entry and exit in consumer goods sectors from the Nielsen Homescan database. Bernard and Okubo (2016) study the role of product adding and dropping within Japanese manufacturing firms over the business cycle. Argente et al. (2018) use the Nielsen Retail Measurement Services (RMS) scanner data and assess the magnitude of product creation and destruction and product reallocation during and after the Great Recession. Berlingieri et al. (2024) use data on French manufacturing firms and document that rapid, simultaneous additions of many new products play a central role in firm innovation and growth. Other studies show that trade liberalization and competition lead firms to focus on their core products and competence (Bernard et al., 2011; Eckel and Neary, 2010; Mayer et al., 2014). Boehm et al. (2022) find that firms choose products with common-input capabilities. This paper contributes to this literature by offering a new direct measure of product-firm match quality and establishing novel facts about the product match-quality ladder within firms and its evolution over the firm life-cycle.

This paper also adds to the vast literature on potential factors or frictions that affect the post-entry dynamics and growth of young firms. One strand of studies emphasizes the importance of financing constraints and the role of collateral values for successful young firms (Evans and Jovanovic, 1989; Holtz-Eakin et al., 1994; Cooley and Quadrini, 2001; Hurst and Lusardi, 2004; Kerr and Nanda, 2009; Robb and Robinson, 2014; Schmalz et al., 2017; Davis and Haltiwanger, 2019). On the other hand, Foster et al. (2016) analyze the process of accumulating demand can create friction for new businesses to grow high. Akcigit and Ates (2019) and Jo and Kim (2024) present barriers to knowledge spillovers as a source to create frictions dampening firm entry and the rapid-growth young firm activities. Furthermore, Kim (2025) demonstrates that uncertain job prospects can pose difficulties to young firms in attracting workers properly and negatively affect firm entry and the growth of high-potential young firms. Along this line, this paper provides a unique channel of product switching to account for young firm growth. In particular, we document new data evidence suggesting that young firms have more difficulties in finding the right product match, and this can give a negative impact on their growth path.

The rest of the paper proceeds as follows. Section 2 describes data sources and main measures used in our analysis. Section 3 presents our main findings on product dropping and adding activities of young and mature firms, the relationship between product dropping and the match quality of added products, the proximity of added products to existing ones, and the impact of product switching on firm growth. Section 4 discusses additional robustness tests for the main results. Section 5 presents a simple model of a learning mechanism that explains our empirical findings. Finally, Section 6 concludes with a discussion on remaining future work.

2 Data and Measurement

Our main data source is the quinquennial Census of Manufacturers (CMF, henceforth) linked to the Longitudinal Business Database (LBD, henceforth) hosted by the U.S. Census Bureau. Our sample covers the following eight quinquennial census years: 1977, 1982, 1987, 1992, 1997, 2002, 2007, and 2012.

The CMF provides comprehensive information on all U.S. manufacturing establishments with one or more paid employees. The data collects establishment-level characteristics such as employment, payroll, worker hours, payroll supplements, cost of materials, selected operating expenses, value added, capital expenditures, inventories, energy consumption, and industry codes. It also provides the list of input materials and expenses used by each establishment. Furthermore, it contains product codes—either five-digit SIC or seven-digit NAICS codes—and the value of shipments for products manufactured by each establishment.[6] More details can be found from Bernard et al. (2010), Kehrig et al. (2011) and Kehrig and Vincent (2021).

The LBD tracks the universe of U.S. private non-farm business establishments and firms with at least one paid employee. It covers all sectors and geographic areas of the economy annually from 1976 onward. Establishments owned by a parent firm are grouped under a common firm identifier, enabling us to aggregate establishment-level activities to the firm level. The LBD contains basic information such as employment, payroll, industry codes, and location. These variables enable us to link to the CMF establishments and identify parent firms to construct firm-level variables such as firm size, age, productivity, employment growth rates, and entry/exit. We refer to Jarmin and Miranda (2002), and Chow et al. (2021) for further details.

Industry-level variables are adopted from the NBER CES Manufacturing Industry Database, assembled by Becker et al. (2013). An industry is defined by the four-digit SIC (or the six-digit NAICS after 1997) code. The NBER-CES Manufacturing Industry Database contains annual industrial data for the U.S. manufacturing sector from 1958 through 2018, sourced from the U.S. Census Bureau, the Bureau of Economic Analysis, and the Bureau of Labor Statistics. The data covers industry-level information on price deflators, payroll, employment size, number of workers, total value of shipments, value added, various input costs and expenditures, and productivity (TFP estimates).

[6] For example, in the Nonferrous Wiredrawing and Insulating industry (SIC 3357), there are thirteen products, including Aluminum Wire (33571), Copper Wire (33572), Telephone Wire (3357B), and Fiber Optic Cable (33579).

2.1 Product Definition and Characteristics

We define a product by a five-digit SIC code for the entire census years.[7] Note that in each Census year, there are two versions of product codes: one based on the previous Census year's classification ("as collected") and another based on the current Census year's classification. For 1977–1997, the "current" classification is based on the 1987 SIC system. Starting from 2002, product codes based on the NAICS classification are used. Importantly, in the 1997 CMF file, both the 1997 NAICS-based product code and the 1987 SIC-based product code appears, allowing us to construct a time-consistent product classification based on the 1987 SIC.

The bridge construction from the 1987 SIC to any version of NAICS follows a rolling approach. Starting with the 1987 SIC-to-1997 NAICS concordance, we then link the 1997 NAICS to the 2002 NAICS using the 2002 Census bridge file, yielding a concordance between the 1997 SIC and 2002 NAICS. We repeat this process for the 2007 and 2012 Censuses, ultimately generating a 1987 SIC to 2002, 2007, and 2012 NAICS concordance. To maximize within-firm consistency across years from 2002 to 2012, we first match each firm-product pair in a given year to its corresponding pair in the previous year. For unmatched cases, we use the bridge file constructed from the previous year to map the NAICS product code to its corresponding 1987 SIC product code. If a NAICS product code maps to multiple 1987 SIC codes, we select the one most frequently matched to that NAICS code.

The CMF reports product-level sales (product value of shipment) and physical quantities shipped. Given the definition of a product, we limit our analyses to observations that have a positive, nonzero value of shipments. Following literature, we drop "administrative record," which are very small establishments that are not required to report the product-level value of shipments. We also exclude observations outside the "tabbed sample," which is the sample used by the Census Bureau for official tabulations. We use

[7] This is based on product trailer information provided by the Census for the U.S. manufacturing firms in the CMF. We extract the information at the SIC5 or NAICS7 level for the pre-1997 and post-1997 Census years, respectively.

the product value of shipment at the product-establishment level and aggregate it up to the product-firm level using LBD firm identifiers. We normalize the product value of shipments using the NBER-CES industry-level price indices (in 1997 U.S. dollars). For each product-firm pair, we measure tenure as the number of years the firm manufactures the product and appears in the record. To improve accuracy, we supplement our data with product-firm information from the Annual Survey of Manufacturers (ASM).

Lastly, for each firm in year t, we flag "added products" as those that were not present in the firm's product portfolio before year t but appear by $t + 5$. In a similar fashion, we flag "dropped products" within each firm in year t as those that are present in the firm's product portfolio up to year t but no longer appear from $t + 5$. This enables us to identify added and dropped products from 1982 to 2007 in our sample.[8] For each added and dropped product, we indicate whether they are initial additions or re-entries, and whether drops are temporary or permanent. Our baseline analysis focuses on initial additions and permanent drops.

2.2 Firm Characteristics and Identifiers

We use firm age variables constructed by the Census using the method in Haltiwanger et al. (2013). Specifically, firm age is defined as the age of the oldest establishment owned by the firm when it is first observed in the data. We indicate young firms as those younger than or equal to age five. Note that because the LBD begins in 1976, all firms are assigned age zero in that year. To reduce misclassification of young firms, we use the 1972 CMF to adjust firm ages accordingly.[9] Firm size is measured using either total employment or total value of shipments.

One limitation of the LBD is the lack of longitudinally consistent firm identifiers. Although the redesigned LBD has a new firm identifier that links firms across time

[8] We use the 1977 data as a buffer to more accurately flag product additions and drops and compute product-firm tenure.

[9] We use Finished Goods Inventory Beginning (FIB) from the 1972 CMF and add 4 to the firm age of LBD firms that own 1972 CMF establishments if FIB equals zero, and 5 years if FIB is greater than zero.

Table 1: Share of Product Switching Firms

variables	Including entry and exit			Continuers only		
	All	Age 0-5	Age 6 +	All	Age 0-5	Age 6 +
			Product adding only			
Share of firms	0.094	0.100	0.093	0.128	0.130	0.128
Output share	0.058	0.098	0.057	0.067	0.139	0.066
			Product dropping only			
Share of firms	0.398	0.329	0.407	0.182	0.143	0.187
Output share	0.282	0.404	0.280	0.169	0.146	0.169
			Product churning			
Share of firms	0.248	0.310	0.239	0.336	0.394	0.327
Output share	0.582	0.284	0.588	0.674	0.409	0.678

Notes: Firms in the manufacturing sector from 1982 to 2007.

by correcting previous firm identifiers that are recycled in the old LBD, as described in Chow et al. (2021), it still has limitations.[10] However, longitudinal consistency of firm identifiers is necessary for our analysis to track firms' history of product portfolios. Therefore, we construct alternative versions of longitudinal firm identifiers from the LBD following Dent et al. (2018) and use them to assess the robustness of our analysis results. Henceforth, we use the term "firm identifier" to refer to the firm identifiers constructed by the Census Bureau (lbdfid). All nominal values are converted to 1997 U.S. dollars using industry-level deflators for the relevant variables.

3 Empirical Models and Main Results

In this section, we investigate firms' product-switching decisions and examine how the decisions differ for young firms. The design of our empirical strategy is discussed in the following subsections.

Table 2: Share of Multi-Product Firms

Classification	Share of firms			Output share		
	All	Age 0-5	Age 6 +	All	Age 0-5	Age 6 +
sic5	0.450	0.432	0.452	0.891	0.615	0.896
sic4	0.332	0.301	0.336	0.838	0.451	0.845
sic2	0.183	0.153	0.187	0.702	0.267	0.711

Notes: Firms in the manufacturing sector from 1982 to 2007.

3.1 Prevalence of Product Switching Firms

Table 1 reports the share of product-switching firms and their output shares by age group, with and without entry and exit. Since firm entry and exit can overstate firm-level product additions and drops, the last three columns report shares for continuing firms only. Focusing on continuing firms, we find that 65% of firms in the pooled sample switch products at least once every five years, and they account for 91% of total output. Thus, product switching is a prevalent behavior, and firms that engage in it account for a substantial share of economic activity, as emphasized by Bernard et al. (2010).

Table 1 also shows that product switching often involves simultaneous add and drop of products (churning). Approximately 52% of product-switching firms (34% out of 65%) both add and drop products, while the remainder either add or drop, but not both. The life-cycle pattern of product switching exhibits distinct dynamics. In particular, product churning is more pervasive among young firms, while the share of drop-only cases is lower compared to their more mature counterparts.

Table 2 additionally reports the share of multi-product firms under alternative definitions of a product: the baseline five-digit SIC product code, the four-digit SIC industry code, and the two-digit SIC sector code. Consistent with existing findings, multi-product firms comprise slightly less than half of all firms (45%) but account for 89% of total output. These multi-product firms also operate across multiple industries and sectors. Multi-product firms are also prevalent among young firms, comprising 43% of

[10] The new firm identifiers haven't still resolved firm reorganization issue. See more discussion in Chow et al. (2021).

Table 3: Number of Products Produced/Added/Dropped

	Including entry and exit			Continuers only		
	All	Age 0-5	Age 6 +	All	Age 0-5	Age 6 +
			Number of products firms produce			
Mean	2.189	1.877	2.233	2.192	1.645	2.269
Stdev.	(2.896)	(1.509)	(3.041)	(3.153)	(1.377)	(3.321)
			Number of products firms add			
Mean	1.27	1.831	1.189	1.244	1.605	1.194
Stdev.	(1.831)	(1.518)	(1.858)	(1.880)	(1.374)	(1.935)
			Number of products firms drop			
Mean	1.273	1.218	1.281	0.941	0.790	0.963
Stdev.	(1.981)	(1.482)	(2.043)	(1.841)	(1.101)	(1.922)

Notes: Firms in the manufacturing sector from 1982 to 2007.

them and generating 62% of their output.

In contrast, while single-product firms make up 55% of all firms, they account for only 11% of total output. Moreover, firms that produce a single product and never switch their product throughout the sample period represent 14.8% of firms but contribute just 2.8% of total output.

Lastly, Table 3 reports the means and standard deviations of the number of products firms produce, add, and drop, based on the full sample including single-product firms. On average, firms produce 2.2 products, add 1.2 products, and drop 0.9 products over five years.[11] Although young firms produce fewer products on average (1.6 vs. 2.3), they tend to add more products (1.6 vs. 1.2) while dropping fewer products (0.8 vs. 1.0) compared to mature firms.

3.2 Firm-Product Match Quality Estimation

We estimate firm-product match quality and examine the relationship between firms' product-switching decisions and resource reallocation. In the CMF, the only performance measure available at the product-firm level is the product value of shipments

[11] Bernard et al. (2010) report that the average number of products firms produce rises to 3.5 when single-product firms are excluded.

(PV).[12] However, using PV directly to assess whether a firm is relatively better at producing one product over another presents several issues. The level of PV may reflect not only firm-specific capabilities but also factors such as the duration of production (e.g., life-cycle pattern of product as in Argente et al. (2024) or customer capital accumulation) and transitory product-level shocks (e.g., market fluctuations).

To address these concerns, we estimate a time-invariant measure of product-firm performance by taking out factors that influence the level of PV other than the firm's product-specific ability. We refer to this measure as match quality, which we interpret as capturing how good the firm is (firm's expertise) in producing a given product. We estimate the following baseline model, similar to Bonhomme et al. (2019):

$$y_{pijt} = \theta_{pi} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + \delta_{pt} + \varepsilon_{pijt}, \tag{3.1}$$

y_{pijt} is the log real PV for firm i (in industry j) and product p in census year t. θ_{pi}, a firm-product fixed effect, is our main interest. This contains time-invariant characteristics associated with the firm-product match that determine the performance of the product within the firm and capture the match quality between them.

We include a rich set of controls and fixed effects to account for sources affecting the firm-product-specific value of shipments, unrelated to the firm-product-specific unobservable characteristics. For example, when firms enter new product markets, it typically takes time to build a customer base, which can affect shipment values independently of match quality. To control for this effect, we include product-firm-specific tenure as of year t and its square. Furthermore, we include a vector of firm-level time-varying characteristics (X_{ijt}), which includes firm size (log employment), firm age, total assets, number of products, number of establishments, cost of advertisements, cost of software, skill and capital intensity (log ratio of non-production workers to total employment and capital to total employment), productivity, and firm-level inputs (log of production workers, equipment capital stock, structural capital stock, material cost,

[12] While quantity data are also available, they cover only a limited set of products.

and energy costs).

Lastly, δ_{pt} is a product-year fixed effect to control for any potential factors affecting the value of shipment for firm i's product p, attributed to time-varying technology or demand structure that differs across each product market. Related to this, several product-specific properties (skill or capital intensity) can also affect the total value of shipment regardless of the firm-product's fundamental match quality. As robustness checks, we further explore alternative specifications to estimate the product-firm match quality. More discussion can be found in the Appendix.

Note that as we control for factors specific to product markets and firms each year, our measure for the product-firm match quality, θ_{pi}, can be compared across different product-firm pairs across different years. We rescale the quality measure to make it normalized and range in [0,1]. Let q_{pi} denote this. In particular, we use the following formula to rescale $\hat{\theta}_{pi}$:

$$q_{pi} \equiv \frac{\hat{\theta}_{pi} - \underline{\theta}_{pi}}{\overline{\theta}_{pi} - \underline{\theta}_{pi}}, \tag{3.2}$$

where $\underline{\theta}_{pi}$ and $\overline{\theta}_{pi}$ are the minimum and maximum value of the quality estimates, respectively (e.g. $\hat{\theta}_{pi} \in [\underline{\theta}_{pi}, \overline{\theta}_{pi}]$). We estimate θ_{pi} using the CMF for the years 1977 to 2012, complemented with the ASM data from 1976 to 2016.

3.3 Product Dropping

In this subsection, we analyze the types of products that firms drop from their existing portfolios and examine how the pattern of dropping products vary between young and mature firms.

3.3.1 Match Quality of Dropped Products

We begin by examining the types of products that firms drop. Specifically, we test whether firms are more likely to drop products with lower performance—that is, products that have poorer firm-product match quality—relative to better-matched ones. This is based on the premise that identifying match quality of products is not straightforward, given the costs associated with searching for and learning about the quality of a product-firm match. This challenge may be more pronounced for younger firms, which lack enough records or information about themselves and products in the market.

To see this, we construct a dummy variable, $\mathcal{I}^{drop}_{pijt}$, to indicate a product being dropped by the beginning of the next period. $\mathcal{I}^{drop}_{pijt}$ is equal to one if firm i in industry j drops product p between period t and $t+5$ (e.g., if product p appears in firm i's portfolio in t but not $t+5$). We regress it on the product-firm performance measures to see how firms' product drop depends on the match quality between product p and firm i:

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta Q_{pit} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + \delta_i + \delta_{pt} + \varepsilon_{pijt}. \tag{3.3}$$

Q_{pit} is either the log of real PV or q_{pi}, the match quality value (3.2) associated with the pair of product p and firm i. X_{pijt} is a vector of time-varying firm-product characteristics (log firm-product specific tenure and square, and log value of shipment if q_{pi} is used for Q_{pit}). X_{ijt} is a vector of firm controls (the same set of controls used in q_{pi} estimation). δ_{pt} is a product-year fixed effect, and δ_i is a firm fixed effect.

The first two columns of Table 4 present results from specifications that include the full set of control variables.[13] As shown in column 1 of Table 4, firms are, on average, more likely to drop products that generate lower revenue. Column 2 further shows that this pattern holds for our time-invariant firm-product performance measure: firms tend to drop products with lower match quality, relative to better-matched ones. These results suggest that, on average, firms are able to identify which products are better matches and drop those that are poorly matched. Dropping poorly matched products would free up the resources and potentially enable firms to reallocate these resources toward their better use. Before examining whether dropping poor-matched products

[13]The corresponding full model results are reported in Table A1 and A2 in Appendix A.1.

Table 4: Probability of Product Drop

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
$\log(PV_{pit})$	-0.052***			-0.052***	
	(0.002)			(0.002)	
Quality$_{pi}$		-1.074***			-1.081***
		(0.021)			(0.022)
Young Firm$_{it}$			-0.075***	-0.141***	-0.368***
			(0.003)	(0.007)	(0.022)
$\log(PV_{pit}) \times$ Young$_{it}$				0.010***	
				(0.001)	
Quality$_{pi}$ $\times$ Young$_{it}$					0.497***
					(0.043)
Observations	1,622,000	1,622,000	1,622,000	1,622,000	1,622,000
Fixed effects	pt, i	pt, i	pt, i	pt, i	pt, i
Controls	Full	Full	Full	Full	Full

Notes: Estimates for product-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

helps firms climb the match-quality ladder and improve their overall performance, we test whether product-dropping behavior varies by firm age.

3.3.2 Product Dropping by Young Firms

As young firms have less experience in producing and selling products, they may struggle to accurately assess whether a product is a good match for them. This limited information and evaluation capacity of young firms could make them drop products less frequently than old firms, particularly those with poor match quality.

To investigate such heterogeneity in product-dropping behavior among young firms, we first estimate the following regression model:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta \mathcal{I}_{ijt}^{young} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + \delta_i + \delta_{pt} + \varepsilon_{pijt}, \tag{3.4}$$

where $\mathcal{I}_{ijt}^{young}$ is a dummy variable equal to one if a firm is with age less than or equal to five in year t.

One thing to note is that single-product firms could choose not to drop their product even though they know that the product they produce is a poor match for them. This is because dropping the product would force them to shut down their business, as it is their only product. Because young firms are more likely single-product firms, including the number of products firms produce as a firm-level control is particularly critical in this regression model.[14] Financial frictions can also matter. The product-switching behavior of financially constrained firms may differ from that of unconstrained firms, as the former face greater difficulty in financing new projects to add products. One way to mitigate this concern is to include a proxy for firms' ability to raise funds. The closest available variable in the CMF is total assets.[15] We include these variables, as well as other firm controls as before. The third column of Table 4 presents the result. This shows that on average, young firms drop products less frequently than mature firms.[16]

To further explore the match quality of products dropped by young firms, we interact the two firm-product performance measures in equation (3.3) with the young firm dummy as follows:

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 Q_{pit} + \beta_2 \mathcal{I}^{young}_{ijt} + \beta_3 Q_{pit} \times \mathcal{I}^{young}_{ijt} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + \delta_i + \delta_{pt} + \varepsilon_{pijt}. \tag{3.5}$$

Columns 4 and 5 of Table 4 lay out the results.[17] In particular, the third row (the coefficient on the young firm dummy) indicates that with match quality controlled, young firms drop products even less frequently than their mature counterparts on average.

However, as shown in the fourth and fifth rows, young firms are more likely to drop products in which they perform well while dropping fewer products with poor match

[14]As shown in Table 2, young firms are approximately 4% less likely to be multi-product firms compared to mature firms (43% vs. 45%).

[15]We are in the process of exploring another way to address financial frictions, such as industry-level differences in external financing arising from the relative importance of intangible versus physical capital.

[16]Table A3 in Appendix A.1 shows the results for including and excluding firm-level controls.

[17]Table A4 and A5 in Appendix A.1 show the results for the full model.

quality, relative to mature firms. In other words, young firms tend to drop products they should have retained while retaining products they should have dropped. Overall, the stickiness with poor match quality products is the dominant factor determining the average product-dropping behavior of young firms.

These results suggests that young firms' limited information for assessing product match quality may constrain their ability to keep better-matched products while dropping poorly matched ones at the early stage of their life-cycle. As a result, young firms may struggle to climb the product match quality ladder. Such a restriction can hinder the potential growth of young firms, especially in environments with greater noise and less accurate information for firms to learn, such as during recessions.[18]

3.4 Firm-Level Evidence for Quality Ladder

Next, we examine whether and how firms climb the match-quality ladder.

3.4.1 Product Adding

We begin by examining whether the probability of adding a new product depends on the firm's prior product-dropping behavior. To see this, we define a product as being added to a firm's portfolio in year t if it is absent in the firm's portfolio in t but appears by the next census year $t+5$. Let $\mathcal{I}_{ijt}^{add}$ denote a dummy variable equal to one if firm i in industry j adds at least one product between t and $t+5$.

We estimate the following conditional probability of adding at least one product conditional on having at least one product dropped, with other factors controlled as before:

$$\mathcal{I}_{ijt}^{add} = \alpha + \beta \mathcal{I}_{ijt}^{drop} + X_{ijt}\gamma + \delta_i + \delta_{jt} + \varepsilon_{ijt}. \tag{3.6}$$

$\mathcal{I}_{ijt}^{drop}$, is a dummy variable equal to one if firm i dropped at least one of its products between years t and $t+5$. δ_i is a firm fixed effect, and δ_{jt} is an industry-year fixed

[18] We also find consistent results over the business cycle, where such patterns of product switching for young firms are more pronounced in recessions. Results are available on request.

Table 5: Product Add and Drop

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$	0.096***		0.070***
	(0.012)		(0.012)
Young Firm$_{it}$		0.148***	0
		(0.005)	(0.005)
$Drop_{t:t+5} \times$ Young$_{it}$			0.295***
			(0.008)
Observations	682,000	682,000	682,000
Fixed effects	i, jt	i, jt	i, jt
Controls	Full	Full	Full

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

effect. The remaining firm-level controls are identical to those used previously.

As shown in column 1 of Table 5, the probability that a firm adds a new product is positively associated with their simultaneous dropping of at least one product.[19,20] Columns 2 and 3 report results from a regression specification that extends equation (3.6) by interacting the product-dropping dummy with the young firm dummy. The estimates show that young firms, on average, are more likely to add products than their mature counterparts, and this is primarily driven by their higher propensity to add products when simultaneously dropping others. This indicates that firms simultaneously add and drop products, with young firms exhibiting a higher propensity to do so, which is a piece of evidence regarding the match-quality ladder.[21]

[19] Table A6-A9 in the Appendix show the full results.

[20] This result is consistent with Bernard et al. (2010).

[21] We find similar results when using the number of products added as the dependent variable. The results are reported in Table A10 in the Appendix.

3.4.2 Match Quality of Added Products: Quality Ladder Evidence

In the previous analyses, we found that the propensity to add a new product is positively associated with the probability of dropping products at the firm level. In this section, we further investigate whether the match quality of newly added products is associated with firms' product dropping behavior to assess whether firms climb up the match-quality ladder through product switching.

To do so, we define $\mathcal{I}_{ijt}^{add,high}$, a dummy variable equal to one if the average match quality of products newly added between t and $t+5$ is higher than the average match quality of the products firms produce in t. Using this variable, we examine whether the probability of adding a product with higher match quality than the existing ones is greater when firms simultaneously drop products. If firms are indeed climbing the match-quality ladder, we would expect this relationship to be positive. We estimate the following regression model using the sample of firms that add at least one product between t and $t+5$:

$$\mathcal{I}_{ijt}^{add,high} = \alpha + \beta \mathcal{I}_{ijt}^{drop} + X_{ijt}\gamma + \delta_i + \delta_{jt} + \varepsilon_{ijt}. \tag{3.7}$$

The fixed effects and firm-level controls are identical to those used previously.

As shown in the first column of Table 6, the probability of adding products with match quality higher than that of existing products becomes higher if at least one product is dropped within the same period.[22] This result confirms that, on average, not only the likelihood of adding a product but also the match quality of the added products is positively associated with firms' product-dropping behavior. This is consistent with the match-quality ladder hypothesis.

We then examine whether the relationship between the match quality of added products and product drop differs for young firms by interacting the drop dummy with the young firm dummy. Columns 2 and 3 of Table 6 show that young firms are less likely to add higher match quality products relative to their mature counterparts, and this dif-

[22] See Table A11-A14 in the Appendix for the full results.

Table 6: Relative Match Quality of Added Products

	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$
$Drop_{t:t+5}$	0.028**		0.049***
	(0.011)		(0.010)
Young Firm$_{it}$		-0.112***	0.044*
		(0.017)	(0.024)
$Drop_{t:t+5} \times$ Young$_{it}$			-0.228***
			(0.024)
Observations	66,000	66,000	66,000
Fixed effects	i, jt	i, jt	i, jt
Controls	Full	Full	Full

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

ferential is primarily driven by instances in which they simultaneously drop products. As shown in column 3 of Table 5, young firms tend to add products more frequently when they simultaneously drop others. Taken together with the previous findings, this suggests that young firms face greater difficulty in identifying and retaining the right products. While they actively experiment by adding new products, many of these additions do not align well with their underlying expertise.

However, when young firms add new products without simultaneously dropping any, they are more likely to add products with higher match quality. Table 1 shows that product adding accompanied by simultaneous dropping (churning) occurs three times more frequently than adding without dropping. Moreover, the average match quality of products added with simultaneous dropping is substantially higher than that of products added without dropping.[23] Therefore, despite the positive outcome in the case of adding without dropping, it is outweighed by the more prevalent and dominant negative case in which young firms churn products.

This provides additional evidence consistent with the match-quality ladder hypothe-

[23]We are currently in the process of disclosing this result again. Thus, it is not included in the current draft.

Table 7: Number of Input Materials Used per Product by Firms

	Including entry and exit			Continuers only		
	all	age 0-5	age 6 +	all	age 0-5	age 6 +
Mean	20.30	19.45	20.43	21.33	21.50	21.31
Stdev.	(20.29)	(19.86)	(20.35)	(21.00)	(21.34)	(20.95)

Notes: Firms in the manufacturing sector from 1982 to 2007.

Table 8: Material-Based Closeness of Added Products

	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$
$Drop_{t:t+5}$	0.098***		0.102***
	(0.004)		(0.004)
Young Firm$_{it}$		-0.003	0.022***
		(0.004)	(0.005)
$Drop_{t:t+5}$ $\times$ Young$_{it}$			-0.037***
			(0.006)
Observations	198,000	198,000	198,000
Fixed effects	i, jt	i, jt	i, jt
Controls	Full	Full	Full

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

sis. Combined with the previous findings, this suggests that firms learn about their expertise while operating, enabling them to reoptimize their product portfolios by adding products that are better matched to their capabilities while dropping the ones that are not. However, young firms appear to face challenges in this process: they are less likely to add products with higher match quality than their existing portfolio and more likely to drop products they should retain. In other words, young firms struggle to climb the match-quality ladder.

3.5 Proximity of Added Products to Existing Products

Up to this point, we have focused on the relationship between product dropping and adding, as well as the relative match quality of products. We now turn to examining the proximity between newly added products and a firm's existing product portfolio. The literature finds that firms tend to produce products close to each other in terms of various measures, such as industry classification or the composition of material inputs used (e.g., Bernard et al., 2010; Boehm et al., 2022). Nonetheless, we also observe many instances in which firms expand into entirely new industries.

To examine whether the proximity of added products to a firm's existing product portfolio varies over the firm life-cycle, we use the share of input materials used to produce a newly added product that are also used for the firm's existing products as a proxy for product proximity.[24,25] Let $MaterialCloseness_{ijt}^{add}$ denote the average of the proximity measure of products added by firm i between t and $t+5$. The mean (standard deviation) of the material-based closeness of added products in the churning case is 0.708 (0.271). Table 7 shows the number of input materials used per product by firms across age groups. Focusing on the continuing firms, we find that young firms use slightly more variety of input materials to produce each product, and the variance is also larger compared to mature firms.

We then estimate the following regression model:

$$MaterialCloseness_{ijt}^{add} = \alpha + \beta \mathcal{I}_{ijt}^{drop} + X_{ijt}\gamma + \delta_i + \delta_{jt} + \varepsilon_{ijt}. \tag{3.8}$$

Column 1 of Table 8 shows that, on average, firms add products that are closer to their existing portfolio when they simultaneously drop products. However, this pattern differs across age groups. Column 3 presents regression results from an extended

[24]The CMF provides establishment-level data on the list of material inputs used and associated expenditures. By focusing on single-product establishments, we identify the set of material inputs used in the production of each product.

[25]We are in the process of exploring an expenditure-weighted version of the material input-based proximity measure, following Boehm et al. (2022).

Table 9: Product Add/Drop and Firm Performance

	$\Delta Vadd$	ΔEmp	ΔTFP	ΔLP
$Add_{t:t+5}$	0.830***	0.802***	0.735***	0.762***
	(0.019)	(0.019)	(0.019)	(0.019)
$Drop_{t:t+5}$	-0.754***	-0.731***	-0.686***	-0.713***
	(0.019)	(0.018)	(0.017)	(0.018)
Observations	682,000	682,000	648,000	648,000
Fixed effects	i, jt	i, jt	i, jt	i, jt
Controls	Full	Full	Full	Full

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

specification that interacts the drop dummy with the young firm dummy. The results indicate that, relative to mature firms, young firms tend to add products that are more distant from their existing product portfolio.[26] Table A19 in the Appendix presents the results using industry-based proximity, and the findings are qualitatively similar.

3.6 Product Switching and Firm Performance

In this section, we further examine whether firms' product-adding or dropping behavior affects firm performance.

3.6.1 The Impact of Product Adding and Dropping

We begin by using the following regression model to estimate the relationship between the decision to add or drop a product and firm performance:

$$\Delta y_{ijt} = \alpha + \beta_1 \mathcal{I}^{drop}_{ijt} + \beta_2 \mathcal{I}^{add}_{ijt} + X_{ijt}\gamma + \delta_i + \delta_{jt} + \varepsilon_{ijt} \;, \tag{3.9}$$

[26]See Table A15-A18 in the Appendix for the full results.

Table 10: Firm-Level Output and Match Quality Growth Decomposition

	Output			Match quality		
	all	age 0-5	age 6 +	all	age 0-5	age 6 +
Total changes	0.112	0.662	0.104	0.017	0.130	0.016
Within share	0.543	0.444	0.545	0	0	0
Between share	0.008	0.002	0.009	0.318	0.126	0.320
Cross share	0.009	-0.005	0.010	0	0	0
Addition share	0.424	0.554	0.422	0.574	0.853	0.572
Drop share	0.015	0.005	0.015	0.107	0.022	0.108

Notes: Firms in the manufacturing sector from 1982 to 2007.

where Δy_{ijt} is the log difference of i) real value added, ii) total employment, iii) total factor productivity, or iv) labor productivity between t and $t+5$.[27]

Table 9 presents the result, indicating that product dropping is negatively associated with subsequent growth across the four performance measures, while product adding is positively correlated with them.[28] When considering product switching—defined as the combination of adding and dropping products—it is positively associated with subsequent changes in all four performance measures.[29]

3.6.2 Decomposition of Firm-Level Growth in Output and Match Quality

To understand the importance of within-firm reallocation of resources through product switching to firm growth further, we conduct an accounting decomposition of output and match quality growth at the firm-product level. This decomposition allows us to distinguish between the effects of changes in the share of output across products and output and match quality growth within each firm-product pair.

Define within-firm output share of product p at t for firm i as $\omega_{pit} = \frac{PV_{pit}}{\sum_{p \in \mathcal{P}_{it}} PV_{pit}}$, where

[27]Value added is Total Value of Shipments + Final Inventory Investment + Work-in-Progress Goods - Resales - Material Inputs - Energy Expenditures. Labor productivity is the Real value of shipments/Total employment. We use the Census TFP beta 8 available in the CMF.

[28]Table A20 in the Appendix reports the full set of results.

[29]These results are consistent with previous findings by Bernard et al. (2010) and Argente et al. (2018).

PV_{pit} denotes the real product value of shipments of product p by firm i at t, and $\mathcal{P}_{it}$ is the set of products in firm i's product portfolio at t. Let y_{pit} denote ether the log of real product value of shipments, $\log(PV_{pit})$, or the firm-product match quality, q_{pi}. We compute the firm-level average output or match-quality as $y_{it} = \sum_{p\in\mathcal{P}_{it}} \omega_{pit} y_{pit}$.

We then decompose the growth in firm-level output or match quality as follows:

$$\Delta y_{it} = \underbrace{\sum_{p\in\mathcal{C}_{it}} \omega_{pit-5}\Delta y_{pit}}_{\text{within term}} + \underbrace{\sum_{p\in\mathcal{C}_{it}} (y_{pit-5} - y_{it-5})\Delta\omega_{pit}}_{\text{between term}} + \underbrace{\sum_{p\in\mathcal{C}_{it}} \Delta\omega_{pit}\Delta y_{pit}}_{\text{cross term}}$$
$$+ \underbrace{\sum_{p\in\mathcal{N}_{it}} \omega_{pit}(y_{pit} - y_{it-5})}_{\text{addition term}} - \underbrace{\sum_{p\in\mathcal{X}_{it}} \omega_{pit-5}(y_{pit-5} - y_{it-5})}_{\text{drop term}}. \tag{3.10}$$

$\Delta X_{\cdot t} = X_{\cdot t} - X_{\cdot t-5}$ is the change in any variable $X_{\cdot t}$ between $t-5$ and t, $\mathcal{C}_{it}$ is the set of continuing products that firm i produces in both $t-5$ and t, $\mathcal{N}_{it}$ is the set of products newly added by firm i in t, and $\mathcal{X}_{it}$ is the set of products dropped by firm i in t.

Table 10 presents the decomposition results for both output (real product value of shipments) and match quality. We normalize each term by the total change to quantify its contribution to overall growth. We refer to these normalized values as shares. The first three columns show that output growth is primarily driven by within-product growth (within share) and new product addition (addition term). For young firms, however, new product addition plays a more prominent role than within-product growth. In fact, the combined contribution of product-switching components, addition and drop shares, is 28% higher for young firms than for mature firms (0.554 + 0.005 vs. 0.422 + 0.015).

Taken together, these results provide suggestive evidence that firms foster growth by reallocating resources through product switching, effectively climbing the match-quality ladder. However, young firms struggle in this process, often devoting time and resources to discovering their areas of expertise by experimenting with a wider range of products.

4 Robustness Tests

As we show in the Appendix, our results remain robust to different sets of control variables. The results are also robust to using different firm identifiers and alternative specifications for estimating the match quality measure. For analyses of firms' product-dropping behavior, product drops due to firm exit could affect our results in various ways. To address this concern, we re-estimate our models after excluding all exiting firms. The results remain robust.[30]

Financial frictions may provide an alternative explanation for some of our results. To mitigate this concern and focus on the learning channel, we control for total assets in the current analysis and are exploring additional approaches to test and account for this mechanism. One of the alternative ways is to use industry-level variation in external funding, such as differences in physical versus intangible capital intensity.

5 Potential Mechanism

One potential interpretation centers on the nascency of young firms and their limited information about product markets. Young firms may lack insights into market dynamics and may not fully understand their own potential (Jovanovic, 1982; Kim, 2025). As a result, they may struggle to assess whether their current products are a good match, unlike their mature counterparts with more experience and information. This idea is formalized in the following model of learning about match quality between firms and products.

5.1 Environment

Suppose firms are assigned a product at birth and must decide whether to keep and operate it or drop it. Operating the product requires the firm to pay a fixed cost, c_f.

[30]The results using different firm identifiers, alternative match quality estimations, and restricting the sample to continuing firms only are available upon request.

Each product is characterized by propinquity θ_{pi}, relative to the firm's expertise, which is drawn from normal distribution $\theta_{pi} \sim N(\theta_0, \sigma_0^2)$. The higher the value of θ_{pi}, the better the match between the product and the firm. As a result, propinquity determines the output level y_{pit} when producing this product as follows:

$$y_{pit} = \theta_{pi} + \varepsilon_{pit},$$

where $\varepsilon_{pit} \sim N(0, \sigma_\varepsilon^2)$ is an i.i.d. shock.

Suppose firms already know their expertise, so when matched with a product, they can observe the propinquity θ_{pi} of the match. Consequently, their value function is:

$$V(\theta_{pi}) = \max\{0, \theta_{pi} - c_f + \beta V(\theta_{pi})\}.$$

However, young firms have limited knowledge of their expertise and cannot directly observe θ_{pi}. Instead, they observe y_{pit} and need to learn about θ_{pi}. Suppose learning follows Bayesian updating based on y_{pit} and a signal s_{pit} each period (Farboodi et al., 2019; Farboodi and Veldkamp, 2021; Baley and Veldkamp, 2025), where the signal is extracted with the firm's ability D_{it} to process observable information:

$$s_{pit} = \theta_{pi} + \eta_{pit}, \quad \eta_{pit} \sim N(0, \frac{\sigma_\varepsilon^2}{D_{it}}). \tag{5.11}$$

The firm's information-processing ability D_{it} depends on firm characteristics x_{it}—such as age, experience, or managerial practices—so that $D_{it} = D(x_{it})$ with $D'(x_{it}) > 0$. This ability increases the precision of the signals firms draw.

Given this structure, learning proceeds as follows. Firm i enters product market p at $t = 1$ with an initial belief about θ_{pi}, given by the prior $\theta_{pi} \sim N(\theta_0, \sigma_0^2)$. In periods $t \geq 2$, the firm updates its belief using the following information set (accumulated up to $t - 1$),

$$\mathcal{I}_{pit} \equiv \{y_{pi\tau}, s_{pi\tau}\}_{\tau=1}^{t-1},$$

leading to the posterior:

$$E(\theta_{pi}|\mathcal{I}_{pit}) = \frac{\left(\frac{\theta_0}{\sigma_0^2} + \frac{(t-1)}{\sigma_\varepsilon^2}\frac{\sum_{\tau=1}^{t-1} y_{pi\tau}}{(t-1)} + \frac{\sum_{\tau=1}^{t-1} D_{i\tau}s_{pi\tau}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{(t-1)}{\sigma_\varepsilon^2} + \frac{\sum_{\tau=1}^{t-1} D_{i\tau}}{\sigma_\varepsilon^2}\right)} \tag{5.12}$$

$$Var(\theta_{pi}|\mathcal{I}_{pit}) = \frac{1}{\left(\frac{1}{\sigma_0^2} + \frac{(t-1)}{\sigma_\varepsilon^2} + \frac{\sum_{\tau=1}^{t-1} D_{i\tau}}{\sigma_\varepsilon^2}\right)}, \tag{5.13}$$

where $E(\theta_{pi}|\mathcal{I}_{pit})$ and $Var(\theta_{pi}|\mathcal{I}_{pit})$ is the mean and variance of the firm's posterior belief about θ_{pi}, respectively. Importantly, the posterior mean is a weighted average of the prior θ_0, the average observed outcome $\frac{1}{t-1}\sum_{\tau=1}^{t-1} y_{pi\tau}$, and the signals $s_{pi\tau}$, with weights determined by market tenure $(t-1)$ and the firm's information-processing ability $D_{i\tau}$. This framework allows us to identify multiple sources of learning and to disentangle the role of the firm's information-processing ability (which depends on firm age) from the effect of its tenure in the market.

Given this, the value function of firms in the learning process is

$$V(\mathcal{I}_{pit}, t, \{D_{i\tau}\}_{\tau=1}^{t-1}) = \max\{0, E(\theta_{pi}|\mathcal{I}_{pit}) - c_f + \beta\mathbb{E}_{y,s}V(\mathcal{I}_{pit+1}, t+1, \{D_{i\tau}\}_{\tau=1}^{t})\}.$$

For simple illustration, suppose D_{it} depends solely on firm age, $D_{it} = a_{it}$. Then the value function simplifies to:

$$V(\mathcal{I}_{pit}, t, a_{it}) = \max\{0, E(\theta_{pi}|\mathcal{I}_{pit}) - c_f + \beta\mathbb{E}_{y,s}V(\mathcal{I}_{pit+1}, t+1, a_{it+1})\}.$$

5.2 Model Implications

There are a couple of features associated with Bayesian learning as follows.

Lemma 1. *Given all else equal, younger firms on average have a lower posterior mean $E(\theta_{pi}|\mathcal{I}_{pit})$ for a product with high $\theta_{pi} > \theta_0$ and have a higher posterior mean for a product with low $\theta_{pi} < \theta_0$.*

Proof.

$$\frac{\partial E(\theta_{pi}|\mathcal{I}_{pit})}{\partial a_{it}} = \frac{(t-1)\left(\frac{\frac{\sum_{\tau=1}^{t-1} s_{pi\tau}}{(t-1)}-\theta_0}{\sigma_0^2} + \frac{\sum_{\tau=1}^{t-1} s_{pi\tau}-\sum_{\tau=1}^{t-1} y_{pi\tau}}{\sigma_\varepsilon^2} + \frac{\frac{\sum_{\tau=1}^{t-1} s_{pi\tau}\sum_{\tau=1}^{t-1} a_{i\tau}}{(t-1)}-\sum_{\tau=1}^{t-1} s_{pi\tau}a_{i\tau}}{\sigma_\varepsilon^2}\right)}{\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2}+\frac{(t-1)}{\sigma_\varepsilon^2}+\frac{\sum_{\tau=1}^{t-1} a_{i\tau}}{\sigma_\varepsilon^2}\right)^2}$$

$$\Rightarrow \mathbb{E}_{y,s}\left(\frac{\partial E(\theta_{pi}|\mathcal{I}_{pit})}{\partial a_{it}}\right) = \frac{(t-1)(\theta_{pi}-\theta_0)}{\sigma_0^2\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2}+\frac{(t-1)}{\sigma_\varepsilon^2}+\frac{\sum_{\tau=1}^{t-1} a_{i\tau}}{\sigma_\varepsilon^2}\right)^2} \lesseqgtr 0 \text{ iff } \theta_{pi} \lesseqgtr \theta_0$$

□

Lemma 1 shows that younger firms have systematically biased posterior beliefs relative to older firms. Because young firms have lower information-processing ability, their signals are noisier and therefore receive less weight in Bayesian updating. As a result, given all else equal, the posterior mean of a young firm places relatively more weight on the prior θ_0. When the true match quality is high ($\theta_{pi} > \theta_0$), this anchoring leads young firms to update insufficiently toward the true high value, producing a posterior mean that is lower than that of older firms. Conversely, when the true match quality is low ($\theta_{pi} < \theta_0$), the prior lies above the truth, so younger firms update insufficiently downward and end up with a higher posterior mean than older firms. Thus, younger firms tend to underestimate good matches and overestimate bad ones, generating systematic directionally biased beliefs early in the lifecycle.

Lemma 2. *Younger firms have higher posterior variance $Var(\theta_{pi}|\mathcal{I}_{pit})$.*

Proof.

$$\frac{\partial Var(\theta_{pi}|\mathcal{I}_{pit})}{\partial a_{it}} = -\frac{1}{\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2}+\frac{(t-1)}{\sigma_\varepsilon^2}+\frac{\sum_{\tau=1}^{t-1} a_{i\tau}}{\sigma_\varepsilon^2}\right)^2} < 0$$

□

Lemma 2 establishes that younger firms also have more dispersed posterior beliefs. Noisier signals imply less informative likelihoods in the Bayesian updating process, so young firms retain more uncertainty about θ_{pi}. As the information-processing ability

a_{it} increases with firm age, signals become more precise and firms place greater weight on observed outcomes and signals, which tightens the posterior distribution. Consequently, older firms exhibit lower posterior variance than younger firms. Together with Lemma 1, this implies that young firms not only bias their estimates toward the prior but also hold more diffuse beliefs, which can lead to systematically different product add/drop decisions in early periods.

Next, we characterize product addition and dropping decisions at different stages of the firm lifecycle. For analytic tractability, we now assume a two-period model and focus on two firms: a young firm still in the learning phase and an older firm that has completed learning. Suppose both firms are assigned a product with the same match quality θ_{pi}. In this environment, we derive the following propositions.

Proposition 1. *If the match is good with $\theta_{pi} > \theta_0$ and $\theta_{pi} > c_f$, the younger firm is more likely to drop it.*

Proof. The older firm adds the product as $\theta_{pi} > c_f$ under full information. The younger firm has the information of $\mathcal{I}_{pi1} = (y_{pi1}, s_{pi1})$ and decide whether to add or drop a product based on the posterior belief determined by

$$E(\theta_{pi}|\mathcal{I}_{pi1}) = \frac{\left(\frac{\theta_0}{\sigma_0^2} + \frac{y_{pi1}}{\sigma_\varepsilon^2} + \frac{a_{i1}s_{pi1}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{a_{i1}}{\sigma_\varepsilon^2}\right)} \gtreqless c_f.$$

Thus, if $E(\theta_{pi}|\mathcal{I}pi1) < c_f$, the young firm may drop the product despite its high true match quality. This outcome is more likely for younger firms because, as shown in Lemma 1, their noisier signals lead to a downward-biased posterior in expectation, $\mathbb{E}y, s[E(\theta_{pi}|\mathcal{I}pi1)] < \theta pi$. □

Proposition 1 shows that even when the underlying match quality is good enough to keep—that is, $\theta_{pi} > \theta_0$ and $\theta_{pi} > c_f$—a young firm is more likely than an older firm to drop the product. The intuition is straightforward. The older firm has already completed learning and therefore knows the true match quality. Because $\theta_{pi} > c_f$, it will always add the product. By contrast, the younger firm faces imperfect information in period 1 and decides based on the posterior belief $E(\theta_{pi}|\mathcal{I}pi1)$. Even for a good match, the posterior can fall below the threshold c_f for some realizations of $(ypi1, s_{pi1})$, leading the young firm to drop the product. The likelihood of this event is higher for younger firms because their signals are noisier (due to lower information-processing ability $D(a_{i1})$ than the older firm's), which makes their posterior less accurate and more dispersed. As shown in Lemma 1, younger firms' beliefs are biased downward in expectation relative to the true θ_{pi}. Thus, despite having the same above-average underlying match quality, young firms are systematically more prone to mistakenly dropping good products.

Proposition 2. *If the match is bad with $\theta_{pi} < \theta_0$ and $\theta_{pi} < c_f$, the younger firm is more likely to keep it.*

Proof. The older firm who has completed learning drops the product as $\theta_{pi} < c_f$. The younger firm can still keep the product with $\mathcal{I}_{pi1} = (y_{pi1}, s_{pi1})$ s.t.

$$E(\theta_{pi}|\mathcal{I}_{pi1}) = \frac{\left(\frac{\theta_0}{\sigma_0^2} + \frac{y_{pi1}}{\sigma_\varepsilon^2} + \frac{a_{i1}s_{pi1}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{a_{i1}}{\sigma_\varepsilon^2}\right)} > c_f,$$

and this likelihood increases for younger firm following Lemma 1 and $\mathbb{E}_{y,s}(E(\theta_{pi}|\mathcal{I}_{pi1})) > \theta_{pi}$. □

Following the same logic, Proposition 2 shows that young firms are more likely to retain bad products. Because they learn with noisy signals, their posterior beliefs about low match quality can be overly optimistic, pushing $E(\theta_{pi}|\mathcal{I}pi1)$ above the adoption threshold c_f. Older firms, having learned the true θpi, correctly drop such products. Thus, learning frictions make young firms prone to mistakenly keeping low-quality matches.

To illustrate these results, we simulate the model for 30,000 firms. We first consider the case with $\theta_{pi} > \theta_0$, using parameters calibrated to $\theta_{pi} = 3.5$, $\theta_0 = 3$, $\sigma_0 = 1.1$, and

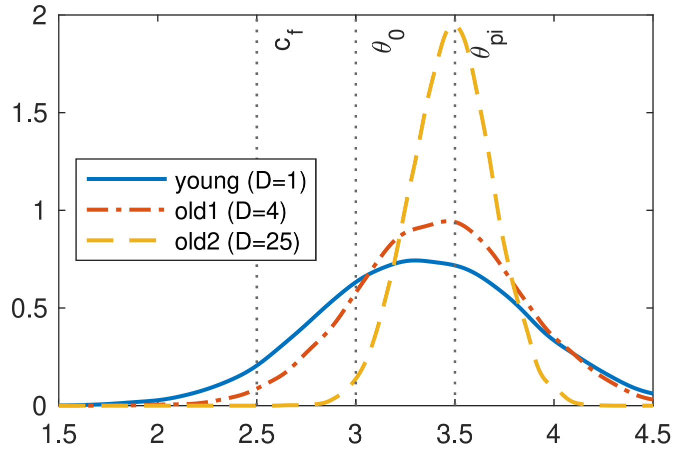

Figure 1: Distribution of Posterior Means: Young vs. Old (High θ_{pi})

$c_f = 2.5$.

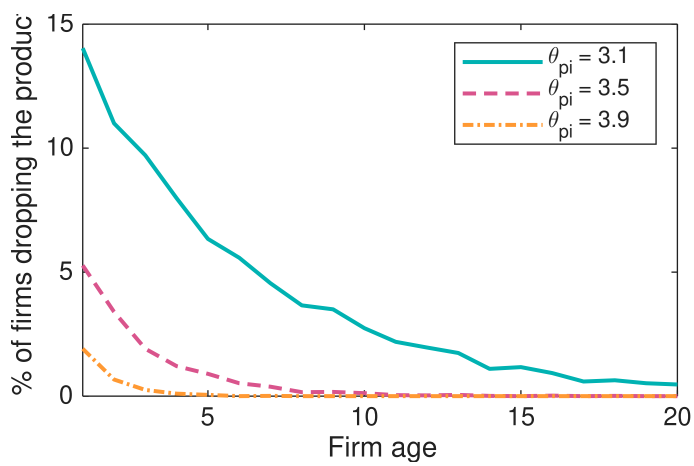

Figure 2: Fraction of Firms Dropping Products with High θ_{pi}

Figure 1 plots the distribution of posterior means across young and old firms: the blue line corresponds to young firms of age 1, the red dashed line to medium-aged firms of age 4, and the yellow dashed line to old firms of age 25. The figure shows that older firms have posterior beliefs that are both higher and less dispersed. Consequently, older firms have a higher probability of correctly keeping products with good match quality, $\theta_{pi} > \theta_0$. Figure 2 plots the fraction of firms that drop the product. Consistent with Proposition 1, this fraction is highest for young firms and declines with firm age. Moreover, the drop rate falls for all firms when the underlying match quality is higher. This

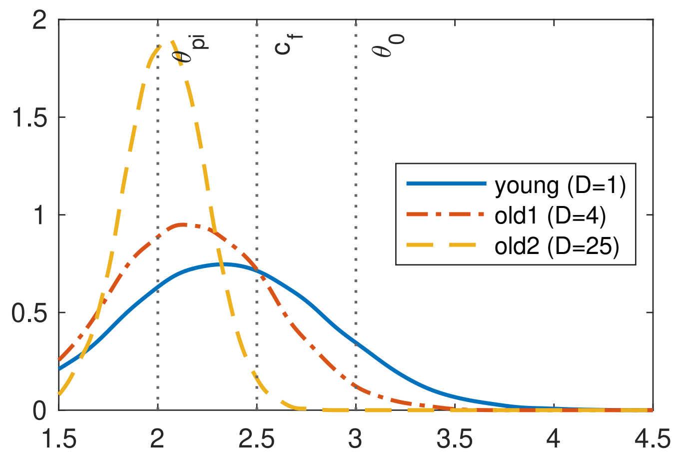

Figure 3: Distribution of Posterior Means: Young vs. Old (Low θ_{pi})

is because higher match quality generates stronger signals, enabling firms to update more accurately from the outset.

Next, we calibrate the model to the other case with $\theta_{pi} < \theta_0$, using $\theta_{pi} = 2$, $\theta_0 = 3$, $\sigma_0 = 1.1$, and $c_f = 2.5$. Figure 3 plots the distribution of posterior means across firms at different ages for a low–match-quality product. Older firms' posterior beliefs are lower and less dispersed, giving them a higher probability of correctly dropping the product. Figure 4 shows the fraction of firms that keep the product. Consistent with Proposition 2, this fraction is highest for young firms and declines with age. As before, retention rates fall for all firms when the underlying match quality is lower, since stronger negative signals allow firms to update more quickly.

Together, these results show that younger firms make noisier product-portfolio decisions than older firms. With imperfect information and limited information-processing ability, young firms systematically misestimate match quality: they are more likely to drop good products because their posterior is downward biased, and more likely to retain bad products because their posterior is upward biased. In contrast, older firms—having completed learning—know the true match quality and make correct add/drop decisions. These learning frictions generate lifecycle patterns in product dynamics consistent with the empirical evidence.

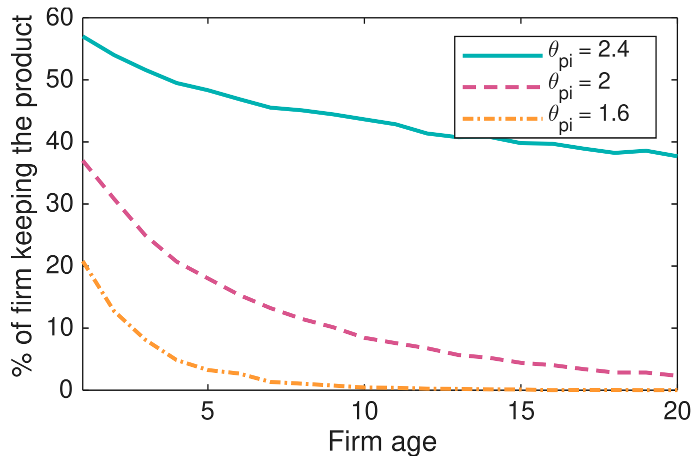

Figure 4: Fraction of Firms Keeping Products with Low θ_{pi}

6 Concluding Remarks

In this paper, we propose product switching over the firm life-cycle as an important source of firm growth and performance by highlighting the specific patterns observed for young firms. We use a comprehensive administrative dataset that tracks U.S. manufacturing output at the product-firm level and identify several key aspects: how firms add or drop products in general, how the match quality of added or dropped products looks like and is correlated with each other, how product dropping and adding matter for firm performance, and how such patterns are different for young firms.

Our findings provide a basis for understanding how firms optimally switch products and climb up the match-quality ladder over their life-cycle. We show that firms tend to drop products with poor match quality, but this pattern is less pronounced among young firms. Interestingly, young firms are more likely to retain products with poor match quality rather than those with high match quality.

We also find that the probability of adding products with a match quality higher than that of existing products is higher if at least one product is dropped within the same period. However, young firms are less likely to do so than mature firms. Taken together, these results suggest that while young firms actively experiment by adding new products distant from their existing portfolio, they face greater difficulty climbing the match-quality ladder and improving performance, due to their limited ability to drop poorly matched products and add better-matched ones early in their life-cycle.

Through the lens of a simple model with learning about match quality between products and firms, we find that the learning can account for the observed patterns. In particular, the model predicts that younger firms with limited information are more likely to drop a good match-quality product and add a bad match-quality product, relative to mature counterparts. This indicates that the learning process helps explain the observed patterns of product switching over the firm life-cycle. We are currently extending the model into a full-fledged set up to quantify the aggregate implications of the product-firm match quality ladder and derive additional testable predictions.

This also raises important policy considerations. Policies that strengthen young firms' information-processing ability can improve early-stage learning and reduce misallocation in product decisions. For example, subsidies that expand digital or data-analytics capabilities, or programs that support managerial and organizational practices, can increase the precision of the signals young firms extract. Moreover, if information-processing ability depends on spillovers from the behavior of other firms, this channel introduces externalities that further justify policy intervention. A full exploration of these implications is left to future work.

References

Abowd, John M, Francis Kramarz, and David N Margolis, "High wage workers and high wage firms," *Econometrica*, 1999, *67* (2), 251–333.

Akcigit, Ufuk and Sina T Ates, "What Happened to US Business Dynamism?," Technical Report, National Bureau of Economic Research 2019.

Argente, David, Munseob Lee, and Sara Moreira, "Innovation and product reallocation in the great recession," *Journal of Monetary Economics*, 2018, *93*, 1–20.

_ , _ , and _ , "The life cycle of products: Evidence and implications," *Journal of Political Economy*, 2024, *132* (2), 337–390.

Baley, Isaac and Laura L Veldkamp, "The data economy: Tools and applications," in "The Data Economy," Princeton University Press, 2025.

Becker, Randy, Wayne Gray, and Jordan Marvakov, "NBER-CES manufacturing industry database: Technical notes," *NBER Working Paper*, 2013, *5809.*

Berlingieri, Giuseppe, Maarten De Ridder, Danial Lashkari, and Davide Rigo, "Growth through innovation bursts," 2024.

Bernard, Andrew B and Toshihiro Okubo, "Product switching and the business cycle," Technical Report, National Bureau of Economic Research 2016.

_ , Stephen J Redding, and Peter K Schott, "Multiple-product firms and product switching," *American economic review*, 2010, *100* (1), 70–97.

_ , _ , and _ , "Multiproduct firms and trade liberalization," *The Quarterly journal of economics*, 2011, *126* (3), 1271–1318.

Boehm, Johannes, Swati Dhingra, and John Morrow, "The comparative advantage of firms," *Journal of Political Economy*, 2022, *130* (12), 3025–3100.

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa, "A distributional framework for matched employer employee data," *Econometrica*, 2019, *87* (3), 699–739.

Broda, Christian and David E Weinstein, "Product Creation and Destruction: Evidence and Price Implications," *American Economic Review*, June 2010, *100* (3), 691–723.

Chow, Melissa C, Teresa C Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T Kirk White, "Redesigning the Longitudinal Business Database," Technical Report, National Bureau of Economic Research 2021.

Cooley, Thomas F and Vincenzo Quadrini, "Financial markets and firm dynamics," *American economic review*, 2001, *91* (5), 1286–1310.

Davis, Steven J and John C Haltiwanger, "Dynamism diminished: The role of housing markets and credit conditions," Technical Report, National Bureau of Economic Research 2019.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Where has all the skewness gone? The decline in high-growth (young) firms in the US," *European Economic Review*, 2016, *86*, 4–23.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda, "The role of entrepreneurship in US job creation and economic dynamism," *Journal of Economic Perspectives*, 2014, *28* (3), 3–24.

Dent, Robert C, Benjamin W Pugsley, Harrison Wheeler et al., "Longitudinal Linking of Enterprises in the LBD and SSL," Technical Report, Center for Economic Studies, US Census Bureau 2018.

Eckel, Carsten and J Peter Neary, "Multi-product firms and flexible manufacturing in the global economy," *The Review of Economic Studies*, 2010, *77* (1), 188–217.

Evans, David S and Boyan Jovanovic, "An estimated model of entrepreneurial choice under liquidity constraints," *Journal of political economy*, 1989, *97* (4), 808–827.

Farboodi, Maryam and Laura Veldkamp, "A model of the data economy," Technical Report, National Bureau of Economic Research Cambridge, MA, USA 2021.

_ , Roxana Mihet, Thomas Philippon, and Laura Veldkamp, "Big data and firm dynamics," in "AEA papers and proceedings," Vol. 109 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203 2019, pp. 38–42.

Foster, Lucia, Cheryl Grim, John C Haltiwanger, and Zoltan Wolf, "Innovation, productivity dispersion, and productivity growth," Technical Report, National Bureau of Economic Research 2018.

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

Haltiwanger, John, "Job creation and firm dynamics in the United States," *Innovation policy and the economy*, 2012, *12* (1), 17–38.

_ , Ron S Jarmin, and Javier Miranda, "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

_ , _ , Robert B Kulick, and Javier Miranda, "High growth young firms: Contribution to job, output and productivity growth," *US Census Bureau Center for Economic Studies Paper No. CES-WP-16-49*, 2016.

Holtz-Eakin, Douglas, David Joulfaian, and Harvey S Rosen, "Sticking it out: Entrepreneurial survival and liquidity constraints," *Journal of Political economy*, 1994, *102* (1), 53–75.

Hurst, Erik and Annamaria Lusardi, "Liquidity constraints, household wealth, and entrepreneurship," *Journal of political Economy*, 2004, *112* (2), 319–347.

Jarmin, Ron S and Javier Miranda, "The longitudinal business database," *Available at SSRN 2128793*, 2002.

Jo, Karam and Seula Kim, "Heterogeneous Innovations and Growth Under Imperfect Technology Spillovers," *IZA Discussion Paper No. 17581*, 2024.

Jovanovic, Boyan, "Selection and the Evolution of Industry," *Econometrica: Journal of the Econometric Society*, 1982, pp. 649–670.

Kehrig, Matthias and Nicolas Vincent, "The micro-level anatomy of the labor share decline," *The Quarterly Journal of Economics*, 2021, *136* (2), 1031–1087.

_ et al., "The cyclicality of productivity dispersion," *US Census Bureau Center for Economic Studies Paper No. CES-WP-11-15*, 2011.

Kerr, William R and Ramana Nanda, "Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship," *Journal of Financial Economics*, 2009, *94* (1), 124–149.

Kim, Seula, "Workers' Job Prospects and Young Firm Dynamics," *IZA Discussion Paper No. 17655*, 2025.

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

Robb, Alicia M and David T Robinson, "The capital structure decisions of new firms," *The Review of Financial Studies*, 2014, *27* (1), 153–179.

Schmalz, Martin C, David A Sraer, and David Thesmar, "Housing collateral and entrepreneurship," *The Journal of Finance*, 2017, *72* (1), 99–132.

Appendix

A Full Models

A.1 Product Dropping

Table A1: Probability of Product Drop (PV)

VARIABLES	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
$\log(PV_{pit})$	-0.055***	-0.054***	-0.053***	-0.053***	-0.052***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Emp)			-0.020***	-0.009***	-0.012***
			(0.002)	(0.002)	(0.002)
log(Total Assets)			0.003***	0.019***	0.019***
			(0.001)	(0.004)	(0.004)
# establishments			-0.002***	-0.002***	-0.002***
			(0.000)	(0.000)	(0.000)
# products			0.007***	0.007***	0.006***
			(0.000)	(0.000)	(0.000)
log(CA)			-0.002***	-0.002***	-0.002***
			(0.001)	(0.001)	(0.001)
log(CS)			-0.004***	-0.004***	-0.003***
			(0.001)	(0.001)	(0.001)
TFP			-0.004*	-0.006**	-0.007***
			(0.002)	(0.002)	(0.003)
log(Prod. Emp)				-0.009***	-0.010***
				(0.001)	(0.001)
log(Equipment)				-0.028***	-0.029***
				(0.004)	(0.004)
log(Structure)				0.011***	0.011***
				(0.003)	(0.003)
log(Material)				-0.004***	-0.004***
				(0.001)	(0.001)
log(Energy)				0.004***	0.003***
				(0.001)	(0.001)
Tenure		0.004***			0.004***
		(0.000)			(0.001)
Tenure squared		-0.000***			-0.000***
		(0.000)			(0.000)
Constant	0.943***	0.942***	0.965***	0.978***	1.004***
	(0.010)	(0.010)	(0.015)	(0.016)	(0.017)

Notes: Estimates for product-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A2: Probability of Product Drop (Match Quality)

VARIABLES	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Quality$_{pi}$	-1.212***	-1.028***	-1.189***	-1.187***	-1.074***
	(0.029)	(0.022)	(0.029)	(0.029)	(0.021)
log(Emp)			-0.035***	-0.015***	-0.016***
			(0.002)	(0.002)	(0.002)
log(Total Assets)			0.002*	0.023***	0.021***
			(0.001)	(0.004)	(0.004)
# establishments			-0.002***	-0.002***	-0.002***
			(0.000)	(0.000)	(0.000)
# products			0.005***	0.005***	0.005***
			(0.000)	(0.000)	(0.000)
log(CA)			0	0	0.002***
			(0.001)	(0.001)	(0.001)
log(CS)			-0.005***	-0.005***	-0.002***
			(0.001)	(0.001)	(0.001)
TFP			-0.011***	-0.020***	-0.013***
			(0.002)	(0.002)	(0.002)
log(Prod. Emp)				-0.009***	-0.010***
				(0.001)	(0.001)
log(Equipment)				-0.025***	-0.025***
				(0.004)	(0.004)
log(Structure)				0.005**	0.006**
				(0.003)	(0.003)
log(Material)				-0.013***	-0.008***
				(0.001)	(0.001)
log(Energy)				0.001	0.002*
				(0.001)	(0.001)
$\log(PV_{pit})$		-0.021***			-0.017***
		(0.001)			(0.001)
Tenure		0.041***			0.042***
		(0.001)			(0.001)
Tenure squared		-0.001***			-0.001***
		(0.000)			(0.000)
Constant	1.053***	0.963***	1.164***	1.221***	1.111***
	(0.015)	(0.014)	(0.021)	(0.022)	(0.022)

Notes: Estimates for product-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Probability of Product Drop (Young Firm)

VARIABLES	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young Firm$_{it}$	-0.084***	-0.073***	-0.092***	-0.093***	-0.075***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
log(Emp)			-0.050***	-0.025***	-0.015***
			(0.002)	(0.002)	(0.002)
log(Total Assets)			-0.008***	0.015***	0.019***
			(0.001)	(0.005)	(0.004)
# establishments			-0.004***	-0.004***	-0.002***
			(0.000)	(0.000)	(0.000)
# products			0.011***	0.011***	0.006***
			(0.001)	(0.001)	(0.000)
log(CA)			-0.003***	-0.002***	-0.001**
			(0.001)	(0.001)	(0.001)
log(CS)			-0.002**	-0.002**	-0.003***
			(0.001)	(0.001)	(0.001)
TFP			-0.014***	-0.027***	-0.008***
			(0.002)	(0.003)	(0.003)
log(Prod. Emp)				-0.008***	-0.010***
				(0.001)	(0.001)
log(Equipment)				-0.032***	-0.029***
				(0.004)	(0.004)
log(Structure)				0.011***	0.011***
				(0.003)	(0.003)
log(Material)				-0.019***	-0.005***
				(0.001)	(0.001)
log(Energy)				-0.002*	0.003***
				(0.001)	(0.001)
$\log(PV_{pit})$		-0.054***			-0.052***
		(0.002)			(0.002)
Tenure		0.002***			0.003***
		(0.000)			(0.000)
Tenure squared		-0.000***			-0.000***
		(0.000)			(0.000)
Constant	0.591***	0.951***	0.828***	0.918***	1.038***
	(0.000)	(0.011)	(0.015)	(0.016)	(0.018)

Notes: Estimates for product-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Probability of Product Drop (PV × Young)

VARIABLES	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
$\log(PV_{pit})$	-0.056***	-0.055***	-0.054***	-0.054***	-0.052***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Young Firm$_{it}$	-0.163***	-0.142***	-0.159***	-0.160***	-0.141***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
$\log(PV_{pit})$ × Young$_{it}$	0.012***	0.011***	0.011***	0.011***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Emp)			-0.025***	-0.013***	-0.015***
			(0.002)	(0.002)	(0.002)
log(Total Assets)			0.001	0.019***	0.019***
			(0.001)	(0.004)	(0.004)
# establishments			-0.002***	-0.002***	-0.002***
			(0.000)	(0.000)	(0.000)
# products			0.007***	0.007***	0.006***
			(0.000)	(0.000)	(0.000)
log(CA)			-0.002***	-0.001*	-0.001*
			(0.001)	(0.001)	(0.001)
log(CS)			-0.003***	-0.003***	-0.003***
			(0.001)	(0.001)	(0.001)
TFP			-0.005**	-0.008***	-0.009***
			(0.002)	(0.003)	(0.003)
log(Prod. Emp)				-0.009***	-0.010***
				(0.001)	(0.001)
log(Equipment)				-0.029***	-0.029***
				(0.004)	(0.004)
log(Structure)				0.011***	0.011***
				(0.003)	(0.003)
log(Material)				-0.004***	-0.005***
				(0.001)	(0.001)
log(Energy)				0.004***	0.003***
				(0.001)	(0.001)
Tenure		0.003***			0.003***
		(0.000)			(0.000)
Tenure squared		-0.000***			-0.000***
		(0.000)			(0.000)
Constant	0.960***	0.957***	1.012***	1.027***	1.044***
	(0.011)	(0.011)	(0.016)	(0.017)	(0.018)

Notes: Estimates for product-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A5: Probability of Product Drop (Quality × Young)

VARIABLES	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Quality$_{pi}$	-1.221***	-1.032***	-1.196***	-1.194***	-1.081***
	(0.030)	(0.022)	(0.030)	(0.030)	(0.022)
Young Firm$_{it}$	-0.411***	-0.371***	-0.402***	-0.403***	-0.368***
	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)
Quality$_{pi}$ × Young$_{it}$	0.395***	0.514***	0.367***	0.368***	0.497***
	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
log(Emp)			-0.040***	-0.020***	-0.018***
			(0.002)	(0.002)	(0.002)
log(Total Assets)			0	0.022***	0.020***
			(0.001)	(0.004)	(0.004)
# establishments			-0.002***	-0.002***	-0.001***
			(0.000)	(0.000)	(0.000)
# products			0.005***	0.005***	0.005***
			(0.000)	(0.000)	(0.000)
log(CA)			0	0.001*	0.002***
			(0.001)	(0.001)	(0.001)
log(CS)			-0.004***	-0.004***	-0.002***
			(0.001)	(0.001)	(0.001)
TFP			-0.012***	-0.021***	-0.014***
			(0.002)	(0.002)	(0.002)
log(Prod. Emp)				-0.009***	-0.010***
				(0.001)	(0.001)
log(Equipment)				-0.026***	-0.026***
				(0.004)	(0.004)
log(Structure)				0.005*	0.006**
				(0.003)	(0.003)
log(Material)				-0.014***	-0.008***
				(0.001)	(0.001)
log(Energy)				0	0.002*
				(0.001)	(0.001)
$\log(PV_{pit})$		-0.021***			-0.017***
		(0.001)			(0.001)
Tenure		0.039***			0.039***
		(0.001)			(0.001)
Tenure squared		-0.001***			-0.001***
		(0.000)			(0.000)
Constant	1.071***	0.980***	1.222***	1.280***	1.146***
	(0.015)	(0.014)	(0.021)	(0.023)	(0.022)

Notes: Estimates for product-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

A.2 Firm-Level Evidence

Table A6: Product Add and Drop

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$	0.096***		0.070***
	(0.012)		(0.012)
Young Firm$_{it}$		0.148***	0
		(0.005)	(0.005)
$Drop_{t:t+5}$ $\times$ Young$_{it}$			0.295***
			(0.008)
log(Emp)	0.022***	0.029***	0.030***
	(0.002)	(0.002)	(0.002)
log(Total Assets)	-0.007*	-0.005	-0.006*
	(0.004)	(0.004)	(0.004)
# establishments	0.015***	0.012***	0.014***
	(0.004)	(0.003)	(0.004)
# products	-0.034***	-0.027***	-0.034***
	(0.003)	(0.002)	(0.003)
log(CA)	-0.001	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)
log(CS)	-0.005***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)
TFP	0.007***	0.008***	0.010***
	(0.003)	(0.003)	(0.003)
log(Prod. Emp)	-0.006***	-0.008***	-0.005***
	(0.001)	(0.001)	(0.001)
log(Equipment)	0.022***	0.021***	0.023***
	(0.003)	(0.003)	(0.003)
log(Structure)	-0.010***	-0.008***	-0.008***
	(0.003)	(0.003)	(0.003)
log(Material)	0.010***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)
log(Energy)	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
Constant	0.172***	0.174***	0.116***
	(0.018)	(0.018)	(0.018)
Observations	682,000	682,000	682,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A7: Product Add and Drop (Baseline)

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$	0.066***	0.095***	0.096***
	(0.014)	(0.013)	(0.012)
log(Emp)		0.027***	0.022***
		(0.002)	(0.002)
log(Total Assets)		0.008***	-0.007*
		(0.001)	(0.004)
# establishments		0.015***	0.015***
		(0.004)	(0.004)
# products		-0.034***	-0.034***
		(0.003)	(0.003)
log(CA)		-0.001	-0.001
		(0.001)	(0.001)
log(CS)		-0.005***	-0.005***
		(0.001)	(0.001)
TFP		-0.002	0.007***
		(0.002)	(0.003)
log(Prod. Emp)			-0.006***
			(0.001)
log(Equipment)			0.022***
			(0.003)
log(Structure)			-0.010***
			(0.003)
log(Material)			0.010***
			(0.001)
log(Energy)			0.006***
			(0.001)
Constant	0.325***	0.221***	0.172***
	(0.008)	(0.015)	(0.018)

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A8: Product Add and Drop (Young Firm)

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
Young Firm$_{it}$	0.140***	0.148***	0.148***
	(0.005)	(0.005)	(0.005)
log(Emp)		0.032***	0.029***
		(0.003)	(0.002)
log(Total Assets)		0.010***	-0.005
		(0.001)	(0.004)
# establishments		0.012***	0.012***
		(0.004)	(0.003)
# products		-0.027***	-0.027***
		(0.002)	(0.002)
log(CA)		-0.003***	-0.003**
		(0.001)	(0.001)
log(CS)		-0.006***	-0.007***
		(0.001)	(0.001)
TFP		-0.001	0.008***
		(0.003)	(0.003)
log(Prod. Emp)			-0.008***
			(0.001)
log(Equipment)			0.021***
			(0.003)
log(Structure)			-0.008***
			(0.003)
log(Material)			0.010***
			(0.001)
log(Energy)			0.006***
			(0.001)
Constant	0.350***	0.220***	0.174***
	(0.002)	(0.015)	(0.018)

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A9: Product Add and Drop (Drop × Young)

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$	0.039***	0.069***	0.070***
	(0.013)	(0.012)	(0.012)
Young Firm$_{it}$	-0.015***	-0.001	0
	(0.005)	(0.005)	(0.005)
$Drop_{t:t+5}$ × Young$_{it}$	0.303***	0.295***	0.295***
	(0.008)	(0.008)	(0.008)
log(Emp)		0.037***	0.030***
		(0.002)	(0.002)
log(Total Assets)		0.011***	-0.006*
		(0.001)	(0.004)
# establishments		0.014***	0.014***
		(0.004)	(0.004)
# products		-0.034***	-0.034***
		(0.003)	(0.003)
log(CA)		-0.003**	-0.003**
		(0.001)	(0.001)
log(CS)		-0.006***	-0.007***
		(0.001)	(0.001)
TFP		0	0.010***
		(0.002)	(0.003)
log(Prod. Emp)			-0.005***
			(0.001)
log(Equipment)			0.023***
			(0.003)
log(Structure)			-0.008***
			(0.003)
log(Material)			0.011***
			(0.001)
log(Energy)			0.006***
			(0.001)
Constant	0.325***	0.168***	0.116***
	(0.008)	(0.016)	(0.018)

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A10: Number of Products Added and Drop

	$nAdd_{t:t+5}$	$nAdd_{t:t+5}$	$nAdd_{t:t+5}$
$Drop_{t:t+5}$	0.130***		0.086***
	(0.026)		(0.025)
Young Firm$_{it}$		0.206***	-0.044***
		(0.014)	(0.012)
$Drop_{t:t+5}$ × Young$_{it}$			0.490***
			(0.024)
log(Emp)	0.071***	0.081***	0.082***
	(0.009)	(0.009)	(0.009)
log(Total Assets)	-0.006	-0.004	-0.006
	(0.008)	(0.007)	(0.007)
# establishments	0.077***	0.074***	0.077***
	(0.026)	(0.025)	(0.026)
# products	-0.150***	-0.140***	-0.149***
	(0.022)	(0.021)	(0.022)
log(CA)	-0.039***	-0.041***	-0.041***
	(0.005)	(0.005)	(0.005)
log(CS)	-0.070***	-0.071***	-0.071***
	(0.007)	(0.007)	(0.007)
TFP	0.014*	0.015*	0.017**
	(0.008)	(0.008)	(0.008)
log(Prod. Emp)	-0.013***	-0.015***	-0.011***
	(0.003)	(0.004)	(0.003)
log(Equipment)	0.028***	0.027***	0.029***
	(0.007)	(0.007)	(0.007)
log(Structure)	-0.01	-0.008	-0.008
	(0.007)	(0.007)	(0.007)
log(Material)	0.017***	0.016***	0.018***
	(0.003)	(0.003)	(0.003)
log(Energy)	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.004)
Constant	0.393***	0.394***	0.324***
	(0.042)	(0.047)	(0.044)
Observations	682,000	682,000	682,000
Fixed effects	i, jt	i, jt	i, jt
Controls	Full	Full	Full

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A11: Relative Match Quality of Added Products

	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$
$Drop_{t:t+5}$	0.028**		0.049***
	(0.011)		(0.010)
Young Firm$_{it}$		-0.112***	0.044*
		(0.017)	(0.024)
$Drop_{t:t+5}$ $\times$ Young$_{it}$			-0.228***
			(0.024)
log(Emp)	-0.011	-0.018**	-0.019**
	(0.009)	(0.009)	(0.009)
log(Total Assets)	0.039***	0.037***	0.037***
	(0.012)	(0.012)	(0.012)
# establishments	-0.007***	-0.007***	-0.007***
	(0.003)	(0.003)	(0.003)
# products	0.019***	0.020***	0.019***
	(0.003)	(0.003)	(0.003)
log(CA)	0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)
log(CS)	-0.005	-0.003	-0.003
	(0.003)	(0.003)	(0.003)
TFP	-0.031***	-0.034***	-0.034***
	(0.009)	(0.009)	(0.009)
log(Prod. Emp)	0.022***	0.021***	0.021***
	(0.003)	(0.003)	(0.003)
log(Equipment)	-0.025***	-0.025***	-0.025***
	(0.009)	(0.009)	(0.009)
log(Structure)	-0.016*	-0.015*	-0.015*
	(0.009)	(0.009)	(0.009)
log(Material)	-0.015***	-0.016***	-0.017***
	(0.005)	(0.004)	(0.004)
log(Energy)	-0.014***	-0.013***	-0.014***
	(0.005)	(0.005)	(0.005)
Constant	0.430***	0.516***	0.487***
	(0.050)	(0.049)	(0.048)
Observations	66,000	66,000	66,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A12: Relative Match Quality of Added Products (Drop)

	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$
$Drop_{t:t+5}$	0.052***	0.026**	0.028**
	(0.011)	(0.011)	(0.011)
log(Emp)		-0.008	-0.011
		(0.008)	(0.009)
log(Total Assets)		-0.006	0.039***
		(0.005)	(0.012)
# establishments		-0.007***	-0.007***
		(0.003)	(0.003)
# products		0.020***	0.019***
		(0.003)	(0.003)
log(CA)		0.002	0.001
		(0.003)	(0.003)
log(CS)		-0.005	-0.005
		(0.003)	(0.003)
TFP		-0.018**	-0.031***
		(0.008)	(0.009)
log(Prod. Emp)			0.022***
			(0.003)
log(Equipment)			-0.025***
			(0.009)
log(Structure)			-0.016*
			(0.009)
log(Material)			-0.015***
			(0.005)
log(Energy)			-0.014***
			(0.005)
Constant	0.301***	0.382***	0.430***
	(0.007)	(0.041)	(0.050)

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A13: Relative Match Quality of Added Products (Young Firm)

	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$
Young Firm_{it}	-0.115***	-0.114***	-0.112***
	(0.016)	(0.017)	(0.017)
log(Emp)		-0.018**	-0.018**
		(0.008)	(0.009)
log(Total Assets)		-0.007	0.037***
		(0.005)	(0.012)
# establishments		-0.007***	-0.007***
		(0.003)	(0.003)
# products		0.020***	0.020***
		(0.003)	(0.003)
log(CA)		0.003	0.002
		(0.003)	(0.003)
log(CS)		-0.004	-0.003
		(0.003)	(0.003)
TFP		-0.020**	-0.034***
		(0.008)	(0.009)
log(Prod. Emp)			0.021***
			(0.003)
log(Equipment)			-0.025***
			(0.009)
log(Structure)			-0.015*
			(0.009)
log(Material)			-0.016***
			(0.004)
log(Energy)			-0.013***
			(0.005)
Constant	0.347***	0.463***	0.516***
	(0.003)	(0.041)	(0.049)

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A14: Relative Match Quality of Added Products (Drop × Young)

	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$	$Add^{high}_{t:t+5}$
$Drop_{t:t+5}$	0.073***	0.047***	0.049***
	(0.010)	(0.010)	(0.010)
Young Firm_{it}	0.043*	0.042*	0.044*
	(0.023)	(0.024)	(0.024)
$Drop_{t:t+5} \times \text{Young}_{it}$	-0.231***	-0.227***	-0.228***
	(0.025)	(0.024)	(0.024)
log(Emp)		-0.019**	-0.019**
		(0.008)	(0.009)
log(Total Assets)		-0.007	0.037***
		(0.005)	(0.012)
# establishments		-0.007***	-0.007***
		(0.003)	(0.003)
# products		0.019***	0.019***
		(0.003)	(0.003)
log(CA)		0.003	0.001
		(0.003)	(0.003)
log(CS)		-0.004	-0.003
		(0.003)	(0.003)
TFP		-0.020**	-0.034***
		(0.008)	(0.009)
log(Prod. Emp)			0.021***
			(0.003)
log(Equipment)			-0.025***
			(0.009)
log(Structure)			-0.015*
			(0.009)
log(Material)			-0.017***
			(0.004)
log(Energy)			-0.014***
			(0.005)
Constant	0.295***	0.433***	0.487***
	(0.007)	(0.041)	(0.048)

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A15: Material-Based Closeness of Added Products

	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$
$Drop_{t:t+5}$	0.098***		0.102***
	(0.004)		(0.004)
Young Firm$_{it}$		-0.003	0.022***
		(0.004)	(0.005)
$Drop_{t:t+5}$ × Young$_{it}$			-0.037***
			(0.006)
log(Emp)	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)
log(Total Assets)	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)
# establishments	0.006***	0.005***	0.006***
	(0.002)	(0.002)	(0.002)
# products	-0.028***	-0.024***	-0.028***
	(0.003)	(0.002)	(0.003)
log(CA)	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
log(CS)	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)
TFP	-0.008***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)
# materials	0.004***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)
log(Prod. Emp)	0	-0.001	0
	(0.001)	(0.001)	(0.001)
log(Equipment)	-0.004*	-0.005*	-0.005*
	(0.003)	(0.003)	(0.003)
log(Structure)	0.004	0.004*	0.003
	(0.002)	(0.002)	(0.002)
log(Material)	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
log(Energy)	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)
Constant	0.458***	0.521***	0.457***
	(0.013)	(0.013)	(0.013)
Observations	198,000	198,000	198,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A16: Material-Based Closeness of Added Products (Drop)

	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$
$Drop_{t:t+5}$	0.093***	0.098***	0.098***
	(0.007)	(0.004)	(0.004)
log(Emp)		-0.010***	-0.002
		(0.002)	(0.003)
log(Total Assets)		-0.004***	-0.001
		(0.001)	(0.004)
# establishments		0.006***	0.006***
		(0.002)	(0.002)
# products		-0.028***	-0.028***
		(0.003)	(0.003)
log(CA)		-0.003***	-0.003***
		(0.001)	(0.001)
log(CS)		-0.007***	-0.007***
		(0.001)	(0.001)
TFP		-0.003	-0.008***
		(0.002)	(0.002)
# materials		0.004***	0.004***
		(0.000)	(0.000)
log(Prod. Emp)			0
			(0.001)
log(Equipment)			-0.004*
			(0.003)
log(Structure)			0.004
			(0.002)
log(Material)			-0.005***
			(0.001)
log(Energy)			-0.007***
			(0.001)
Constant	0.454***	0.427***	0.458***
	(0.006)	(0.010)	(0.013)
Observations	198,000	198,000	198,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A17: Material-Based Closeness of Added Products (Young Firm)

	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$
Young Firm$_{it}$	-0.005	-0.003	-0.003
	(0.005)	(0.004)	(0.004)
log(Emp)		-0.012***	-0.003
		(0.002)	(0.003)
log(Total Assets)		-0.004***	-0.001
		(0.001)	(0.004)
# establishments		0.005***	0.005***
		(0.002)	(0.002)
# products		-0.024***	-0.024***
		(0.002)	(0.002)
log(CA)		-0.003***	-0.003***
		(0.001)	(0.001)
log(CS)		-0.007***	-0.007***
		(0.001)	(0.001)
TFP		-0.003	-0.007***
		(0.002)	(0.002)
# materials		0.005***	0.005***
		(0.000)	(0.000)
log(Prod. Emp)			-0.001
			(0.001)
log(Equipment)			-0.005*
			(0.003)
log(Structure)			0.004*
			(0.002)
log(Material)			-0.005***
			(0.001)
log(Energy)			-0.007***
			(0.001)
Constant	0.520***	0.489***	0.521***
	(0.003)	(0.011)	(0.013)
Observations	198,000	198,000	198,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A18: Material-Based Closeness of Added Products (Drop $\times$ Young)

	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$	$Mat^{add}_{t:t+5}$
$Drop_{t:t+5}$	0.097***	0.101***	0.102***
	(0.007)	(0.004)	(0.004)
Young Firm$_{it}$	0.028***	0.023***	0.022***
	(0.006)	(0.005)	(0.005)
$Drop_{t:t+5}$ $\times$ Young$_{it}$	-0.046***	-0.037***	-0.037***
	(0.006)	(0.006)	(0.006)
log(Emp)		-0.010***	-0.003
		(0.002)	(0.003)
log(Total Assets)		-0.004***	-0.001
		(0.001)	(0.004)
# establishments		0.006***	0.006***
		(0.002)	(0.002)
# products		-0.028***	-0.028***
		(0.003)	(0.003)
log(CA)		-0.003***	-0.003***
		(0.001)	(0.001)
log(CS)		-0.007***	-0.007***
		(0.001)	(0.001)
TFP		-0.003	-0.008***
		(0.002)	(0.002)
# materials		0.004***	0.004***
		(0.000)	(0.000)
log(Prod. Emp)			0
			(0.001)
log(Equipment)			-0.005*
			(0.003)
log(Structure)			0.003
			(0.002)
log(Material)			-0.005***
			(0.001)
log(Energy)			-0.007***
			(0.001)
Constant	0.451***	0.426***	0.457***
	(0.006)	(0.010)	(0.013)
Observations	198,000	198,000	198,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A19: Industry Closeness of Added Products

	$Ind4^{add}_{t:t+5}$	$Ind4^{add}_{t:t+5}$	$Ind4^{add}_{t:t+5}$
$Drop_{t:t+5}$	0.079***		0.081***
	(0.006)		(0.006)
Young Firm$_{it}$		0.018***	0.032***
		(0.006)	(0.008)
$Drop_{t:t+5}$ × Young$_{it}$			-0.019**
			(0.009)
log(Emp)	0.010***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)
log(Total Assets)	-0.004	-0.004	-0.003
	(0.005)	(0.005)	(0.005)
# establishments	0.003**	0.001	0.003**
	(0.001)	(0.001)	(0.001)
# products	-0.007***	-0.003*	-0.007***
	(0.002)	(0.002)	(0.002)
log(CA)	0.002*	0.002	0.002
	(0.001)	(0.001)	(0.001)
log(CS)	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
TFP	-0.005	-0.004	-0.004
	(0.003)	(0.003)	(0.003)
log(Prod. Emp)	-0.009***	-0.011***	-0.009***
	(0.002)	(0.002)	(0.002)
log(Equipment)	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)
log(Structure)	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
log(Material)	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)
log(Energy)	0.003	0.003*	0.003
	(0.002)	(0.002)	(0.002)
Constant	0.213***	0.253***	0.200***
	(0.016)	(0.017)	(0.017)
Observations	198,000	198,000	198,000
Fixed effects	i, jt	i, jt	i, jt

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

Table A20: Product Add/Drop and Firm Performance

	$\Delta Vadd$	ΔEmp	ΔTFP	ΔLP
$Add_{t:t+5}$	0.830***	0.802***	0.735***	0.762***
	(0.019)	(0.019)	(0.019)	(0.019)
$Drop_{t:t+5}$	-0.754***	-0.731***	-0.686***	-0.713***
	(0.019)	(0.018)	(0.017)	(0.018)
log(Emp)	-0.187***	-0.604***	0.099***	0.200***
	(0.009)	(0.008)	(0.007)	(0.007)
log(Total Assets)	-0.071***	-0.021***	-0.026**	-0.018
	(0.006)	(0.006)	(0.012)	(0.011)
# establishments	-0.027***	-0.024***	-0.026***	-0.028***
	(0.008)	(0.007)	(0.008)	(0.008)
# products	0.077***	0.079***	0.070***	0.072***
	(0.006)	(0.005)	(0.005)	(0.006)
log(CA)	-0.003*	0.006***	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
log(CS)	0.014***	0.014***	0.011***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
TFP	-0.561***	0.130***	-0.369***	-0.088***
	(0.012)	(0.006)	(0.022)	(0.026)
log(Prod. Emp)	0.021***	0.028***	0.019***	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
log(Equipment)	0.030***	0.075***	0.059***	0.029***
	(0.005)	(0.005)	(0.007)	(0.006)
log(Structure)	-0.046***	-0.028***	-0.028***	-0.035***
	(0.005)	(0.005)	(0.008)	(0.007)
log(Material)	-0.049***	0.068***	0.023***	-0.042***
	(0.006)	(0.003)	(0.006)	(0.008)
log(Energy)	-0.030***	0.042***	0.010***	0.035***
	(0.004)	(0.002)	(0.003)	(0.004)
Constant	2.252***	0.424***	-0.415***	-0.633***
	(0.052)	(0.047)	(0.081)	(0.100)
Observations	682,000	682,000	648,000	648,000
Fixed effects	i, jt	i, jt	i, jt	i, jt
Controls	Full	Full	Full	Full

Notes: Estimates for industry-year, firm fixed effects, and the constant are suppressed. Robust standard errors clustered at the firm's modal five-digit SIC product level are reported in parentheses. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * p<0.1, ** p<0.05, *** p<0.01.

B Alternative Match Quality Estimation

One alternation of the quality estimation is to use product-year and firm-year fixed effects as follows, instead of controlling for the time-varying firm and industry characteristics:

$$y_{pijt} = \theta_{pi} + X_{pijt}\gamma + \delta_{pt} + \delta_{it} + \varepsilon_{pijt}, \tag{B.14}$$

where δ_{pt} is a product-year fixed effect, and δ_{it} is a firm-year fixed effect.

δ_{pt} controls for product specific characteristics as well as product-year specific shocks. Again, this is because each product is subject to different production technology or demand structure. Therefore, it is possible that there are several other effects affecting the value of shipment, attributed to product-year specific technology or demand shocks.

In a similar fashion, firms or entrepreneurs have different base sets of available resources or ability to manufacture products (i.e. a financing constraint, customer capital, brand values, and marketing resources, etc.). The value of shipment for each product can also be influenced by these firm-level properties. Furthermore, any types of industry-specific characteristics that can give a substantial impact on the total value of shipment are absorbed by the firm-year fixed effect. Therefore, equation (B.14) could be one alternative of the baseline quality estimation in (3.1).

However, estimation based on (B.14) faces several limitations due to the inclusion of multiple fixed effects. In particular, estimating firm-product and firm-year fixed effects simultaneously leads to the exclusion of a non-negligible portion of the sample, as some products appear in only one firm or some firms produce only a single product in a given year. Therefore, an alternative approach is to replace the firm-year fixed effect δ_{it} with an extensive set of firm-level controls X_{ijt}, which is our baseline specification (3.1).

Alternatively, we could implement an AKM-style specification (Abowd et al., 1999) and estimate the firm-product match quality by taking the time average of the residuals.

These specifications include

$$y_{pijt} = X_{pijt}\gamma + \delta_{pt} + \delta_{it} + \varepsilon_{pijt} \tag{B.15}$$

$$y_{pijt} = X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{pt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt} \tag{B.16}$$

$$y_{pijt} = X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + \delta_{pt} + \delta_i + \delta_t + \varepsilon_{pijt}. \tag{B.17}$$

A critical limitation of this approach is the lack of clarity regarding what the time-varying residuals capture, and whether their average offers a more accurate measure of firm-product match quality than the baseline model.