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. 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 likelihood of adding products and the quality of products added subsequently, 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 source accounting for procyclical young firm activities.

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Keywords: product entry and exit, product switching, young firm dynamics, firm growth, innovation, business cycle

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1 Introduction

Finding an optimal set of products to produce is important for firms to allocate their resources efficiently. Proper product adding and dropping exert significant impact on the scope and outcomes of firms, which are tightly linked to the potential growth of firms (Bernard et al., 2010; Argente et al., 2018). Given the importance, several recent works have documented empirically the relationship between product entry and exit, firm-product attributes, and the innovation activities of firms.

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

However, relatively less is known about what types of products firms add or drop, how they climb up a quality ladder of products by properly switching the set of products (e.g. adding products with better match quality while dropping products with worse match quality for them) along the firm life-cycle, how such patterns differ specifically for young firms, and how such activities affect firm growth and performance.

In order to tackle these questions, 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 the data, we define a "product" as either five-digit Standard Industrial Classification (SIC) categories for the pre-2002 years or seven-digit North American Industry Classification System (NAICS) for the years from 2002 and identify product-firm pairs in each Census year. Most importantly, we estimate product-firm pair match quality by identifying time-invariant characteristics associated with each product-firm pair using a pair fixed effect of real value of shipments. To our knowledge, this is one of the novel parts in our paper.

In the dataset, we observe that firms in general drop products that have poor match quality with them. Young firms, however, specifically drop less products with poor match quality, while drop more products with relatively better match quality, relative to mature firms. And overall, the stickiness with products with worse match quality dominates the behavior of dropping better-quality products, which makes them drop less products on average.

Next, we examine how firms climb up a 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 in a given census year have higher likelihood to add new products and also obtain higher quality of the added products in the next census year. Moreover, there exists a negative correlation between the quality of products dropped and and added. In other words, as firms drop products having poor match quality with them, they are more likely to add a new product with better match quality in the next period.

Furthermore, we find that the product switching and the product quality ladder matters for firm growth and performance in the subsequent period. In particular, we observe that dropping products with low match-quality positively affects the growth of the firm-level total value of shipments and labor productivity, while the counterpart for added products has a negative impact on firm growth.

Combining these with the young firms' product switching behavior, we can infer that young firms are less likely to climb up the quality ladder as faster as established incumbent firms, and this could be a source to slow down their potential growth.

Lastly, we extend the analyses to investigate cyclical dynamics. We use the NBER recession indicator and look at how firms drop products and how does the quality of dropped products look like in the recession periods. We document that firms on average are more likely to drop products in recessions, but the quality of dropped products, on average, is less likely to have poor match quality. This might be because of the fact that recession contains higher noise which could disrupt the quality of information firms can use to infer how good their match with products is.

This gets clear once we divide data into young vs. mature firms. In particular, when we look into young firms, we find that young firms in general drop products even less during recessions and the pattern that firms drop less products with poor quality is mostly driven by young firms. In other words, the baseline fact that young firms drop less products with poor quality gets more pronounced in recessions. Linking these facts to the previous findings on the negative relationship between the quality of dropped products and firm performance, the quality-ladder channel through product switching can also be a source to account for the well-known procyclical young firm activities.

The rest of the paper proceeds as follows. Section 2 briefly discusses related literature. Section 3 describes data sources and main measures used for our analysis. Section 4 shows the main results we find on the product dropping and adding activities of young and mature firms, the relationship between the 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 specifically for young firms. Section 5 documents further robustness tests for the main results. Section 6 concludes with the discussion of the remaining future work.

2 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 good sectors from the Nielsen Homescan database. Bernard and Okubo (2016) study the role of product adding and dropping within Japanese manufacturing firms over the business cycle. Argente et al. (2018) use the 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. This paper contributes to this literature by offering a new direct measure of product-firm match quality and establishing novel facts about product match-quality ladder within firms. The paper further pays special attention to young firms through this channel, which has not well been documented in previous studies.

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 a friction for new businesses to grow high. Akcigit and Ates (2019) and Jo and Kim (2021) present barriers to knowledge spillovers as a source to create frictions dampening firm entry and the rapid-growth young firm activities. Furthermore, Kim (2022) 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 a right product match, and this can give negative impact on their growth path.

Lastly, our paper relates to the literature on procyclical quality of resources matched with firms and a sullying effect of recessions. Most of 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 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 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.

3 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 contains a comprehensive set of information about the universe of 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 by five-digit Standard Industrial Classification (SIC) or seven-digit North American Industry Classification System (NAICS) codes—and value of shipments for products manufactured by each establishment. More details can be found from Bernard et al. (2010), Kehrig et al. (2011) and Kehrig and Vincent (2021).

The LBD tracks the universe of U.S. private non-farm business establishments and firms with at least one paid employees. It covers all sectors and geographic areas of the economy annually form 1976 and onward. Establishments that are owned by a parent firm are grouped under a common firm identifier, which allows us to aggregate establishment-level activity 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 about price deflator, payroll, employment size, number of workers, total value of shipments, value added, the costs and expenditure of various types of inputs, 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.

3.1 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.[1] Note that there is a break of the product definitions from 1997 as the SIC codes are only available until 1997 and the 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

[1] 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.

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 2012.[2][3][4]

The CMF reports product-level sales (total value of shipment) and physical quantity shipped. Given the definition of a product, we limit our analyses to observations that have positive and nonzero value of shipment. 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. And we normalize the total value of shipment 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, 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

[2] 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.

[3] We find that a large fraction of product codes preserve unique mappings, but as 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.

[4] 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.

initial entry or re-entry of the entering product or temporary or permanent exit of the exiting product.

3.2 Firm Characteristics and Identifiers

We use firm age variables constructed by the Census using the method as in Haltiwanger et al. (2013). Specifically, firm age is defined as the age of the oldest establishment that the firm owns when the firm is first observed in the data. We indicate young firms by those younger or equal to age five. Firm size is measured as 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.[5] 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.

3.3 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.

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

4 Empirical Models and Main Results

In this section, we investigate firms' product switching choices over the business cycle, and how these vary for young firms. We discuss the design of our empirical strategies in the following subsections.

4.1 Firm-Product Match Quality Estimation

To understand the relationship between firms' product switching decisions and resource reallocation, we first estimate product-firm pair match quality using the following baseline model:

$$y_{pijt} = \theta_{pi} + \beta_2 PT_{pijt} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_{pt} + \varepsilon_{pijt}, \tag{4.1}$$

where y_{pijt} is 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 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, which determines performance of the product in the firm and captures 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 customer base when they newly enter into 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 baseline, we use log employment size and firm age as firm-level controls.[6] Related to this, several industry-specific properties can also affect the total value of shipment regardless of the firm-product's fundamental match quality. X_{jt} indicates a set of time-varying industry controls, where we add the industry-level log skill and capital intensities.

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 differ across each product market.

As robustness checks, we further explore alternative specifications to estimate the product-firm match quality. More discussion can be found in 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 $\hat{\theta}_{pi}$:

$$q_{pi} \equiv m \times \frac{\hat{\theta}_{pi} - \underline{\theta}_{pi}}{\overline{\theta}_{pi} - \underline{\theta}_{pi}}, \tag{4.2}$$

where $\underline{\theta}_{pi}$ and $\overline{\theta}_{pi}$ are the minimum and maximum value of the quality estimates, respectively (e.g. $\hat{\theta}_{pi} \in [\underline{\theta}_{pi}, \overline{\theta}_{pi}]$). We use $m = 0.99$. For the recession analysis, we used the inverse match quality measure by transforming the match quality measure as:

$$q_{pi}^{inv} \equiv 1 - q_{pi}, \tag{4.3}$$

which makes the inverse match quality ranged in $[0.01, 1]$. This helps us make the interpretation of regression results intuitive.

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

4.2 Product Dropping

In this subsection, we analyze how firms drop their existing products, and how these patterns depend on the product-firm match quality as well as firm-level characteristics.

4.2.1 Match Quality of Dropped Products

We first study what types of products firms drop from their existing product portfolio. Specifically, we test whether firms drop poorly matched products more relative to better-matched ones. This is because it might not be obvious for firms to identify products with good or bad match quality as it is costly to search and learn about quality between a given product and themselves. This might be more pronounced for younger firms not having enough records or information about themselves and products in a market.

To see this, we construct a dummy variable equal to one if a product is dropped by the beginning of the next period and run the following regression. The left-hand side variable $\mathcal{I}^{drop}_{pijt}$ denotes this dummy variable, where $\mathcal{I}^{drop}_{pijt} = 1$ 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 depends on the match quality between product p and firm j

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 q^{inv}_{pi} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \qquad (4.4)$$

where q^{inv}_{pi} is the inverse quality value (4.3) 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} is a vector of the industry controls as before. 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

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.

controls.[7] 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 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 firms' dropping poor-matched products leads to match-quality ladder climbing and performance improvement, we test whether the product-dropping behavior is different for young firms.

4.2.2 Product Dropping by Young Firms

As young firms have less experience producing and selling products, they might face difficulties in evaluating whether the product they produce 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 not having good match qual-

[7] 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.

ity with them.

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

$$\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 \mathcal{I}^{young}_{ijt} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \tag{4.5}$$

where $\mathcal{I}^{young}_{ijt}$ 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 a product leads them to shut down their businesses—they only have one product to produce. 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 X_{pijt}, X_{ijt}, X_{jt}, δ_p, δ_i, and δ_t 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.[8]

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 4.5 as follows:

$$\begin{aligned}\mathcal{I}^{drop}_{pijt} = \alpha + \beta_1 q^{inv}_{pi} + \beta_2 \mathcal{I}^{young}_{ijt} + \beta_3 q^{inv}_{pi} \times \mathcal{I}^{young}_{ijt} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 \\ + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}.\end{aligned} \tag{4.6}$$

The third column of Table 1 lays out the result.[9] 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

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

[9]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.

on average. This is in contrast to the previous result found from specification 4.5 without having the match quality controlled.

However, as the third row shows that young firms indeed drop less 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. And overall, the stickiness with products having poor quality is dominant and determines average young firm dropping behavior (the result from specification 4.5).

This set of results suggests that young firms' limited resources and information to infer product match quality could constrain themselves from adding or dropping products with better or worse quality, respectively, at an earlier stage of firm life-cycle. Thus, it gets difficult for young firms to properly climb up a quality ladder of products. 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.

4.3 Firm-Level Evidence for Quality Ladder

Next, we test how firms climb up match-quality ladder and how the quality of products being dropped can be associated with the quality of products newly added in a set of firms' product portfolio.

4.3.1 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 a product before and on the quality of products dropped.

To see this, we define a product to be added to a firm in a given year if that product does not exist in the firm's product portfolio in the focal year t but appears in the next

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.

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.)

First, 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:

$$\mathcal{I}_{ijt}^{add} = \alpha + \beta_1 \mathcal{I}_{ijt}^{drop} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \varepsilon_{ijt}, \tag{4.7}$$

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 we can see from the first column of Table 2, the probability of firms adding a product is positively associated with the history of firms' dropping at least one product.[10] This indicates that firms simultaneously add and drop products, which is one evidence regarding a match-quality ladder.

Here, firms could drop many products at once as they either have already added a

[10]Table A5 in Appendix shows the full results.

well-matched product or plan to do so. To rule out this, as robustness check, we further include controls for the number or share of dropped products as controls. The result stays robust, which can be found in Section 5.

Next, we further investigate how the quality of products dropped affects the firm's decision to add a product. The following regression shows it:

$$\mathcal{I}_{ijt}^{add} = \alpha + \beta_1 \overline{q}_{ijt}^{drop} + \beta_2\, nd_{ijt} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \varepsilon_{ijt}, \tag{4.8}$$

where $\overline{q}_{ijt}^{drop}$ is the value of unweighted average of the match qualities for dropped products b/w t and t+5, where the match quality is defined as equation 4.2. nd_{ijt} is the number of dropped products. We use the ratio of the number of dropped products to total products as an alternative measure in our robustness test.

As we see in the second column of Table 2, the probability to add a product is positively correlated with the average match quality of dropped products. In other words, firms that drop products with poor quality on average are more likely to add a new product in the subsequent period.

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

In the previous analyses, we learn that firms' product dropping behavior and the match quality of the dropped products are positively associated with the probability of adding a product. In the section, we further investigate whether firms climb up the match quality ladder through product switching by exploring the impact on the quality of the added products.

We first examine whether the match quality of products being added right after or along with a product dropping process differs from those without having any products being dropped. Note that if firms climb up a match quality ladder, they would be likely to drop poor matched products and add new products that are potentially a better match for them.

To test this hypothesis, we replace the product-add dummy in equation 4.7 with the

Table 3: Match Quality of Added Products

	$q^{add}_{t:t+5}$	$q^{add}_{t:t+5}$
$Drop_{t:t+5}$	+	
	(***)	
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.

average quality of added product and estimate the following regression model:

$$\overline{q}^{add}_{ijt} = \beta_1 \mathcal{I}^{drop}_{ijt} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt} \, , \tag{4.9}$$

where $\overline{q}^{add}_{ijt}$ is the average quality of products added by firm i (in industry j) in a given year t.

As shown in the first column of Table 3, the average quality of added products is higher if there exists at least a product being dropped in the same year.[11] This result confirms that firms' product drop is positively associated with quality of products being added on average. 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 of which match quality is not good. To see this, we replace the product-add dummy in the left-hand side of equation 4.8 with the average quality of added products and estimate the following regression model:

$$\overline{q}^{add}_{ijt} = \beta_1 \overline{q}^{drop}_{ijt} + \beta_2 \, nd_{ijt} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt}. \tag{4.10}$$

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

As we can find from the second column of Table 3, the quality of the added product is higher (lower) if firms drop products that are poor (better) match to them. This suggests that it is not just the tendency of adding a product, but also the quality of that product being added is correlated with the average quality of dropped products in the same period. This is closely linked to the match-quality ladder hypothesis.

4.4 Product Switching and Firm Performance

In this section, we further delve into whether firms' product adding or dropping behavior can give impact on firm performance.

4.4.1 The Impact of Product Adding and Dropping

We first use the following regression to estimate the relationship between the choice to add or drop a product and firm performance:

$$\Delta y_{ijt} = \beta_1 \mathcal{I}_{ijt}^{drop} + \beta_2 \mathcal{I}_{ijt}^{add} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt} \, , \tag{4.11}$$

where Δy_{ijt} is the log difference of i) 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, showing that dropping a product is negatively associated with the subsequent growth of total value of shipments, while adding a product is positively correlated with it.[12] This result is consistent with previous findings by (Bernard et al., 2010; Argente et al., 2018). The association between product add and the growth of labor productivity is also positive, however, the relationship gets more ambiguous for product drop.

[12]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.

4.4.2 The Impact of Match Quality of Added and Dropped Products

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

$$\Delta y_{ijt} = \beta_1 \overline{q}_{ijt}^{sw} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_i + \delta_t + \alpha + \varepsilon_{ijt} \, . \tag{4.12}$$

We run the equation 4.12 separately for the average quality of added products ($sw = add$) and dropped products ($sw = drop$). Here, we add another firm-level control variable, the log number of products added or dropped, for the analysis for products added ($sw = add$) and for products dropped ($sw = drop$), respectively.

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.[13] This indicates that both performance measures are negatively associated with the match quality of dropped products, while they are positively associated with the match quality of added products. In other words, dropping products with poor match quality can enhance firm performance in the subsequent period, while adding products with better match quality can also improve

[13] 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.

firm performance right after.

4.5 Product Switching over the Business Cycle

In this section, we investigate how firms switch products over the business cycle. 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 knowledge, this is the first time to document cyclical dynamics of firms' product switching behavior. This is one of the main contributions our paper adds to previous studies on product switching activities such as Bernard et al. (2010).

4.5.1 Product Dropping in Recessions

We use the following regression to see how firms drop products from their portfolio during recessions:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta_1 \mathcal{I}_t^r + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \varepsilon_{pijt}, \tag{4.13}$$

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.

where $\mathcal{I}_t^r$ 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, since the drop dummy variable identifies products dropped in the following period from the focal year. Note that the controls and fixed effects are the same as before, except for the year fixed effect we drop due to using the recession dummy.

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

4.5.2 Quality of Products Dropped in Recessions

In this section, we study what quality of products firms drop in recessions with the following regression:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta_1 q_{pi}^{inv} + \beta_2 q_{pi}^{inv} \times \mathcal{I}_t^r + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \tag{4.14}$$

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.

where q_{pi}^{inv} is the inverse quality measure for a given pair of product p and firm i, $\mathcal{I}_t^r$ is the recession dummy defined as before, X_{pijt}, X_{ijt}, and X_{jt} are the identical sets of product, firm, industry controls, respectively, and δ_p, δ_i, δ_t are the product, firm, year fixed effects, respectively, as before. Note that we drop the recession dummy $\mathcal{I}_t^r$ as we use the year fixed effect in this regression.

β_2 is the main coefficient of our interest, which captures how the impact of match quality on the likelihood of dropping products varies in recessions. In other words, this presents how pronounced it is for firms to drop low quality products during the recession periods. Also, relative to this, β_1 shows how firms drop products with low quality in non-recession years.

The first column of Table 7 shows the result, where the first row indicates β_1 and the third row shows β_2. This suggests that firms drop low-quality products in normal period, but less so in the recession years. Table A11 in Appendix shows the results with different sets of firm controls in each column. We find the results being robust across all of them.

4.5.3 Products Dropping by Young Firms in Recessions

Next, we further explore how young firms in particular drop products in recessions. To do this, we run the following regression where we interact the recession dummy with a young firm dummy indicating firms aged 5 or less:

$$\mathcal{I}_{pijt}^{drop} = \alpha + \beta_1 \mathcal{I}_{ijt}^{young} + \beta_2 \mathcal{I}_{ijt}^{young} \times \mathcal{I}_t^r + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt} \,. \tag{4.15}$$

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

Products Dropping in Recessions for Young Firms and match quality

Furthermore, we investigate what quality of products that young firms drop in recession. To do this, we further interact the previous regression (4.15) with the quality measure and run the following regression:

$$\begin{aligned} \mathcal{I}_{pijt}^{drop} = \alpha &+ \beta_1 q_{pi}^{inv} + \beta_2 \mathcal{I}_{ijt}^{young} + \beta_3 q_{pi}^{inv} \times \mathcal{I}_t^r + \beta_4 q_{pi}^{inv} \times \mathcal{I}_{ijt}^{young} + \beta_5 \mathcal{I}_t^r \times \mathcal{I}_{ijt}^{young} \\ &+ \beta_6 q_{pi}^{inv} \times \mathcal{I}_t^r \times \mathcal{I}_{ijt}^{young} + X_{pijt}\gamma_1 + X_{ijt}\gamma_2 + X_{jt}\gamma_3 + \delta_p + \delta_i + \delta_t + \varepsilon_{pijt}, \end{aligned} \tag{4.16}$$

In particular, we shed light on the following four coefficients associated with young firms: the coefficient β_2 presents how young firms drop good-quality products (with the inverse quality measure being zero), β_4 indicates how young firms drop low-quality products in normal times, and β_5 and β_6 show how the pattern of dropping good-quality (with the inverse quality measure being zero) and low-quality products becomes for young firms, respectively, in the recession periods.

The third column of Table 7 shows the result. This shows that young firms are less likely drop low-quality products in normal times as we find $\beta_2 > 0$ and $\beta_4 < 0$. Furthermore, as $\beta_5 > 0$ and $\beta_6 < 0$ indicate, such pattern gets more pronounced in recessions. In other words, young firms are much more less likely to drop products having poor match quality with them in recessions. These results stay robust across different sets of firm controls as before, which can be found from Table A13 in Appendix.

The result is consistent with our intuition as young firms might not have enough information to infer product match quality properly at the earlier stage. Furthermore, such nature would be more pronounced in recession periods when noise is higher. Also, in recessions, younger firms may still want to keep those products not having the best fit even after they realize it as they tend to lack a diversified set of product portfolio to focus on by optimally dropping low-quality products. We are in the process of testing such hypotheses that can provide potential explanation on these results.

5 Robustness Tests

In this section, we conduct several robustness tests. First, the current main sample consists of firms having quality estimates from the regression (estimation1) which is a subset of the whole product-firm pairs in the CMF. As robustness check, we use the whole product-firm level sample in data and rerun the product-firm level regressions not using the quality measures, such as for the regressions (4.5), (4.13), and (4.15). The following two subsections 5.1 and 5.2 discuss these more in detail.

Second, we further investigate different measures of product drop and add in the regressions on product quality ladder (such as 4.7, 4.8, 4.9, and 4.10). The baseline measure we use is simply a dummy variable indicating whether firms drop or add any products in a given period. On top of that, we can further explore more quantitative measures such as the total number of products added or dropped or the share of those products out of firms' product portfolio. This would further allow us to experiment whether the current results depend on how many products (or how much fraction of total products) firms drop or add and vary across them. The last subsection 5.3 provides further details about it.

5.1 Product Dropping: using the full sample

We rerun the regression (4.5) showing how young firms drop products in general with the full sample in the CMF. Table A14 in Appendix contains the results being robust. As before, each column of the table includes a different set of firm controls. Across all cases, this consistently presents that younger firms are less likely to drop their products.

5.2 Product Dropping in Recessions: using the full sample

In a similar fashion, we rerun the other two regressions (4.13) and (4.15) with the full sample. Table A15 in 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 in recessions. In addition, Table A16 shows similar results about the pattern of young firms to drop their products in normal period, but the significance gets muted for recessions.

5.3 Firm-Level Evidence for Quality Ladder

We revisit the four regressions (4.7), (4.8), (4.9), and (4.10), which are related to product quality ladder, and use alternative measures discussed before for products dropped and added.

Table A17 in Appendix shows the results for the regression (4.7) by including the following alternative measures for product drop: log number and the share of products dropped. This shows that across all specifications, their exists a positive association between firm-level activities of dropping and adding products. In particular, the last two columns of the table indicates 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 to add 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 holds. These are all noteworthy results supporting the original finding.

In addition, Table A18 replicates the regression (4.8) with the number and share of dropped products included. The baseline result remains robust here as well, where we find the lower the quality of dropped products, the more firms likely to add products, even after controlling for the number of share of dropped products. Here again, we can further find the positive relationship between the number and share of products dropped and the tendency of firms to add products.

Furthermore, Table A19 investigates the previous result in (4.9) about the quality of added products after including the number and share of dropped products. Again, the results stay robust even after having them included. It is also noteworthy from this table that the number and share of dropped products enhance the quality of new products added. Thus, the amount of dropped products increases not just the likelihood of firms adding a new product but also the quality of the new product.

Lastly, we rerun the regression (4.10) with the same sets of variables included. Table A20 contains the results showing that the main results stay intact even after having 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 quality of products newly added.

6 Concluding Remarks

This paper analyzes 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. The paper uses a comprehensive administrative dataset that tracks the U.S. manufacturing output at the product-firm level and identifies how firms add or drop products in general, how the 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 build a product-quality ladder over the firm life-cycle. We demonstrate that firms tend to drop products with poor match quality, but this pattern is more muted for young firms. Interestingly, young firms are more likely to stick to products having low match quality than those with high match quality. We also find that firms' product dropping can enhance subsequent product adding in terms of both frequency and quality. This provides the evidence of product-firm match quality ladder. Furthermore, we show that adding products with good match quality or dropping products with bad match quality can promote firm growth.

We additionally extend the analyses to a business cycle context, and further document that firms have more tendency to drop products but those with "less" low quality in economic downturns. We also find that such cyclical patterns get mainly driven by young firms, as the pattern of dropping less products with poor quality in recessions gets 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 by lacking the ability to drop products with bad match quality at the initial stage. Moreover, such barriers for young firms to find a right product match can be more amplified in recessions, which can be a source to account for the well-known procyclicality of young firm activities.

Though our findings provide salient features of product switching patterns over the firm life-cycle as well as the business cycle, we are still yet silent on identifying a solid underlying mechanism. Potentially, there are several mechanisms that can account for the current findings with special focus on the product switching behavior of young firms. One potential interpretation would be through the nascency of young firms and their lack of information about product markets. Unlike mature firms, young firms might find it harder to evaluate product match quality.

Another explanation could be driven by search costs and network effects. Even though young firms can identify product match quality well, they still cannot drop those poor matches right away if they are faced with a higher search cost of finding a better product with limited network connection to the market.[14] Investigating potential mechanisms with an extended set of empirical analyses along with a structural framework is in progress.

[14]We also had an additional alternative hypothesis which could be made through young firms' limited set of product portfolio and less ability to diversify. Young firms might want to avoid dropping a product even though the product is not the first-best just to insure themselves. However, our results hold even after controlling for the number of products, which weakens this hypothesis.

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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

	$q_{t:t+5}^{add}$	$q_{t:t+5}^{add}$	$q_{t:t+5}^{add}$
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:

$$y_{pijt} = \theta_{pi} + \beta_2 PT_{pijt} + \delta_{pt} + \delta_{it} + \varepsilon_{pijt}, \tag{C.17}$$

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.17) could be one alternative of the baseline quality estimation in (4.1).

However, (C.17) 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 (4.1). The following specification shows this idea:

$$y_{pijt} = \theta_{pi} + \beta_2 PT_{pijt} + \beta_3 X_{pt} + X_{ijt}\gamma_1 + X_{jt}\gamma_2 + \delta_{pt} + \varepsilon_{pijt}, \tag{C.18}$$

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.