Product Switching and Young Firm Dynamics*

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Abstract

Do firms seek a better product match and grow by dropping existing products and adding new ones? How does this behavior vary over the firm life cycle and business cycle? This paper investigates a "product match-quality ladder" channel empirically by using a detailed product-firm level administrative database for the U.S. manufacturing sector and documents salient features of product switching by firms along their life cycle. We newly estimate the match quality of product-firm pairs and obtain the following set of results: i) young firms are less likely to drop products with low match quality than mature firms; ii) dropping low match-quality products can increase the match quality of products added, and iii) has a positive impact on firm performance and growth. These indicate that proper product switching is important for young firms to climb up the product match-quality ladder and achieve fast growth. Lastly, we further look into cyclical variations of the channel and find that iv) the product switching pattern of young firms gets even more pronounced in recessions. This provides a potential explanation for procyclical young firm activities. We develop a simple model of learning about match quality between products and firms and find that the learning process over the firm lifecycle can explain the observed patterns.

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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 literature finds that this product-switching behavior is prevalent and has a profound impact on a firm's scope and performance, closely linked to its growth potential (Bernard et al., 2010; Argente et al., 2018). Given the importance, recent studies have empirically documented the relationship between product entry and exit, firm-product attributes, and the innovation activities of firms.

However, less is known about the types of products firms choose to add or drop to optimize their product portfolio and how these decisions vary across different stages of the firm life cycle. When switching products, firms often remain close to their existing ones but also venture into entirely new industries. Such radical product switching can lead to significant performance improvements and contribute to firm success.[1] Yet, some firms fail to successfully introduce new products, suggesting that they may excel in certain areas, while struggling in others.[2] This is not surprising, as firms are essentially collections of entrepreneurs or decision-makers whose capabilities may limit the firm's potential.

Furthermore, the decisions to add or drop products should in particular matter for young firms, as the marginal gain for young firms to find an optimal set of products is substantial. Their scope of production and specialty have not been well identified in a deterministic manner at the early stage, and this requires more search efforts for them to find the right product. Also, it is important 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

[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.

et al., 2016; Foster et al., 2018).

In this paper, we study how firms add and drop products over the firm life cycle and how the product switching behavior contributes to firm growth. In particular, we look into the types of products firms switch by introducing a new concept termed "product-firm match quality." This concept measures the match quality between a pair of products and firms, reflecting how well a firm can produce a specific product and the extent of its expertise in that area.[3] We investigate whether firms climb up the match quality ladder of products by switching the right set of products properly—adding products with better match quality while dropping those with poor match quality. We then analyze how this pattern evolves throughout their life cycle, in particular for young firms, its impact on firm growth and performance. Lastly, we extend our analysis to examine cyclical variations.

We use a detailed product-firm level dataset for the manufacturing sector from the U.S Census Bureau from 1972 to 2007 and investigate the margin of adding and dropping products across the firm life cycle and its impact on firm performance. 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. To our knowledge, this approach represents one of the novel contributions of our paper.

In the dataset, we observe that firms generally drop products that have poor match quality with them. Young firms, however, exhibit a distinct pattern: they drop fewer products with poor match quality and relatively more products with better match quality compared to mature firms. Overall, their tendency to retain products with worse match quality dominates their behavior of dropping better match quality products,

[3] A product type with higher match quality can serve as a proxy for the right set of products for a firm.

which makes them drop fewer products on average.

Next, we examine how firms climb up the match-quality ladder of products by testing the association between the quality of products dropped and added. We find that firms that have ever dropped a product between two census years are more likely to add new products simultaneously. Moreover, there exists a negative correlation between the quality of products being dropped and added. In other words, as firms drop products with poor match quality, they are more likely to add a new product with better match quality.

Furthermore, we find that the product switching and the product match quality ladder matter for firm growth and performance. In particular, we observe that dropping products with low match quality is positively associated with growth in the firm-level total value of shipments and labor productivity, while adding products with better match quality positively impacts firm growth.

Combining these findings with the product-switching pattern of young firms, it is inferred that young firms are less likely to climb up the match quality ladder as fast as established firms, which can create a source to slow down their potential growth.

We also extend our analysis to investigate cyclical dynamics. We use the NBER recession indicator and examine how firms' product-dropping behavior and the quality of dropped products change during recession periods. We find that, on average, firms are more likely to drop products during recessions. However, if we see the types of the dropped products, firms are less likely to drop poor match quality products in recessions. This pattern may be attributed to higher uncertainty and noise in recessions, which could disrupt the quality of information firms can use to infer how good their match with products is.

We further decompose the results into young versus mature firms, which provides a clearer picture. In particular, we find that young firms tend to drop even fewer products overall and are even less likely to drop those with poor match quality in recessions. In other words, the baseline fact that young firms drop fewer products with poor match quality becomes more pronounced during recessions. This indicates that the general pattern for firms to drop fewer products with poor match quality in recessions is mostly driven by young firms. This, along with the previous findings, suggests that the match quality-ladder channel through product switching can also be a source to account for the well-known procyclical young firm activities.

Lastly, 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 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 add a bad match quality product compared to mature counterparts. This suggests that the learning process over the firm lifecycle 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 a similar dataset as Broda and Weinstein (2010), 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. Other studies show 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.

Lastly, our paper relates to the literature on the procyclical quality of resources matched with firms and the sullying effect of recessions. Most of the prior research has mainly focused on labor margin by documenting the quality of firm-worker matches across different economic conditions. Moscarini (2001) documents that the cost of waiting in economic downturns raises a worker's willingness to accept an offer that does not provide her the first-best value in the market. Barlevy (2002) shows that job quality is procyclical and jobs created in recessions are more temporary and pay less. Haltiwanger et al. (2012) document that worker churning rates fall in recessions, which implies a decline in match quality between firms and workers. Haltiwanger et al. (2018) also present the collapse of the firm wage ladder in downturns, where recessions hamper match quality between firms and workers by slowing down poaching.

Our paper revisits this discussion by shedding light on a new margin of the "product match-quality ladder" and providing new evidence on the lowered match quality between products and firms in recessions.

The rest of the paper proceeds as follows. Section 2 describes data sources and main measures used in our analysis. Section 3 presents the main results we find on the product dropping and adding activities of young and mature firms, the relationship between the match quality of products dropped and added, the impact of product dropping and adding on firm growth, and how these patterns vary over the business cycle, particularly for young firms. Section 4 discusses additional robustness tests for the main results. Section 5 presents a simple model of 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 seven quinquennial census years: 1977, 1982, 1987, 1992, 1997, 2002, and 2007.

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. 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.[4] More details can be found from Bernard et

[4]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).

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, employer identification numbers, business name, and location information. 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).

We use the NBER recession indicator to identify recessions in our sample period. The following three recessions occur in our sample period, 1982, 1990, and 2001, and we label the census year prior to each recession year as a "pre-recession" year.

2.1 Product Definition and Characteristics

We define a product by a five-digit SIC code for the pre-2002 period and a seven-digit NAICS code for 2002 and later census years.[5] Note that there is a break in product

[5]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.

definitions from 1997 as SIC codes are only available until 1997 and NAICS codes are only available from 1997. In 1997, the CMF provides information on both five-digit SIC and seven-digit NAICS product codes for each product-establishment observation. We rely on this information to bridge the two sub-periods. Across censuses within each of the sub-periods (pre-1997 and from 1997), we use a concordance that is internally generated by the Census through revisions they undergo each census year. For instance, SIC categories go through revisions in each census year and the Census records both of the SIC codes collected (in the focal census year) and those revised to be comparable across different code versions. This gives us a longitudinal mapping between industry codes in each census year, which enables us to analyze for the whole sample period from 1977 through 2007.[6,7,8]

The CMF reports product-level sales (total 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. We use the total value of shipment at the product-establishment pair level, and aggregate it up to the product-firm pair level by linking to the LBD through establishment and firm identifiers. We normalize the total value of shipments by the NBER-CES industry-level price indices. For each of the product-firm pairs, we calculate tenure by the number of census years in which the product is manufactured by the firm and appears in the record.

Lastly, for each firm in a given year t, we flag "products to enter" by products that did not show up until the focal period t and appear from $t + 5$. In a similar fashion,

[6] In case of non-unique mappings between the SIC and NAICS in 1997 or between the collected and revised industry codes in each census year, we use the modal code. For instance, if there are four observations having the five-digit SIC code "35xxx", and if three of them are assigned the seven-digit NAICS code "33yyyyy" and the last one is assigned the other code "33zzzz", then the SIC code "35xxx" is mapped into "33yyyyy". For ties, we randomly pick one of them.

[7] We find that a large fraction of product codes preserve unique mappings, but as a robustness check, we could also limit our analyses to the set of unique mappings and drop the rest to be more conservative. Also, as another check to rule out potential noise that pertains to the mappings and the consistency of product codes, we could use those that appear in all censuses in our sample period.

[8] We also tried to use the concordance between the ten-digit HS product codes and SIC/NAICS classes, constructed by Pierce and Schott (2012), to bridge our sample period. However, they only provide the concordance at the industry level, which is more aggregated than the level of products of our main interest. Thus, using the existing HS product concordance would not be appropriate in our context.

we capture "products to exit" within each firm at a given census year t by those that show up in the product portfolio of the firm until the focal period t but disappear from $t+5$. In other words, we label entering and exiting products for each firm at a given census year t by those being added and dropped from the firm portfolio, respectively, between the focal census year t and the following census year $t+5$. This enables us to identify entering and exiting products from 1977 through 2002 based on our sample. For each of these entering and exiting products, we also indicate whether these are initial entry or re-entry of the entering product or temporary or permanent exit of the exiting product.

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 by those younger or equal to age five. Firm size is measured by total employment.

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 by correcting previous firm identifiers that are recycled in the old LBD, as described in Chow et al. (2021), it is still not yet a true longitudinal identifier.[9] However, longitudinal consistency of firm identifiers is necessary for our analysis to track firms' history of product portfolios. Therefore, we construct and use longitudinal firm identifiers from the LBD following Dent et al. (2018). Henceforth, we will use the term "firm identifier" to refer to the longitudinal firm identifiers constructed using this latter method.

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

2.3 Industry-level Variables

From the NBER CES Manufacturing Industry Database, we use the industry-level deflator for the value of shipments for manufacturing industries. All nominal values are converted to 1997 U.S. dollars using this industry-level deflator for the value of shipments for manufacturing industries. Also, we construct the industry-level skill intensity by the number of non-production workers divided by total employment size, and the industry-level capital intensity by total capital stock divided by total employment size.

3 Empirical Models and Main Results

In this section, we first investigate firms' product-switching decisions and examine how the decisions differ for young firms. We then extend it to see how our findings vary over the business cycle. The design of our empirical strategy is discussed in the following subsections.

3.1 Firm-Product Match Quality Estimation

To understand the relationship between firms' product-switching decisions and resource reallocation, we first estimate product-firm pair time-invariant match quality using the following baseline model. This measures how good a firm is at producing a certain product, or the level of expertise the firm has in producing it.

$$y_{pijt} = \theta_{pi} + \beta_2 PT_{pijt} + X_{ijt}\gamma + \delta_{pt} + \varepsilon_{pijt}, \tag{3.1}$$

y_{pijt} is the log real value of shipment of a given pair of firm i (in industry j) and product p in a given census year t. The real value of shipment is computed by the product-firm level total value of shipment from the CMF divided by the industry-level price deflator from the NBER-CES. Most importantly, θ_{pi} is of our main interest, which is a fixed effect for the pair of firm i and product p. 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 the following set of controls and fixed effects to properly control for sources affecting the firm-product-specific value of shipments, unrelated to the firm-product-specific unobservable characteristics. For instance, it takes time for firms to build a customer base when they newly enter a new product market, which can affect the value of shipment regardless of their match quality. PT_{pijt} is the product-firm specific tenure as of year t, which controls for this component.

Furthermore, X_{ijt} is a vector of firm-level time-varying characteristics, such as firm size (log employment size), age (log firm age), total value of shipments, skill and capital intensity (log ratio of non-production workers to total employment, log ratio of capital to total employment, resp.), and productivity. As a baseline, we use log employment size and firm age as firm-level controls.[10]

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 industry-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 ranged in [0,m] with an arbitrary value $m \in (0,1)$. Let q_{pi} denote this. In particular, we use the following formula to rescale $\hat{\theta}_{pi}$:

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

[10]As robustness checks, we explore additional variables to include in the set of firm controls.

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 use $m = 0.99$. When it helps us interpret regression results more straightforward, we use the inverse match quality measure by transforming the match quality measure as:

$$q_{pi}^{inv} \equiv 1 - q_{pi}, \tag{3.3}$$

which makes the inverse match quality ranged in $[0.01, 1]$.

3.2 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.

3.2.1 Match Quality of Dropped Products

We begin by studying what types of products are dropped by firms. Specifically, we test whether firms drop poorly matched products more relative to better-matched ones. This is based on the premise that it may not be straightforward for firms to identify products with good or bad match quality, 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 to indicate a product being dropped by the beginning of the next period and run the following regression. The left-hand side variable $\mathcal{I}_{pijt}^{drop}$ denotes this dummy variable, where $\mathcal{I}_{pijt}^{drop} = 1$ 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 quality measure to see how firms' product drop

Table 1: Probability of Product Drop

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Inv. quality$_t$	+		+
	(***)		(***)
Young firm$_t$		-	+
		(***)	(***)
Inv. quality$_t$ $\times$ Young firm$_t$			-
			(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t
Controls	Full	Full	Full

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

depends on the match quality between product p and firm j

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 q^{inv}_{pi} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \tag{3.4}$$

where q^{inv}_{pi} is the inverse quality value (3.3) 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 log value of shipment). X_{ijt} is a vector of firm controls (log firm size, age, and the number of operating products), and X_{jt} indicates a set of time-varying industry controls, where we add the industry-level log skill and capital intensities. δ_p is a product fixed effect, δ_i is a firm fixed effect, and δ_t is a year fixed effect.

The first column of Table 1 shows the results including all the firm and industry controls.[11] As indicated in the first column of Table 1, firms, on average, drop products that are a poor match to them compared to better-matched ones. This result shows that firms, on average, know what products are a better match for them and what

[11]The first column of Table A1 in Appendix A.1 shows the results for the full model, and Table A2 shows the results for including and excluding firm controls.

are not, and drop the poor-matched ones. Dropping poor-matched products would free up the resources and potentially enable firms to reallocate these resources toward their better use. Before we investigate whether dropping poor-matched products leads firms to climb the match-quality ladder and improve performance, we test whether the product-dropping behavior is different for firms of different ages.

3.2.2 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:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta_1 \mathcal{I}_{ijt}^{young} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \tag{3.5}$$

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. We include this variable as one of our firm controls as before. The remaining variables stay the same as before. The second column of Table 1 presents the result. This shows that on average, young firms drop products less frequently than mature firms.[12]

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

To further explore the quality of products dropped by young firms, we include the inverse match quality interacted with the young firm dummy to equation (3.5) as follows:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta_1 q_{pi}^{inv} + \beta_2 \mathcal{I}_{ijt}^{young} + \beta_3 q_{pi}^{inv} \times \mathcal{I}_{ijt}^{young} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}. \tag{3.6}$$

The third column of Table 1 lays out the result.[13] In particular, the second row (the coefficient associated with the young firm dummy) indicates that with match quality controlled, young firms drop products more frequently than their mature counterparts on average. This is in contrast to the previous result found from specification (3.5) without having the match quality controlled.

However, as shown in the third row, young firms indeed drop fewer products with poor match quality with themselves relative to mature firms. In other words, on average, young firms drop products they should have kept (products that are a good match to them) but keep those they should have dropped (products that are a poor match to them) more often than mature firms. Overall, the stickiness with poor match quality products is the dominant factor determining the average product-dropping behavior of young firms.

This set of results suggests that young firms' limited resources and information for assessing product match quality may constrain their ability to add better-matched products or drop poorly matched ones at the early stage of their life cycle. As a result, young firms may struggle to effectively climb the product quality ladder. Such restriction can be a source to hamper potential growth of young firms, which can be more pronounced in recessions where noise is higher and information is less accurate for firms to learn.

[13] The third column of Table A1 in Appendix A.1 shows the results for the full model, and Table A4 in Appendix A.1 shows the results for including and excluding firm controls.

3.3 Firm-Level Evidence for Quality Ladder

Next, we test how firms climb up the match-quality ladder and how the quality of products being dropped is associated with the quality of products being added.

3.3.1 Product Adding

We aim to understand how firms add new products and whether the probability of adding a new product depends on the history of firms dropping products before and on the quality of those dropped products.

To see this, we define a product as being added to a firm's portfolio in a given year t if it is not present in the firm's portfolio in the focal year t but appears in the portfolio 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 year t and $t+5$. (e.g. if at least one product newly appears in firm i's portfolio in $t+5$, which was not shown in t.)

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:

$$\mathcal{I}_{ijt}^{add} = \alpha + \beta_1 \mathcal{I}_{ijt}^{drop} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \varepsilon_{ijt}, \tag{3.7}$$

where $\mathcal{I}_{ijt}^{drop}$ is a dummy variable equal to one if firm i dropped at least one of its products between t and $t+5$. The rest controls and fixed effects remain the same as before.

As shown in Table 2, the probability of firms adding a new product is positively associated with their history of dropping at least one product.[14,15] This indicates that firms simultaneously add and drop products, which is a piece of evidence regarding the match-quality ladder.

Here, firms could drop many products at once as they either have already added a well-matched product or plan to do so. To rule out this, as a robustness check, we further include controls for the number or share of dropped products as controls. The

[14] Table A5 in Appendix shows the full results.
[15] This result is consistent with Bernard et al. (2010).

Table 2: Product Add and Drop

	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$	+	
	(***)	
Dropping product quality		+
		(***)
Observations	402,000	75,000
Fixed effects	i,t	i,t
Controls	Full	Full

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

result stays robust, which can be found in Section 4.

3.3.2 Match Quality of Added and Dropped Products: Quality Ladder Evidence

In the previous analyses, we learn that the propensity to drop a product is positively associated with the probability of adding a new product at the firm level. In this section, we further investigate whether the quality of products being dropped and dropped is associated with each other to understand if firms climb up the match-quality ladder through product switching.

We first examine whether the match quality of products being added right after or along with a product-dropping process differs from those added without dropping any products. Note that if firms are indeed climbing up the match-quality ladder, we would expect them to drop poorly matched products and add new products that are potentially a better match for them.

To test this hypothesis, we first replace the product-add dummy in Equation (3.7) with the average match quality of added products and estimate the following regression

Table 3: Match Quality of Added Products

	$q_{t:t+5}^{add}$	$q_{t:t+5}^{add}$
$Drop_{t:t+5}$	+	
	(***)	
Dropping product quality		-
		(***)
Observations	81,000	29,000
Fixed effects	i,t	i,t
Controls	Full	Full

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

model:

$$\overline{q}_{ijt}^{add} = \beta_1 \mathcal{I}_{ijt}^{drop} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt}\ . \tag{3.8}$$

$\overline{q}_{ijt}^{add}$ is the unweighted average of the match quality of products added by firm i (in industry j) between t and $t+5$, where match quality is defined as in Equation 3.2

As shown in the first column of Table 3, the average quality of added products is higher if there exists at least one product being dropped within the same period.[16] This result confirms that, on average, not only the likelihood of adding a product but also the quality of the added products is positively associated with firms' product-dropping behavior. This is consistent with the match-quality ladder hypothesis.

We then test whether the match quality of added products is higher if firms drop products with poor match quality. To see this, we replace the product-drop dummy on the right-hand side of Equation (3.8) with the average match quality of dropped

[16] See Table A6 in Appendix for more details.

products and estimate the following regression model:

$$\overline{q}_{ijt}^{add} = \beta_1 \overline{q}_{ijt}^{drop} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt}. \tag{3.9}$$

$\overline{q}_{ijt}^{drop}$ is the unweighted average of the match qualities of products dropped between t and $t+5$.

As shown in the second column of Table 3, the quality of the added product is higher (lower) if firms drop products that are a poor (better) match to them. This provides additional evidence consistent with the match-quality ladder hypothesis. Furthermore, this suggests that firms learn about their expertise while operating, enabling them to add products that are better matched to their capabilities compared to those they have dropped.

3.4 Product Switching and Firm Performance

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

3.4.1 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:

$$\Delta y_{ijt} = \beta_1 \mathcal{I}_{ijt}^{drop} + \beta_2 \mathcal{I}_{ijt}^{add} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt}\ , \tag{3.10}$$

where Δy_{ijt} is the log difference of i) the real value of shipments or ii) labor productivity (real value of shipments divided by employment size) between t and $t+5$.

Table 4 presents the result, indicating that dropping a product is negatively associated with subsequent growth in the total value of shipments, while adding a product is positively correlated with it.[17] This result is consistent with previous findings by

[17]Table A7 in Appendix shows the full results.

Table 4: Product Add/Drop and Firm Performance

	$\Delta TVS_{t:t+5}$	$\Delta LP_{t:t+5}$
$Drop_{t:t+5}$	-	-
	(***)	
$Add_{t:t+5}$	+	+
	(***)	(***)
Observations	402,000	402,000
Fixed effects	i,t	i,t
Controls	Full	Full

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Bernard et al. (2010) and Argente et al. (2018). The association between adding a product and the growth of labor productivity is also positive. However, the relationship is less clear for dropping a product.

3.4.2 The Impact of Match Quality of Added and Dropped Products

Lastly, we estimate the association between the match quality of dropped or added products and firm performance using the following regression model:

$$\Delta y_{ijt} = \beta_1 \overline{q}_{ijt}^{sw} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt} \ . \tag{3.11}$$

We run the equation (3.11) separately for the average match quality of added products ($sw = add$) and dropped products ($sw = drop$). Here, we add an additional firm-level control variable: the log number of products added or dropped. This control is applied separately for added products ($sw = add$) and dropped products ($sw = drop$).

Table 5 shows the results, where the first two columns are for the dropped products, and the last two columns are for the added products.[18] This indicates that both drop-

[18]Table A8 in Appendix contains the results in full.

Table 5: Match Quality of Added/Dropped Products and Firm Performance

	$\Delta TVS_{t:t+5}$	$\Delta LP_{t:t+5}$	$\Delta TVS_{t:t+5}$	$\Delta LP_{t:t+5}$
Dropping product quality	-	-		
	(***)	(***)		
Adding product quality			+	+
			(***)	(***)
Observations	75,000	75,000	81,000	81,000
Fixed effects	i,t	i,t	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

ping products with poor match quality and adding products with better match quality are positively associated with firm performance improvement.

The above set of results provides suggestive evidence that firms drive growth by reallocating resources through adding and dropping the right set of products, thereby effectively climbing up the match quality ladder.

3.5 Product Switching over the Business Cycle

In this section, we investigate how firms switch products over the business cycle and how this pattern differs for young firms. We use the NBER recessions and identify that there are three recession years in our sample period, which are 1982, 1991, and 2001.

To the best of our knowledge, this is the first study to document the cyclical dynamics of firms' product-switching behavior across their life cycle. This is one of the main contributions our paper adds to the existing line of literature on product-switching activities (e.g., Bernard et al., 2010; Argente et al., 2018).

Table 6: Probability of Product Drop in Recessions

	$Drop_{t:t+5}$
Recession	+
	(***)
Observations	682,000
Fixed effects	p,i
Controls	Full

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

3.5.1 Product Dropping in Recessions

We use the following regression model to analyze how firms drop products from their portfolios during recessions:

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 \mathcal{I}^r_t + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \varepsilon_{pijt}, \tag{3.12}$$

where $\mathcal{I}^r_t$ is a recession dummy variable that flags the years 1982, 1991, and 1997. Note that we use 1997 instead of 2002 for the 2001 recession, as the drop dummy variable identifies products dropped in the period following the focal year. Note that the controls and fixed effects remain the same as before, except that we omit the year fixed effect due to the inclusion of the recession dummy.

The main coefficient of our interest is β_1, which estimates the probability of dropping a product during recessions. Table 6 presents results showing that firms are more likely to drop a product during recession periods. Table A9 in the Appendix provides the full results with different sets of control variables included in each column. The results stay consistent across all specifications.

3.5.2 Quality of Products Dropped in Recessions

We then analyze the match quality of products that firms drop during recessions using the following regression model:

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 q^{inv}_{pi} + \beta_2 q^{inv}_{pi} \times \mathcal{I}^r_t + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \tag{3.13}$$

where q^{inv}_{pi} is the inverse match quality measure for a given pair of product p and firm i, $\mathcal{I}^r_t$ is the recession dummy defined as before. X_{pijt}, X_{ijt}, and X_{jt} are the identical sets of product, firm, and industry controls, respectively, and δ_p, δ_i, and δ_t are the product, firm, and year fixed effects, respectively, as before. Note that we omit the recession dummy $\mathcal{I}^r_t$ in this regression due to the inclusion of the year fixed effects.

β_2 is the main coefficient of our interest, which captures how the association between match quality and the likelihood of dropping products varies during recessions relative to non-recession years. In other words, it measures the extent to which firms are more likely to drop products with poor match quality during recession periods. In contrast, β_1 estimates the tendency of firms to drop products with poor match quality in non-recession years.

The first column of Table 7 presents the result, where the first row shows β_1 and the third row shows β_2. This suggests that firms drop products with poor match quality more frequently during normal periods but do so less during recession years. Table A11 in the Appendix provides results with different sets of firm controls in each column. We find the results remain robust across all specifications.

3.5.3 Products Dropping by Young Firms in Recessions

Next, we further explore how young firms, in particular, drop products during recessions. To do this, we estimate the following regression model, where we interact the

Table 7: Probability of Product Drop in Recessions

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Inv. quality	+		+
	(***)		(***)
Young		-	+
		(***)	(**)
Recession x Inv. quality	-		+
	(***)		(***)
Inv. quality x Young			-
			(***)
Recession x Young		-	+
		(***)	(***)
Inv. quality x Young x Recession			-
			(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t
Controls	Full	Full	Full

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

recession dummy with a young firm dummy indicating firms aged 5 years or less:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta_1 \mathcal{I}_{ijt}^{young} + \beta_2 \mathcal{I}_{ijt}^{young} \times \mathcal{I}_t^r + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt} \ . \tag{3.14}$$

Here the main coefficients of our interest are β_1 and β_2, where β_1 shows how young firms drop products during normal periods, and β_2 indicates how they do so during recessions. The second column of Table 7 lays out the results, showing that young firms are less likely to drop products during normal times, and this pattern gets more pronounced during recessions. Table A12 in the Appendix shows these results stay robust across different sets of firm controls as before.

3.5.4 Products Dropping in Recessions for Young Firms and Match Quality

Lastly, we investigate the match quality of products that young firms drop during recessions. To do this, we further interact the previous regression model (3.14) with the match quality measure and estimate the following regression model:

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 q^{inv}_{pi} + \beta_2 \mathcal{I}^{young}_{ijt} + \beta_3 q^{inv}_{pi} \times \mathcal{I}^{r}_{t} + \beta_4 q^{inv}_{pi} \times \mathcal{I}^{young}_{ijt} + \beta_5 \mathcal{I}^{r}_{t} \times \mathcal{I}^{young}_{ijt} + \beta_6 q^{inv}_{pi} \times \mathcal{I}^{r}_{t} \times \mathcal{I}^{young}_{ijt} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \tag{3.15}$$

We focus on the following four key coefficients associated with young firms: compared to their mature counterparts, β_2 shows how young firms drop products with good match quality (where the inverse match quality measure is zero), β_4 indicates how young firms drop poor match-quality products during normal periods, and β_5 and β_6 show how the pattern of dropping good match-quality products (with the inverse quality measure being zero) and poor match-quality products, respectively, evolve for young firms during recessions.

The third column of Table 7 presents the results. We find that young firms are less likely to drop products with poor match quality during normal times compared to their mature counterparts, as indicated by $\beta_2 > 0$ and $\beta_4 < 0$. Moreover, as shown by $\beta_5 > 0$ and $\beta_6 < 0$, such pattern becomes more pronounced during recessions. This suggests that young firms are much less likely to drop products having poor match quality with them during recessions compared to mature firms. These results remain robust across different sets of firm controls as before, as detailed in Table A13 in the Appendix.

The result is consistent with our intuition as young firms may lack sufficient information to accurately assess product match quality in their early stages. This tendency is likely to be more pronounced during recession periods when uncertainty is higher. Additionally, in recessions, young firms might continue to retain poorly matched products even after recognizing their suboptimal fit, due to their limited and less diversified product portfolios. We are currently testing hypotheses that could further explain these findings.

4 Robustness Tests

In this section, we perform several robustness tests. First, our main sample currently includes firms with quality estimates from the regression (3.1), representing a subset of the whole product-firm pairs in the CMF. As a robustness check, we use the full product-firm level sample in data and rerun the product-firm level regressions that do not require the quality measures, such as regressions (3.5), (3.12), and (3.14). The following two subsections 4.1 and 4.2 discuss these more in detail.

Second, we extend our analysis by exploring different measures of products being dropped and added in the regressions on the product quality ladder, e.g., (3.7), (3.8), and (3.9). The baseline measure we use is simply a dummy variable indicating whether firms drop or add any products within a given period. Beyond this, we can further explore more quantitative measures such as the total number of products added or dropped or the share of those products relative to the firms' overall product portfolio. This would further allow us to experiment with whether the current results depend on how many products (or how much fraction of total products) firms drop or add, and how the relationships vary across them. The last subsection 4.3 provides further details on this analysis.

4.1 Product Dropping: Using the Full Sample

We rerun the regression (3.5) showing how young firms drop products in general using the full sample from the CMF. The results, presented in Table A14 in the Appendix, remain robust. As before, each column of the table includes a different set of firm controls. Consistently across all specifications, the results show that younger firms are less likely to drop their products.

4.2 Product Dropping in Recessions: Using the Full Sample

In a similar fashion, we rerun the other two regressions (3.12) and (3.14) using the full sample. Table A15 in the Appendix lays out the results for the first regression. This shows that the results hold the same, where firms are more likely to drop their products during recessions. In addition, Table A16 shows similar results about the pattern of young firms dropping their products in normal periods, but the significance gets muted for recessions.

4.3 Firm-Level Evidence for Quality Ladder

Here, we revisit the three regressions (3.7), (3.8), and (3.9), which are related to product quality ladder, and use the alternative measures for products dropped and added discussed earlier.

Table A17 in the Appendix shows the results for the regression (3.7) by using the following alternative measures for product drop: the log number and the share of products dropped. This shows that across all specifications, there exists a positive association between firm-level decisions of dropping and adding products. In particular, the last two columns of the table indicate that it is not only the fact that firms drop at least one product in the focal year, but also the number or share of products dropped that is positively correlated with the firms' likelihood of adding a product. Also, the third and fourth columns of the table show that even after controlling for the number and share of dropped products, the original results about the positive relationship between dropping and adding products hold. These are all noteworthy results supporting the original finding.

Table A19 investigates the previous result from (3.8) regarding the quality of added products after including the number and share of dropped products as additional controls. Again, the results stay robust even after having these variables included. It is also noteworthy from this table that both the number and share of dropped products are positively associated with the match quality of new products added. This suggests that the amount of dropped products increases not just the likelihood of firms adding a new product but also the match quality of the new product.

Lastly, we rerun the regression (3.9) incorporating the same sets of variables. Table A20 contains the results showing that the main results remain consistent even after including the number or share of dropped products in the regression. Here also, we find the positive correlations between the number (or share) of dropped products and the match quality of products newly added.

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. The heightened uncertainty during recessions can exacerbate this information friction, leading young firms to make suboptimal decisions. This idea is formalized in the following two-period 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.

Each product is characterized by propinquity $\bar{y}$, relative to the firm's expertise. The higher the value of $\bar{y}$, the better the match between the product and the firm. As a result, propinquity determines the output level y when producing this product as follows:

$$y = \bar{y} + \varepsilon,$$

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

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

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

However, young firms have limited knowledge of their expertise and cannot directly observe $\bar{y}$. Instead, they observe y and learn about $\bar{y}$ through Bayesian updating.

Suppose startups initially guess $\bar{y} \sim N(\bar{\nu}_0, \sigma_0^2)$ and update it with

$$\bar{\nu}_{a,\tilde{y}} = \frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2} + \frac{a\tilde{y}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{a}{\sigma_\varepsilon^2}\right)}, \ \sigma_{a,\tilde{y}}^2 = \frac{1}{\left(\frac{1}{\sigma_0^2} + \frac{a}{\sigma_\varepsilon^2}\right)}, \tag{5.16}$$

where a is firm age and $\tilde{y}$ is the past-average level of the realized y up to the current period. Note that $(a, \tilde{y})$ is a set of sufficient variables to track posterior distribution of firms about the match quality.

Given this, the value function of firms learning about $\bar{y}$ is

$$V(a, \tilde{y}) = \max\{0, \bar{\nu}_{a,\tilde{y}} - c_f + \beta \mathbb{E}_{\tilde{y}'|\tilde{y}} V(a+1, \tilde{y}')\}.$$

If $a = 0$, this implies startups and $\bar{\nu}_{0,\cdot} = \bar{\nu}_0$. If $a > 0$, this indicates that the firm is still in the learning process with the average realized output $\tilde{y}$.[19]

5.2 Model Implications

For simplicity, let's assume a two-period model. For firms who know $\bar{y}$, the value function becomes

$$V(\bar{y}) = \max\{0, (1+\beta)(\bar{y} - c_f)\},$$

[19]Note that a refers to firm age instead of product tenure of firms. The underlying assumption is that within-firm spillover effects exist in learning across different products. Therefore, when firms are matched with a product at $a > 0$, they can infer the propinquity of the new product based on the previous average $\tilde{y}$ from their existing products.

and firms operate only if $\bar{y} > c_f$.

For those firms in the learning process, the value function becomes

$$\begin{aligned} V(a,\tilde{y}) &= \max\{0, \bar{\nu}_{a,\tilde{y}} - c_f + \beta\left(\bar{\nu}_{a+1,\tilde{y}'} - c_f\right)\} \\ &= \max\{0, \frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2} + \frac{a\tilde{y}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{a}{\sigma_\varepsilon^2}\right)} + \beta\frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2} + \frac{a\tilde{y}+\bar{\nu}_{a,\tilde{y}}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2} + \frac{a+1}{\sigma_\varepsilon^2}\right)} - (1+\beta)c_f\}. \end{aligned}$$

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

Lemma 1. *The posterior mean ($\bar{\nu}_{a,\tilde{y}}$) is increasing in the observed average quality ($\tilde{y}$). It is also increasing in age (a) if the observed past-average quality is above the initial prior mean (i.e., $\tilde{y} > \bar{\nu}_0$), and decreasing in age (a) if the observed past-average quality is below the initial prior mean (i.e., $\tilde{y} < \bar{\nu}_0$).*

Proof.

$$\frac{\partial \bar{\nu}_{a,\tilde{y}}}{\partial \tilde{y}} = \frac{\frac{a}{\sigma_\varepsilon^2}}{\frac{1}{\sigma_0^2} + \frac{a}{\sigma_\varepsilon^2}} > 0 \tag{5.17}$$

$$\frac{\partial \bar{\nu}_{a,\tilde{y}}}{\partial a} = \frac{(\tilde{y} - \bar{\nu}_0)}{\sigma_0^2\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + a\frac{1}{\sigma_\varepsilon^2}\right)^2} \begin{cases} \geq 0 & \text{if} \quad \tilde{y} \geq \bar{\nu}_0 \\ < 0 & \text{if} \quad \tilde{y} < \bar{\nu}_0 \end{cases}. \tag{5.18}$$

□

Lemma 2. *The posterior variance ($\sigma_{a,\tilde{y}}$) is decreasing in age (a).*

Proof.

$$\frac{\partial \sigma_{a,\tilde{y}}^2}{\partial a} = -\frac{1}{\sigma_\varepsilon^2\left(\frac{1}{\sigma_0^2} + a\frac{1}{\sigma_\varepsilon^2}\right)^2} < 0. \tag{5.19}$$

□

Note that the posterior mean in (5.16) is a weighted sum of the initial prior mean and the average observed quality of matches over past periods, with weights determined by firm age. The mean increases with average match quality, where higher average match quality enhances the prospects about the product match. On the other hand, the posterior mean increases with firm age only if the average match quality is above the initial prior mean ($\tilde{y} > \bar{\nu}_0$), while it decreases with firm age if the firm's average match quality with products is below the cross-sectional mean ($\tilde{y} < \bar{\nu}_0$).[20] The posterior variance in (5.16) decreases with firm age, and the posterior converges to a degenerate distribution centered at the true quality $\bar{y}$ as the firm ages.

Equation (5.17) implies that the posterior mean increases with the average match quality level. As firms are observed to have higher average match quality, their prospects about a match improve. Moreover, (5.18) shows that firm age affects the prospects differently depending on the past-average match quality. Specifically, if firm j's average match quality is above the initial prior mean, a higher age implies a better match, while if a firm's average match quality is below the prior mean, a higher age implies a worse match. (5.19) implies that as a firm ages, learning becomes less noisy, and the posterior converges to a degenerate distribution centered at the true match quality $\bar{y}$.

Now suppose the case where a firm in the learning process has observed $\tilde{y} = \bar{y}$. Further assume that this is the actual match quality, and a firm with full information would have noticed it right away. Under this case, the following proposition regarding product adding and dropping decisions of firms can be derived.

Proposition 1. *If the match has been seen good on average with $\bar{y} > \bar{\nu}_0$ and $\bar{y} > c_f$, younger firms are more likely to drop the product.*

Proof. If $\tilde{y} > \bar{\nu}_0$, following Lemma 1, $\frac{\partial \bar{\nu}_{a,\tilde{y}}}{\partial a} > 0$. Furthermore, if firms are old enough, following Lemma 2, their posterior distribution converges to the actual match quality $\bar{y}$. This implies that: for firms with age a and average match quality $\tilde{y}$ in the learning process, the following holds

$$\bar{\nu}_{a,\tilde{y}} < \bar{y},$$

[20]In other words, a higher age indicates a better (worse) inferred match for the former (latter) case.

and thus,

$$\frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2}+\frac{a\tilde{y}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2}+\frac{a}{\sigma_\varepsilon^2}\right)}<\bar{y}, \frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2}+\frac{a\tilde{y}+\bar{\nu}_{a,\tilde{y}}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2}+\frac{a+1}{\sigma_\varepsilon^2}\right)}<\bar{y}.$$

Note that firms with full information would add this product as $\bar{y} > c_f$. On the other hand, firms in the learning process may or may not add this product given their limited information.

To see this, let $y^* = y^*(a, \tilde{y})$ denote the point of match quality at which a learning firm (with $a, \tilde{y}$) is indifferent between adding or dropping the product:

$$\frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2}+\frac{ay^*}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2}+\frac{a}{\sigma_\varepsilon^2}\right)}+\beta\frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2}+\frac{ay^*+\bar{\nu}_{a,\tilde{y}}(y^*)}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2}+\frac{a+1}{\sigma_\varepsilon^2}\right)}=(1+\beta)c_f. \tag{5.20}$$

As the left-hand side of (5.20), indicating the expected benefit of adding a product given the observed average quality $\bar{y}$ is increasing in $\bar{y}$, this firm drops (or add) a product if $\bar{y} < y^*$ ($\bar{y} > y^*$). Thus, if the observed $\bar{y}$ lies below y^*, the firm with imperfect information would drop the product, even though it was supposed to be a good match with $\bar{y} > c_f$, which it would have added under perfect information. □

Proposition 2. *If the match has been seen as bad on average with $\bar{y} < \bar{\nu}_0$ and $\bar{y} < c_f$, younger firms are more likely to drop the product.*

Proof. If $\tilde{y} < \bar{\nu}_0$, following Lemma 1, $\frac{\partial \bar{\nu}_{a,\tilde{y}}}{\partial a} < 0$ holds. With 2, firms with age a and average match quality $\tilde{y}$ in the learning process obtain:

$$\bar{\nu}_{a,\tilde{y}} > \bar{y},$$

and thus,

$$\frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2}+\frac{a\tilde{y}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2}+\frac{a}{\sigma_\varepsilon^2}\right)}>\bar{y}, \frac{\left(\frac{\bar{\nu}_0}{\sigma_0^2}+\frac{a\tilde{y}+\bar{\nu}_{a,\tilde{y}}}{\sigma_\varepsilon^2}\right)}{\left(\frac{1}{\sigma_0^2}+\frac{a+1}{\sigma_\varepsilon^2}\right)}>\bar{y}.$$

Therefore, similarly to the previous case, if $y^* < \bar{y}$ with y^* defined in (5.20), firms with imperfect information would keep the product, although it was supposed to be a bad match with $\bar{y} < c_f$, which they would have dropped under perfect information. $\square$

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 specifically observed 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 demonstrate 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 firms' product dropping is positively correlated with product adding in terms of frequency. This provides evidence of the product-firm match quality ladder. Furthermore, we show that adding products with good match quality or dropping products with poor match quality can promote firm growth.

We additionally extend our analysis to the business cycle context and further document that firms are more likely to drop products but they drop those with poor match quality less during economic downturns. We also find that such cyclical patterns are mainly driven by young firms, as the pattern of dropping fewer products with poor match quality during recessions is even more pronounced for young firms.

Combining them all, this set of results indicates that young firms might have more difficulties in climbing up the match-quality ladder and improving their performance due to their limited ability to drop products with poor match quality in their initial stage. Moreover, such barriers for young firms to find the right product can be more amplified in recessions, which can be a source to account for the procyclicality of young firm activities.

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 lifecycle. 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.

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Appendix

A Full Models

A.1 Product Dropping

Table A1: Probability of Product Drop

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Inv. quality	+		+
	(***)		(***)
Young firm		-	+
		(***)	(***)
Low quality x Young firm			-
			(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)	-	-	-
	(***)		(***)
log(firm age)	+	+	+
	(***)	(**)	(*)
log(number of products)	+	+	+
	(***)	(***)	(***)
Skill intensity	+	+	+
	(*)	(*)	(*)
Capital intensity	+	+	+
	(***)	(***)	(***)
Constant	-	-	-
	(***)	(***)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A2: Probability of Product Drop and Match Quality

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Inv. quality	+	+	+
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
			(***)
log(firm age)		+	+
		(***)	(***)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(**)	(**)	(*)
capital intensity	+	+	+
	(**)	(***)	(***)
Constant	-	-	-
	(***)	(***)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Probability of Product Drop for Young Firms

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young firm	-	-	-
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
		(***)	
log(firm age)		+	+
		(***)	(**)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(**)	(**)	(*)
capital intensity	+	+	+
	(**)	(**)	(***)
Constant	+	-	-
		(*)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Probability of Product Drop and Match Quality for Young Firms

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young firm	+	+	+
	(***)	(***)	(***)
Inv. quality	+	+	+
	(***)	(***)	(***)
Inv. quality x Young firm	-	-	-
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
			(***)
log(firm age)		+	+
		(***)	(*)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(**)	(**)	(*)
capital intensity	+	+	+
	(***)	(***)	(***)
Constant	-	-	-
	(***)	(***)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

A.2 Firm-Level Evidence

Table A5: Product Add and Drop

	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$	+	
	(***)	
Dropping product quality		+
		(***)
log(firm size)	+	+
		(***)
log(firm age)	-	+
		(***)
log(number of products)	-	-
	(***)	(***)
skill intensity	+	+
	(**)	(**)
capital intensity	-	-
		(***)
Constant	+	+
	(***)	(***)
Observations	402,000	75,000
Fixed effects	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A6: Match Quality of Added Products

	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$
$Drop_{t:t+5}$	+	
	(***)	
Dropping product quality		-
		(***)
log(firm size)	-	-
	(**)	(**)
log(firm age)	-	-
	(**)	(**)
log(number of products)	+	-
		(***)
skill intensity	-	-
	(**)	(*)
capital intensity	+	+
	(***)	
Constant	+	+
	(***)	(***)
Observations	81,000	29,000
Fixed effects	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A7: Product Add/Drop and Firm Performance

	$\Delta TVS_{t:t+5}$	$\Delta LP_{t:t+5}$
$Drop_{t:t+5}$	-	-
	(***)	
$Add_{t:t+5}$	+	+
	(***)	(***)
log(dropping product number)	-	-
	(***)	
log(adding product number)	+	+
	(***)	(**)
log(firm size)	-	+
	(***)	(***)
log(firm age)	-	-
	(***)	(***)
log(number of products)	+	-
	(***)	(***)
skill intensity	-	-
	(***)	
capital intensity	+	+
		(**)
Constant	+	-
	(***)	(***)
Observations	402,000	402,000
Fixed effects	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A8: Match Quality of Added/Dropped Products and Firm Performance

	$\Delta TVS_{t:t+5}$	$\Delta LP_{t:t+5}$	$\Delta TVS_{t:t+5}$	$\Delta LP_{t:t+5}$
Dropping product quality	-	-		
	(***)	(***)		
Adding product quality			+	+
			(***)	(***)
log(dropping product number)	-	-		
	(***)			
log(adding product number)			+	+
			(***)	
log(firm size)	-	+	-	+
	(***)	(***)	(***)	(***)
log(firm age)	-	-	-	-
	(***)	(***)	(***)	(***)
log(number of products)	+	-	+	-
	(***)	(**)	(***)	(***)
skill intensity	-	+	-	-
		(**)		
capital intensity	+	+	+	-
Constant	+	+	+	-
	(***)		(***)	(***)
Observations	75,000	75,000	81,000	81,000
Fixed effects	i,t	i,t	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

A.3 Business Cycle

Table A9: Probability of Product Drop in Recessions

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Recession	+	+	+
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	+
		(***)	
log(firm age)		-	-
log(number of products)			+
			(***)
skill intensity	+	+	+
capital intensity	+	+	-
Constant	+	+	+
	(**)		
Observations	682,000	682,000	682,000
Fixed effects	p,i	p,i	p,i

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A10: Probability of Product Drop in Recessions

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Inv. quality	+		+
	(***)		(***)
Young		-	+
		(***)	(**)
Recession x Inv. quality	-		+
	(***)		(***)
Inv. quality x Young			-
			(***)
Recession x Young		-	+
		(***)	(***)
Inv. quality x Young x Recession			-
			(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)	-	-	-
	(***)		(***)
log(firm age)	+	+	+
	(***)	(**)	(*)
log(number of products)	+	+	+
	(***)	(***)	(***)
Skill intensity	+	+	+
	(*)	(*)	(*)
Capital intensity	+	+	+
	(***)	(***)	(***)
Constant	-	-	-
	(***)	(***)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A11: Probability of Product Drop and Match Quality in Recessions

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Inv. quality	+	+	+
	(***)	(***)	(***)
Inv. quality x Recession	-	-	-
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
			(***)
log(firm age)		+	+
		(***)	(***)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(**)	(**)	(*)
capital intensity	+	+	+
	(**)	(***)	(***)
Constant	-	-	-
	(***)	(***)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A12: Probability of Product Drop for Young Firms

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young firm	-	-	-
	(***)	(***)	(***)
Young firm x Recession	-	-	-
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
		(***)	
log(firm age)		+	+
		(***)	(**)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(**)	(**)	(*)
capital intensity	+	+	+
	(**)	(**)	(***)
Constant	+	-	-
			(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A13: Probability of Product Drop in Recessions

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young firm	+	+	+
		(**)	(**)
Inv. quality	+	+	+
	(***)	(***)	(***)
Recession x Inv. quality	+	+	+
	(***)	(***)	(***)
Inv. quality x Young firm	-	-	-
	(***)	(***)	(***)
Recession x Young firm	+	+	+
	(***)	(***)	(***)
Inv. quality x Young firm x Recession	-	-	-
	(***)	(***)	(***)
log(product tenure)	+	+	+
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
			(***)
log(firm age)		+	+
		(**)	(*)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(**)	(**)	(*)
capital intensity	+	+	+
	(***)	(***)	(***)
Constant	-	-	-
	(***)	(***)	(***)
Observations	682,000	682,000	682,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

B Robustness Tests

B.1 Product Dropping: using the Full Sample

Table A14: Probability of Product Drop for Young Firms

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young firm	-	-	-
	(***)	(***)	(***)
log(product tenure)	-	-	-
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
		(***)	(***)
log(firm age)		-	-
			(*)
log(number of products)			+
			(***)
skill intensity	+	+	+
capital intensity	+	+	+
	(***)	(***)	(***)
Constant	+	+	+
	(***)	(***)	(***)
Observations	1,115,000	1,115,000	1,115,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

B.2 Product Dropping in Recessions: using the Full Sample

Table A15: Probability of Product Drop in Recessions

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Recession	+	+	+
	(***)	(***)	(***)
log(product tenure)	-	-	-
	(**)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
		(***)	(***)
log(firm age)		+	+
		(***)	(***)
log(number of products)			+
			(***)
skill intensity	+	+	+
	(***)		
capital intensity	+	+	+
	(***)	(***)	(***)
Constant	+	+	+
	(***)	(***)	(***)
Observations	1,115,000	1,115,000	1,115,000
Fixed effects	p,i	p,i	p,i

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A16: Probability of Product Drop for Young Firms

	$Drop_{t:t+5}$	$Drop_{t:t+5}$	$Drop_{t:t+5}$
Young firm	-	-	-
	(***)	(**)	(***)
Young firm x Recession	-	-	+
log(product tenure)	-	-	-
	(***)	(***)	(***)
log(real value of shipment)	-	-	-
	(***)	(***)	(***)
log(firm size)		+	-
		(***)	(***)
log(firm age)		-	-
			(*)
log(number of products)			+
			(***)
skill intensity	+	+	+
capital intensity	+	+	+
	(***)	(***)	(***)
Constant	+	+	+
	(***)	(***)	(***)
Observations	1,115,000	1,115,000	1,115,000
Fixed effects	p,i,t	p,i,t	p,i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

B.3 Firm-Level Evidence for Quality Ladder

Table A17: Product Add and Drop

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
$Drop_{t:t+5}$		+	+	+		
		(***)	(***)	(***)		
log(dropping product number)			+		+	
			(***)		(***)	
Dropping product share				+		+
				(***)		(***)
log(firm size)	-	+	+	+	-	-
	(***)				(***)	(***)
log(firm age)	-	-	-	-	-	-
	(**)		(*)	(***)	(***)	(***)
log(number of products)	-	-	-	-	-	-
	(***)	(***)	(***)	(***)	(***)	(***)
skill intensity	+	+	+	+	+	+
	(**)	(**)	(**)	(**)	(**)	(*)
capital intensity	-	-	-	-	-	-
				(*)		
Constant	+	+	+	+	+	+
	(***)	(***)	(***)	(***)	(***)	(***)
Observations	402,000	402,000	402,000	402,000	402,000	402,000
Fixed effects	i,t	i,t	i,t	i,t	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A18: Product Add and Drop

	$Add_{t:t+5}$	$Add_{t:t+5}$	$Add_{t:t+5}$
Dropping product quality	+	+	+
	(***)	(***)	(***)
log(dropping product number)		+	
		(***)	
Dropping product share			+
			(***)
log(firm size)	+	+	+
	(***)	(***)	(***)
log(firm age)	+	+	+
	(***)	(***)	(***)
log(number of products)	-	-	-
	(***)	(***)	(***)
skill intensity	+	+	+
	(**)	(**)	(**)
capital intensity	-	-	-
	(***)	(***)	(***)
Constant	+	+	+
	(***)	(***)	(***)
Observations	75,000	75,000	75,000
Fixed effects	i,t	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A19: Match Quality of Added Products

	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$
$Drop_{t:t+5}$	+	+	+		
	(***)	(***)	(***)		
log(dropping product number)		+		+	
		(***)		(***)	
Dropping product share			+		+
			(***)		(***)
log(firm size)	-	-	-	-	-
	(**)	(**)	(**)	(***)	(***)
log(firm age)	-	-	-	-	-
	(**)	(**)	(***)	(***)	(***)
log(number of products)	+	-	+	-	+
		(**)			(***)
skill intensity	-	-	-	-	-
	(**)	(**)	(**)	(*)	(**)
capital intensity	+	+	+	+	+
	(***)	(***)	(***)	(***)	(***)
Constant	+	+	+	+	+
	(***)	(***)	(***)	(***)	(***)
Observations	81,000	81,000	81,000	81,000	81,000
Fixed effects	i,t	i,t	i,t	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

Table A20: Match Quality of Added Products

	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$
Dropping product quality	-	-	-
	(***)	(***)	(***)
log(dropping product number)		+	
		(***)	
Dropping product share			+
			(***)
log(firm size)	-	-	-
	(**)	(**)	(**)
log(firm age)	-	-	-
	(**)	(**)	(**)
log(number of products)	-	-	-
	(***)	(***)	(**)
skill intensity	-	-	-
	(*)		
capital intensity	+	+	+
Constant	+	+	+
	(***)	(***)	(***)
Observations	29,000	29,000	29,000
Fixed effects	i,t	i,t	i,t

Notes: Estimates for product, firm, year fixed effects, and the constant are suppressed. Firm controls include firm size, age, and the number of manufactured products. Industry controls include skill and capital intensities. Due to Census Bureau qualitative disclosure procedures, only signs and significance of the coefficients are allowed to disclose at this moment. Thus, observation counts, exact magnitude of the coefficients and standard errors associated with them are not yet disclosed. Observations are unweighted. * p<0.1, ** p<0.05, *** p<0.01.

C 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:

$$y_{pijt} = \theta_{pi} + \beta_2 PT_{pijt} + \delta_{pt} + \delta_{it} + \varepsilon_{pijt}, \tag{C.21}$$

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

The former 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 (C.21) could be one alternative of the baseline quality estimation in (3.1).

However, (C.21) has several pitfalls given the use of multiple fixed effects. Estimating the product-year or firm-year fixed effect can drop a non-negligible fraction of the sample observations, as a certain product can only show up in a single firm or single-product firms are existent in a given year.

Therefore, another way to estimate the quality measures would be to replace δ_{pt} with a set of time-varying product characteristics (such as the total or average value of shipment) along with a year fixed effect included. Also, the firm-year fixed effect δ_{it} can be substituted by the baseline set of firm-level controls X_{ijt} as well as industry-level controls X_{jt} as in (3.1). The following specification shows this idea:

$$y_{pijt} = \theta_{pi} + \beta_2 PT_{pijt} + \beta_3 X_{pt} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_{pt} + \varepsilon_{pijt}, \tag{C.22}$$

where X_{pt} is the product-level time-varying elements and δ_t is a year fixed effect. This alternative specification enables us to properly estimate the product-firm match quality with a sufficient number of the sample observations intact from the potential issues of estimating fixed effects.