The Adoption and Termination of Suppliers over the Business Cycle*

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Abstract

We assemble a novel firm-level dataset to study the adoption and termination of suppliers over the business cycle. We show that the aggregate number and rate of adoption of suppliers are procyclical. The rate of termination is acyclical at the aggregate level, and it encompasses large differences in the cyclicality of termination across producers. The costs of managing, adopting, and terminating suppliers are significant for producers. With this new evidence, we develop a model with optimizing producers that incur separate costs for the management, adoption, and termination of suppliers. These costs alter the incentives to scale up production and to replace existing with new suppliers. Both forces are critical to replicate the observed cyclicality in the adoption and termination of suppliers at the producer and aggregate levels. Management and adjustment costs amplify the response of aggregate output to a negative TFP shock by 17%.

Keywords: Management and adjustment costs, adoption and termination of suppliers, business cycle fluctuations.
JEL classifications: E32, L14, L24.

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1 Introduction

In modern economies, the production of final output requires inputs from multiple suppliers, and the adoption, termination, and management of suppliers are important choices for the production of final goods. Despite abundant work dedicated to the adoption and termination of suppliers in models of international trade and in operation management textbooks, little is known about the cyclical regularities of these margins of adjustment at the producer level or their effects on the broader aggregate economy.[1] Several fundamental questions remain unanswered: What are the patterns of adoption and termination of suppliers at the producer level, and how are those linked with the business cycle? Are the adoption and termination of suppliers similar across different producers? What critical forces explain the empirical regularities?

We study these questions, combining different datasets and providing novel facts on the adoption and termination of suppliers at the producer and aggregate levels. Based on our new evidence, we develop a model of optimizing producers that manufacture output using both new and existing suppliers. The model shows the central role of the costs of managing and adjusting suppliers to account for the empirical patterns and the amplification of aggregate total factor productivity (TFP) shocks.

Our new evidence on the adoption and termination of suppliers is obtained via merging two datasets: the FactSet Revere Supply Chain Relationships data —which records producer-supplier relations, including adoption and termination of suppliers— and CompuStat Fundamentals —which provides information on the output, the financial positions, and the administrative costs of producers. Our integrated data offer a comprehensive overview of producer-supplier relationships for U.S. producers between 2003 and 2020. Using this merged dataset, we establish five novel facts.

Facts 1 and 2 link sales and profits of producers to the adoption and termination of suppliers. Fact 1 establishes that sales and profits of producers increase with the number of suppliers, evincing *positive returns from more suppliers*. Fact 2 shows *positive returns from establishing new relationships*, compared to relationships that have been developed with existing suppliers, evinced by the decrease in sales and profits for a producer with the average age of the producer's supply-chain relationships.

Facts 3 and 4 study the dynamics of adoption and termination at the *aggregate* level over the business cycle. Fact 3 establishes that the *aggregate* number of suppliers is procyclical: it increases

[1] See Feenstra (2015), Heizer et al. (2016), and Stevenson (2018).

during economic expansions and declines during contractions. Fact 4 decomposes the changes in the aggregate number of suppliers into changes in the adoption and the termination of suppliers. It establishes that the *aggregate* rate of adoption is procyclical and that the *aggregate* rate of termination is acyclical. We show that the acyclical aggregate rate of termination conceals large heterogeneity in the cyclicality of the termination rate across producers having different numbers of suppliers and productivity levels. The termination rate is countercyclical for producers with many suppliers and high productivity but procyclical for producers with few suppliers and low productivity. The aggregate acyclicality in the rate of termination of suppliers results from countervailing behavior of the termination rate across different producers.

Fact 5 documents the prevalence of the distinct costs of managing and adjusting suppliers. Management costs refer to resources the producer expends to oversee the stock of existing suppliers; they are related to the *diminishing returns to management* within firms, as noted in the seminal paper by Coase (1991) on the nature of firms. Adjustment costs refer to costs the producers incur for the adoption and termination of suppliers, including those of searching for and switching suppliers (Farrell and Klemperer, 2007).[2] Using Compustat data, we find that administrative costs account for approximately 20% of net sales of listed companies. Moreover, they are positively correlated with the total number and the adjustments of suppliers, evincing the importance of both management and adjustment costs. Although Compustat does not report the management costs and adjustment costs separately, case studies indicate that they are sizable. For example, Van Deventer (2016) shows that the costs for switching IT vendors, which is part of adjustment costs, can be as high as 15% of the producer's market value. Thus, the empirical evidence clearly supports the relevance of management and adjustment costs.

To account for Facts 1-4, we develop a model with producers that use a continuum of intermediate inputs supplied by two vintages of suppliers, i.e., existing and new suppliers. The producers have different idiosyncratic productivities, and they incur separate costs for the management, adoption, and termination of suppliers (motivated by Fact 5).

These foregoing separate costs have different implications for changes in adoption and termination of suppliers. *Management costs* constrain the scale of operation by decreasing the adoption of new suppliers and increasing the termination of existing suppliers. *Adjustment costs* discourage both adoption of new suppliers and termination of existing suppliers, which influence the vintage composition of suppliers. Accordingly, the two separate costs lead to two

[2]Appendix D reviews the theory and empirical evidence on the switching cost and categorizes its various dimensions into adoption and termination costs.

distinct effects of the aggregate TFP on the adoption and termination of suppliers. One is a *scaling effect*: the higher TFP decreases the relevance of management costs for the profits of the producer, leading to an optimal increase in the measure of suppliers for the production of the final goods. This effect fosters a rise in the adoption and a decline in the termination of suppliers. The second is a *switching effect*: the higher TFP reduces the relevance of adjustment costs for the producer's profits, engendering a greater turnover of suppliers. The denouement is a rise in both the rates of adoption and termination of suppliers.

Scaling and switching effects jointly generate the positive correlation between the total measure of suppliers and the adoption of new suppliers with aggregate TFP; this finding is consistent with Facts 3 and 4. However, the two forces have countervailing effects on the correlation between the rate of termination and TFP: with higher TFP, the switching effect involves an increase in the termination of suppliers and enables producers to renew the vintages of suppliers; the scaling effect, though, decreases the termination of suppliers to enable producers to scale up production.

The model reveals that the producers' different idiosyncratic productivity levels are critical to the heterogeneous responses of the rate of termination across producers to aggregate TFP shocks, as well as to the overall acyclical response in the aggregate rate of termination. For an individual producer, its idiosyncratic productivity and the associated measure of suppliers are central to the relevance of adjustment costs for the adjustment in suppliers. The producer with high idiosyncratic productivity and a large measure of suppliers experiences low adjustment costs relative to its profit. This generates limited benefits from replacing existing with new suppliers when TFP increases (i.e., the scaling effect dominates). The producer with low idiosyncratic productivity and a small measure of suppliers, however, faces high adjustment costs relative to its profit, generating large benefits from replacing existing with new suppliers when TFP increases (i.e., the switching effect dominates). Thus, consistent with our Fact 4, producers with a large (vs. small) measure of suppliers display a negative (vs. positive) response in the rate of termination to changes in aggregate TFP, driven by the dominating scaling (vs. switching) effect. We show that the heterogeneity in the cyclicality of termination critically depends on nontrivial management and adjustment costs. This result vanishes when setting either the management or the adjustment costs close to zero.

At the aggregate level, the cyclicality of the *aggregate* rate of termination depends on the distribution of the idiosyncratic productivity of producers and the size of management and adjustment costs that determine the relative strength of scaling and switching effects. We calibrate the model to the U.S. data and show that it replicates the heterogeneous cyclicality in the termination rate across producers and the acyclical aggregate rate of termination, consistent with our Fact 4. Importantly, our calibration does not use the cyclicality of the observed aggregate rate of termination as a target.

The management and adjustment costs, and the resulting scaling and switching effects, are critical to replicate our empirical findings. Specifically, we show that the two costs jointly amplify the impacts of aggregate TFP shocks on the aggregate output. In response to a negative shock to the aggregate TFP, the scaling effect decreases the scale of production. Furthermore, simultaneously, the switching effect reduces the replacement of existing suppliers with new ones, hence foregoing the termination of existing suppliers having low idiosyncratic productivity. Both effects jointly augment the decline in output that the initial fall in aggregate TFP induced. In our simulation, we find that the management and adjustment costs jointly magnify the fall in aggregate output by 17% relative to a model without these costs.

Our analysis is related to several areas of research. It is linked to the literature on endogenous changes in producer-supplier relations over the business cycle. Previous work primarily focuses on the network structure of producer-supplier relations (Atalay, 2017; Grassi, 2017; Huneeus, 2018) and the cyclical rate of relationship creation (Fernández-Villaverde et al., 2019, 2021). Instead, we document new evidence on the vintage structure of producer-supplier relations and the acyclical rate of relationship separation (i.e., termination of suppliers) and reveal their role as an important amplification mechanism for business cycle fluctuations.

Our study also connects to the literature on the cyclical fluctuations of intermediate input varieties (Gopinath and Neiman, 2014; Jones, 2011), and more generally, consumption goods varieties (Bilbiie et al., 2012; Chugh et al., 2020; Huo and Ríos-Rull, 2016, 2020; Jaimovich and Floetotto, 2008; Lewis and Poilly, 2012). Our work closely accords with Gopinath and Neiman (2014), who show that the variation in the number of imported goods and the incidence of management costs were central to the amplification of negative shocks during the economic crisis in Argentina in 2001-2002. Our research further reveals that both the management and adjustment costs are critical in accounting for the observed empirical regularities, and they jointly amplify the effect of aggregate TFP shocks.

Finally, we contribute to the literature that documents the cyclical reallocation of productive factors such as labor (Caballero and Hammour, 1994; Canova et al., 2013; Davis and Haltiwanger, 1992; Ferraro and Fiori, 2023; Ilut et al., 2018) and capital (Lanteri et al., 2023; Lanteri and Rampini, 2023). While Caballero and Hammour (1994) document a countercyclical destruction of jobs (i.e., "the cleansing effect"), we document that the cleansing effect is absent for the termination of suppliers, which is acyclical at the aggregate level in the data. Similar to Ilut et al. (2018), we show that the cross-sectional cyclical responses to TFP shocks at the firm level amplify the impact of negative aggregate shocks.

The remainder of the paper is structured as follows. Section 2 outlines the construction of the data and defines the empirical variables. Section 3 describes the empirical results. Section 4 develops a simple model to study the empirical evidence. Section 5 presents the analytical results of the model. Section 6 discusses the quantitative results and compares them to the data. Section 7 concludes.

2 Data and variables

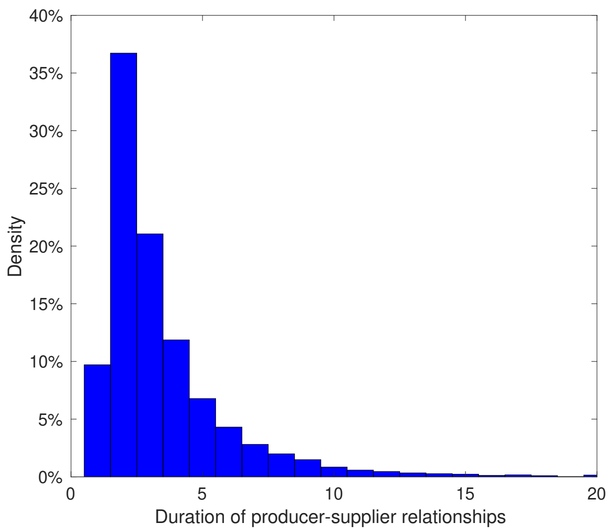
We use the FactSet Revere Supply Chain Relationships data that records producer-supplier relations from several sources, including SEC 10-K annual filings, investor presentations, and press releases that producers and supplier firms report.[3] The data comprises a record of 784,325 producer-supplier relationships that include the beginning and end years of relationships for 152,119 producers and 95,932 suppliers collected between 2003 and 2021. We merge the FactSet Revere Relationships dataset with CompuStat Fundamentals to include income statements, balance sheets, and cash flows for each producer in the sample so that our dataset comprises financial variables (i.e., sales, profits, and administrative costs) for the producers. Appendixes A and B describe the FactSet and Compustat datasets, the merging procedure, and the derivation of the variables used in the analysis. Our final panel data constitutes 3,609 producers with 28,461 producer-year observations, covering 78,193 producer-supplier relationships.

With the above data, we first define our main variables of interest and provide an overview of the main statistics for the producer-supplier relations. Shown in Panel (a) in Figure 1 is the histogram of the duration of each producer-supplier relationship. The mean and the median durations are 3.44 and 3 years, respectively.

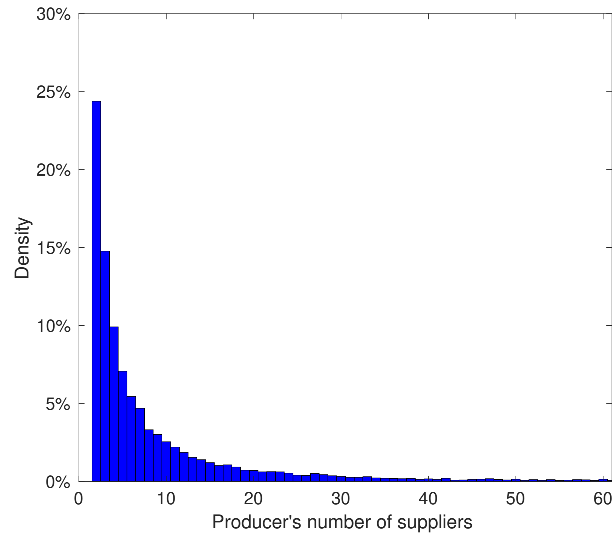
We denote by variable $v_{i,t}$ the number of suppliers that are in partnerships with the producer i in year t. Displayed in Panel (b) in Figure 1 is the histogram for the number of suppliers that

[3]The FactSet Revere Supply Chain Relationships data is more comprehensive than Compustat Customer Segment data; the latter fails to report data for producers contributing under 10% to the revenues of suppliers. Compustat Customer Segments are limited to producer-supplier relationships of publicly traded firms that fulfill the Financial Accounting Standards No. 131. With these limitations, the sample size of the relationships in Compustat Customer Segment is 3.4% of that based on the FactSet Revere Relationships data.

Figure 1: Distributions of producer-supplier relationship durations and the number of suppliers



(a) Distribution of duration of relationships



(b) Distribution of the number of suppliers

Notes: Panels (a) and (b) show the distribution of the duration of producer-supplier relationships and the distribution of the producer's number of suppliers, respectively. The height of each bar equals the percentage of samples within the bin in all samples.

each producer employs, revealing that the mean and the median numbers of suppliers for each producer are equal to 12.2 and 5, respectively. The right skewness of the distribution evinces that a non-trivial fraction of producers employ a large number of suppliers, averaging around 12, despite the majority of producers using five suppliers on average.

Our central interest is measuring the rates of adoption and termination of suppliers. We define the *rate of adoption* of each producer i in period t as $s_{i,N,t} \equiv v_{i,N,t}/v_{i,t-1}$, where $v_{i,N,t}$ is the number of new suppliers that producer i adopted in year t (the subscript N refers to new suppliers). Similarly, we define the *rate of termination* for each producer i in year t as $s_{i,T,t} \equiv v_{i,T,t}/v_{i,t-1}$, where $v_{i,T,t}$ is the number of existing suppliers that producer i terminated in year t (the subscript T refers to the termination of suppliers). Table 1 shows the summary statistics. The rate of termination is on average smaller, and less volatile than the rate of adoption, with means of 0.144 vs. 0.287 and standard deviations of 0.203 vs. 0.449.

To study the economy-wide changes in the total number and turnover of suppliers, we weight the growth rate of the number of suppliers ($\Delta v_{i,t}/v_{i,t-1}$), the adoption rate ($s_{i,N,t}$), and the termination rate ($s_{i,T,t}$) of each producer by their intermediate-input expenditure to construct the indexes $\Delta v_t/v_{t-1}$, $s_{N,t}$, and $s_{T,t}$. These indexes track the growth rate of the aggregate number of suppliers, the aggregate rate of adoption, and the aggregate rate of termination in the economy,

Table 1: Summary statistics of the rates of adoption and termination

VARIABLES	Mean	Standard deviation	Median	Min	Max
Rate of adoption ($s_{i,N,t}$)	0.287	0.449	0.053	0	2
Rate of termination ($s_{i,T,t}$)	0.144	0.203	0	0	0.75

Notes: Rate of adoption ($s_{i,N,t}$) and Rate of termination ($s_{i,T,t}$) are the numbers of new and existing suppliers adopted and terminated by the producer i in year t divided by its total number of suppliers in year $t-1$, respectively. The top and bottom 2.5% of the samples for each rate are winsorized.

respectively.[4] The aggregate adoption rate across producers is twice as large as the aggregate termination rate. Specifically, the mean value for the aggregate adoption rate is 0.28, but the same statistics for the aggregate termination rate equals 0.17 over the sample period. Shown in Figure 3 in the next section are the aggregate series for the total number of suppliers and the rates of adoption and termination of suppliers.

3 Empirical results on adoption and termination of suppliers

In this section, we establish five novel facts on producer-supplier relations. Facts 1 and 2 link the sales and profits of producers to the adoption and termination of suppliers. Facts 3 and 4 focus on the central theme of our study: the association between the rates of adoption and termination and business cycle fluctuations. Fact 5 shows that producers incur significant and separate costs for managing and adjusting suppliers.

Fact 1: Positive returns from more suppliers

We study the relationship between market returns and the total number of suppliers using the following regression:

$$y_{i,t} = \beta \ln(v_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t},$$

where $y_{i,t} \in \{\ln(q_{i,t}),\ \ln(\pi_{i,t})\}$ and $q_{i,t}$ and $\pi_{i,t}$ are the real sales and the real "earnings before interest, taxes, depreciation, and amortization" (EBITDA) for producer i, respectively. α_i and γ_t are producer and year fixed effects.

As shown in column (a) of Table 2, the real sales of the producer is positively correlated with the number of suppliers, and a 1% increase in the number of suppliers is associated with

[4] We use the costs of goods sold by the producer to compute the share of its intermediate input expenditure in the aggregate intermediate input expenditure. Appendix B describes the derivation of the variables.

Table 2: Number of suppliers is positively correlated with sales and profits

	(a)	(b)
VARIABLES	*Sales*	*Profits*
Number of suppliers	0.093***	0.041***
	(0.014)	(0.015)
Observations	22,994	20,110
Number of producers	2,751	2,493
Producer fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	0.214	0.078

Notes: Sales, Profits, and Number of suppliers are the log of the producer's real sales, real earnings before interest, taxes, depreciation, and amortization (EBITDA), and its total number of suppliers, respectively. Data are annual and at the producer level. We restrict our sample to producers whose maximum numbers of suppliers over time exceed one. Producer and year fixed effects are controlled. Standard errors are clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

approximately a 0.1% increase in the real sales of the producer. Shown in column (b) are findings for the same regression for the profits of the producer. A 1% increase in the number of suppliers is associated with about a 0.04% rise in the real profits of the producer, consistent with the result in column (a). These findings concerning the positive returns of the producer from having more suppliers corroborate the central tenet of the "returns from more varieties" in models of product varieties (see Bilbiie et al., 2012; Ethier, 1982; Feenstra et al., 1999; Goldberg et al., 2010; Gopinath and Neiman, 2014; Halpern et al., 2015; Hamano and Zanetti, 2017, 2022).[5]

Fact 2: Positive returns from *new* relationships

We now show that new producer-supplier relationships are associated with higher sales and profits than existing relationships. We refer to this result as the *returns from new relationships*. We examine the issue by estimating the following regressions:

$$y_{i,t} = \eta_1 \ln(v_{i,t}) + \beta_1 \ln(age^{rel}_{i,t}) + \kappa_1 \ln(age^{pro}_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t},$$

where $y_{i,t} \in \{\ln(q_{i,t}),\ \ln(\pi_{i,t})\}$ and $q_{i,t}$ and $\pi_{i,t}$ are producer's real sales and profits, respectively, and $v_{i,t}$ is the number of suppliers. The variable $age^{rel}_{i,t}$ represents the average age of relationships for each producer i in year t, which is the central focus of the regression. We control for the

[5]The return from more suppliers is also important in models with producer-supplier relationships to generate amplification of TFP shocks. Xu (2021) documents a positive relationship between the number of suppliers and the TFP of the producer.

producer's age, $age^{pro}_{i,t}$, which positively affects profits due to selection and is positively correlated with the age of the relationship.[6]

Table 3: Sales, profits and the average age of relationships

	(a)	(b)	(c)	(d)
VARIABLES	Sales	Profits	Sales	Profits
Number of suppliers	0.085***	0.027	0.082***	0.028
	(0.016)	(0.018)	(0.016)	(0.018)
Relationship age	-0.048**	-0.069**		
	(0.024)	(0.028)		
Rate of adoption			0.091***	0.084***
			(0.021)	(0.029)
Producer age	0.401***	0.174	0.363***	0.122
	(0.105)	(0.135)	(0.104)	(0.135)
Observations	18,227	16,077	18,227	16,077
Number of producers	2,607	2,364	2,607	2,364
Producer fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.250	0.0802	0.261	0.090

Notes: Data are annual. Sales, Profits, and Number of suppliers are the log of the producer's real sales, real earnings before interest, taxes, depreciation, and amortization (EBITDA), and its total number of suppliers, respectively. Relationship age is the log of the average age of producer i's producer-supplier relationships in year t. Producer age is the log age of producer i in year t since the establishment of the producer. Rate of adoption ($s_{i,N,t}$) is the number of new suppliers that producer i adopted in year t divided by its total number of suppliers in year $t-1$. Producer and year fixed effects are controlled. We restrict our sample to producers whose maximum numbers of suppliers exceed one over time and the adoption rate is below one. Standard errors are clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Shown in Table 3 are the estimation results. The average age of the relationships has a negative effect on profits, evincing that relationships formed with new suppliers induce larger sales and profits. Conditional on the number of suppliers and the age of the producer, a 1% increase in the average age of the relationships is associated with a 0.048% and a 0.069% decline in the producer's sales and profits, respectively. Consistent with the conventional finding of a positive correlation between the age and the performance of producers (Coad et al., 2013; Haltiwanger et al., 1999), the age of the producer is also positively correlated with the sales in our sample.

[6] The age of a relationship in year t is defined as the difference between year t and the year when this relationship was first formed, and the age of a producer i is defined as the difference between year t and the year of establishment of this producer.

Our result of the negative correlation between the average age of the producer-supplier relationships and sales provides the basis for the positive co-movement of new adoptions with sales and profits. We formally test the significance of this co-movement using the following regression:

$$y_{i,t} = \eta_2 \ln(v_{i,t}) + \beta_2 s_{i,N,t} + \kappa_1 \ln(age^{pro}_{i,t}) + \alpha_i + \gamma_t + \nu_{i,t},$$

where $y_{i,t} \in \{\ln(q_{i,t}),\ \ln(\pi_{i,t})\}$ and $q_{i,t}$ and $\pi_{i,t}$ are the real sales and profits of producer i, respectively, and $s_{i,N,t}$ is the adoption rate of the producer i. As shown in columns (c) and (d) of Table 3, sales and profits significantly increase with the producer's rate of adoption. Conditional on the number of suppliers, a 1% rise in the adoption rate is associated with an increase in the sales and profits of producers by 0.091% and 0.084%, respectively. Thus, these results suggest a positive correlation between profits and sales and the adoption of new suppliers.

Fact 3: Procyclical total number of suppliers

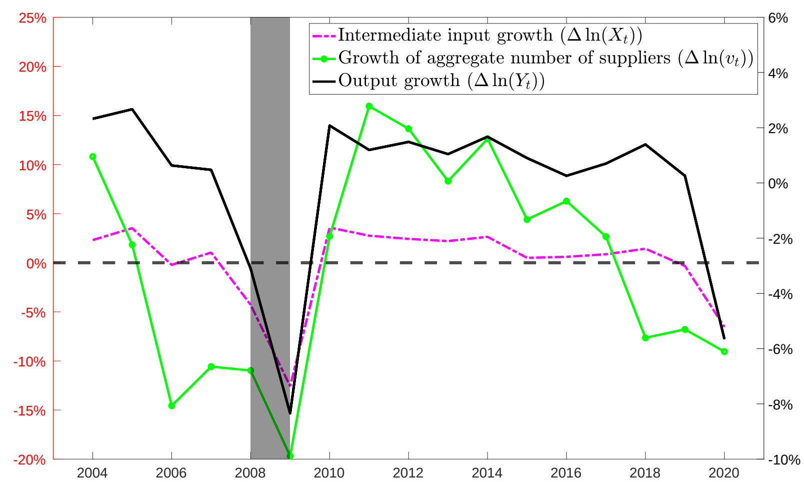


Figure 2: Procyclical number of suppliers

Notes: The figure shows the growth rates of the aggregate real intermediate inputs (i.e., the dash-dotted magenta line), the aggregate number of suppliers (i.e., the solid green line with circles), and real output (i.e., the solid black line). The aggregate index of the number of suppliers is the weighted average of the number of suppliers across all producers, with the costs of goods sold by each producer as the weight. The growth rates of the aggregate real intermediate inputs and the real output are the growth rates of the BEA chain-type quantity indices of intermediate inputs and gross output of private industries, respectively. All aggregate indices are demeaned. Shaded areas indicate NBER-defined recession years. We restrict our sample to producers whose maximum numbers of suppliers over time exceed one.

Shown in Figure 2 are the growth rates of the aggregate number of suppliers (i.e., $\Delta \ln v_t$, the solid green line with circles), the aggregate real intermediate inputs (i.e., $\Delta \ln X_t$, the dash-dotted magenta line), and the real gross output (i.e., $\Delta \ln Y_t$, the solid black line), respectively, for the period 2004-2020.[7] All variables strongly co-moved with production and sharply declined around the Great Recession of 2009, but rebounded back quickly in 2010, when the U.S. economy began recovering. Similarly, the variables dropped considerably in 2020 at the outset of the Covid-19 recession. The correlations of real output growth with the aggregate number of suppliers and the aggregate real intermediate inputs equal 0.65 and 0.98, respectively. These co-movements manifest strong synchronization between the aggregate number of suppliers, the aggregate use of intermediate inputs, and the aggregate output. While we are the first study to document these co-movements in the U.S. economy, our findings are consistent with the results in Gopinath and Neiman (2014). They document a strong procyclicality in the imported intermediate input varieties in Argentina, thus showing a similarly sharp contraction in the number of imported intermediate input varieties during the recession of 2001-2002.

Fact 4: Procyclical adoption and acyclical termination of suppliers

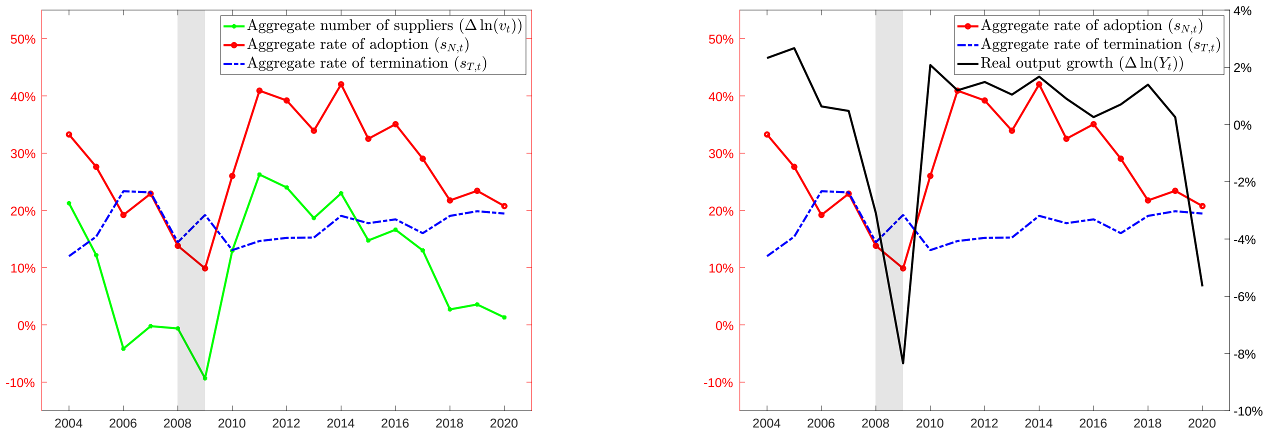
We now focus on aggregate adoption and termination rates that jointly determine the aggregate number of suppliers. Panel (a) in Figure 3 decomposes the growth rate of the aggregate index of the number of suppliers (i.e., Δv_t, the solid green line with circles) into the following metrics: (i) the aggregate rate of adoption (i.e., $s_{N,t}$, the solid red line with circles), and (ii) the aggregate rate of termination (i.e., $s_{T,t}$, the dash-dotted blue line) of suppliers, according to $\Delta v_t = s_{N,t} - s_{T,t}$.[8] The strong co-movement between the changes in the aggregate number of suppliers (Δv_t) and the aggregate rate of adoption ($s_{N,t}$) shows that fluctuations in the aggregate number of suppliers are primarily driven by the large fluctuations in the aggregate adoption rate while the aggregate termination rate ($s_{T,t}$) remains substantially unchanged over the sample period.[9] The changes in the aggregate adoption rate are large and procyclical: the aggregate rate of adoption ranges from

[7] We measure aggregate real intermediate inputs and output, X_t and Y_t, with the U.S. Bureau of Economic Analysis (BEA) chain-type quantity indices of intermediate inputs and gross output that cover the universe of the U.S. private firms, respectively.

[8] By definition, the aggregate rates of adoption and termination are positive, as they represent the rates of the numbers of suppliers adopted and terminated, respectively. By construction, the growth rate of the aggregate index of the number of suppliers is the positive aggregate rate of adoption net of the positive aggregate rate of termination.

[9] The movement in the total number, the adoption, and the termination of suppliers may be related to the associated creation and destruction of products. However, we do not have sufficiently detailed data on the list of products for the producers, and there are no data linking products to the required input suppliers by them. Therefore, we are unable to study whether the adoption and termination of suppliers are systematically linked to the creation (destruction) of new (existing) products, or whether they reflect the improvement in the production efficiency or the quality of existing products.

Figure 3: Procyclical adoption and acyclical termination of suppliers



(a) Decompose growth of number of suppliers (b) Aggregate adoption and termination

Notes: Aggregate number of suppliers is the growth rate of the aggregate index of the number of suppliers ($\Delta \ln(v_t)$). Aggregate rate of adoption ($s_{N,t}$) and Aggregate rate of termination ($s_{T,t}$) are the weighted averages of $s_{i,N,t}$ and $s_{i,T,t}$ across all producers, respectively, with the costs of goods sold of each producer as the weight. Real output growth is the demeaned growth rate of the BEA chain-type quantity index for the gross output of private industries. Shaded areas indicate NBER-defined recession years. We restrict our sample to producers whose maximum numbers of suppliers over time exceed one.

10% in 2009 to 42% in 2014. In general, the aggregate adoption rate is higher than the aggregate termination rate, generating an upward trend in the aggregate number of suppliers.[10]

To study the co-movements between the aggregate rates of adoption and termination and the aggregate economic activity, Panel (b) in Figure 3 shows the aggregate rates of adoption (i.e., the solid red line with circles) and termination (i.e., the dash-dotted blue line) together with the growth rate of real output (i.e., the solid black line). The aggregate rate of adoption closely comoves with the growth rate of real output and is highly procyclical, and the two series have a pair-wise correlation of 0.67. In contrast, the aggregate rate of termination is substantially acyclical, with a pair-wise correlation with the growth rate of output of 0.27.

We examine the separate contributions of the aggregate adoption and termination rates to the changes in the aggregate number of suppliers using the following variance decomposition:[11]

$$\frac{Cov\left(\Delta \ln(v_t), s_{N,t}\right)}{Var\left(\Delta \ln(v_t)\right)} + \frac{Cov\left(\Delta \ln(v_t), -s_{T,t}\right)}{Var\left(\Delta \ln(v_t)\right)} = 1. \tag{1}$$

[10] The upward trend in the aggregate number of suppliers is consistent with the increasingly denser Input-Output networks (Acemoglu and Azar, 2020; Ghassibe, 2021).

[11] Appendix B describes the derivation of equation (1).

Doing so establishes that the contribution of the aggregate adoption rate to total changes in the number of suppliers (first term in the equation) equals 82%, while the contribution of the aggregate termination rate equals 18%. Together with the results shown in Panel (a) in Figure 3, the analysis consistently reveals that the aggregate adoption rate is the main driver of fluctuations in the aggregate number of suppliers, while the aggregate termination rate plays a subsidiary role.

In sum, our results show that the processes of adoption and termination of suppliers are notably different from the creation and destruction of jobs in the labor market, as discussed in the seminal studies by Blanchard et al. (1990) and Caballero and Hammour (1994). Although the labor market features the cleansing effect of recessions that leads to a countercyclical job destruction that cleanses the labor market from low-productivity jobs in recessions, the destruction margin remains inactive in producer-supplier relationships.

Heterogeneous cyclicality in the termination rate among producers. The first part of Fact 4 established that procyclicality in the adoption of new suppliers at the aggregate level uniquely drives the procyclicality in the aggregate number of suppliers. This is because the aggregate termination of suppliers is substantially insensitive to business cycle conditions.

In this second part of Fact 4, we link this acyclicality of the aggregate termination to the different cyclicality in the termination rate across producers with the different numbers of suppliers. Shown in Figure 4 is the bin scatter plot of the logarithm of the number of suppliers (x-axis) against the correlation between the termination rate and (log) real sales (y-axis) for the producers in our sample. The latter displays large heterogeneity across producers with different numbers of suppliers. The correlation between termination and sales is positive for producers with a small number of suppliers. In particular, they terminate extant suppliers during economic expansions but retain them during economic downturns. In contrast, the correlation is negative for producers with a large number of suppliers. Specifically, they retain existing suppliers during economic expansions but terminate them during economic downturns.

As shown in Figure 4, the shares of producers displaying positive and negative correlations of the termination rate with sales are both large, which balance out on average. The average correlation between the rate of termination and sales is approximately equal to zero, consistent with the acyclical rate of termination at the aggregate level (documented in the first part of Fact 4).

Table 6 in Appendix C uses panel regressions to investigate the heterogeneous responses

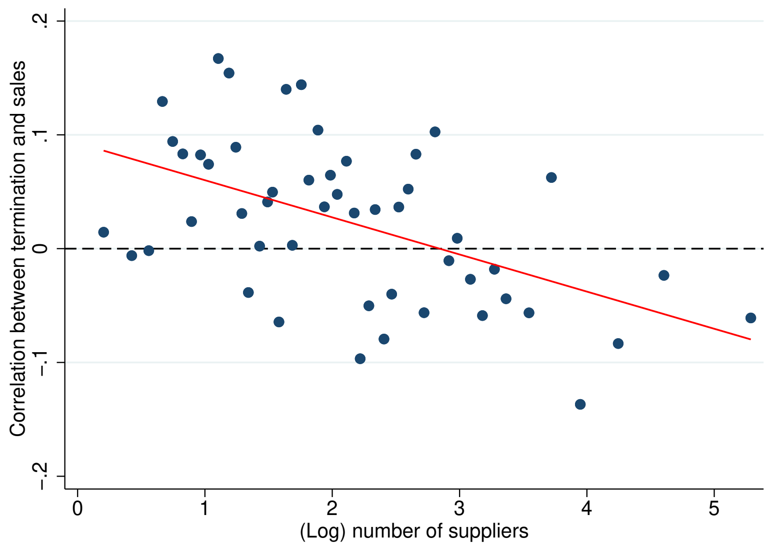


Figure 4: Termination rate vis-a'-vis sales for producers with different numbers of suppliers

Notes: The bin scatter plot shows the (log) number of suppliers (x-axis) against the correlation between the termination rate and the (log) real sales (y-axis) for the producers in our sample. Producers are divided into 50 bins according to their (log) number of suppliers. For the y-axis, we first compute the correlation between the rate of termination and (log) real sales over years for each producer, then average this correlation across producers within the same bin. Similarly, for the x-axis, we first compute the average number of suppliers over years for each producer, then average it across producers within the same bin. The solid red line is a linear fit of the correlation (between the termination rate and the log sales) on the (log) number of suppliers. Our sample excludes producers with no more than ten observation years for both the termination rate and the log sales for the calculation of their correlation.

of the rate of termination to sales across different producers. The results are consistent with Figure 4. That is, the response of termination to sales is positive (vs. negative) for producers with a small (vs. large) number of suppliers, and on average, the response is almost zero and statistically insignificant.

Productivity and the number of suppliers. Why is the correlation of the termination rate with sales related to the number of suppliers? A logical conjecture is that the heterogeneous number of suppliers reflects the different producer-specific productivity levels among producers, which could account for the heterogeneous dynamics of the termination rate. Portrayed in Figure 5 is the bin scatter plot of the logarithm of the labor productivity (x-axis) against the logarithm of the number of suppliers (y-axis) for different producers. The strong positive correlation between the two variables in Figure 5 suggests a systematic relationship between the number of suppliers and the productivity of the producers. Overall, our results reveal that the differences in the number of suppliers and in the productivity level across different producers are important for the cyclicality in the rate of termination.

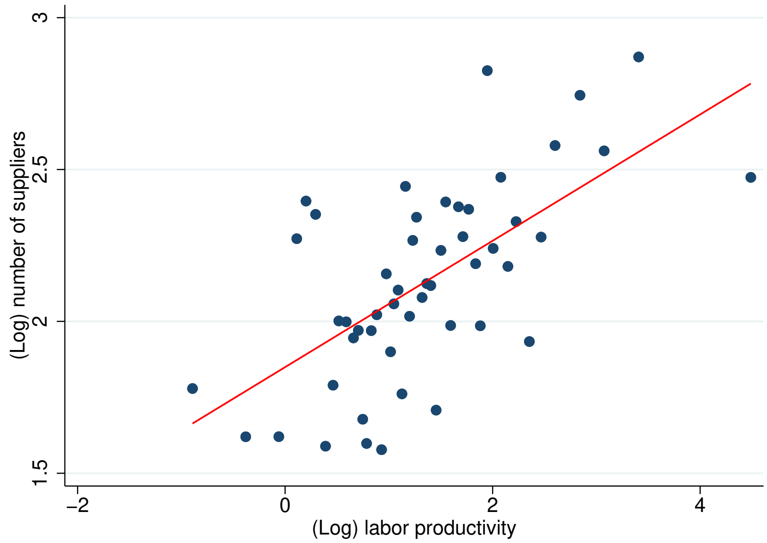


Figure 5: (Log) labor productivity and number of suppliers for different producers

Notes: The bin scatter plot shows the (log) labor productivity (x-axis) against the (log) number of suppliers (y-axis). We use Compustat "Sales/Turnover," deflated by the GDP deflator, as the producer's real sales. The labor productivity is computed as the ratio of real sales to employment. Producers are divided into 50 bins according to their (log) labor productivity, and each dot represents a bin. For the y-axis, we first compute the average number of suppliers over years for each producer, then average it across producers within the same bin. Similarly, for the x-axis, we first compute the average labor productivity over years for each producer, then average it across producers within the same bin. The solid red line is a linear fit of the log number of suppliers on the log labor productivity.

Fact 5: Management and adjustment costs of suppliers

In this section, we use Compustat data to explore the prevalence of the administrative costs for producers, which include the costs of managing and adjusting suppliers.[12] On average, these costs account for approximately 20% of a producer's net sales, evincing substantial resources devoted to administration-related activities.

Compustat data omit the separate components in the general administrative costs, thus precluding the direct measurement of the distinct costs of management and adjustment of suppliers. To illustrate that the management and adjustment costs are significant components of the large administrative costs, we investigate the correlation of the administrative cost to

[12]Our variable in Compustat data for administrative costs is under the name "Selling, General, and Administrative Expense" (mnemonic *xsga*). See the survey by Bond and Van Reenen (2007) and the more recent studies by Bloom et al. (2016) and Lanteri (2018) for an overview of the literature on adjustment costs.

the total number of suppliers and the rates of adoption and termination. Our conjecture is that the correlation must be positive and significant for the management and adjustment costs to play an important role in the changes of the number of suppliers and the rates of adoption and termination. We test our hypothesis with the following regression:

$$\ln(xsga_{i,t}) = \eta \ln(v_{i,t}) + \beta s_{i,N,t} + \kappa s_{i,T,t} + \alpha_i + \gamma_t + \epsilon_{i,t},$$

where $xsga_{i,t}$ is the administrative cost deflated by the GDP deflator, $v_{i,t}$ is the number of suppliers, and $s_{i,N,t}$ and $s_{i,T,t}$ are the adoption and termination rates, respectively. α_i and γ_t are fixed effects for producer and year, respectively.

Table 4: Administrative cost increases with supplier number, adoption, and termination

DEPENDENT VARIABLE	Admin cost
Number of suppliers	0.104***
	(0.015)
Rate of adoption	0.044**
	(0.020)
Rate of termination	0.054**
	(0.022)
Observations	15,228
Number of producers	2,280
Producer fixed effect	Yes
Year fixed effect	Yes
R^2	0.296

Notes: Admin cost is the log producer's Selling, General, and Administrative Expense deflated by the GDP deflator. Number of suppliers is the log producer's total number of suppliers. Rate of adoption ($s_{i,N,t}$) and Rate of termination ($s_{i,T,t}$) are the numbers of new and existing suppliers adopted and terminated by the producer i in year t divided by its total number of suppliers in year $t-1$, respectively. Data are annual and at the producer level. We restrict our sample to producers whose maximum numbers of suppliers exceed one over time and rates of adoption and termination are both below one. Producer and year fixed effects are controlled. Standard errors are clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Shown in Table 4 are the estimation results. The administrative cost is positively and significantly related to the number of suppliers. More concretely, a one percent increase in the number of suppliers is associated with a 0.104% rise in the administrative cost. Similarly, higher adoption and termination rates are also associated with an elevation in the administrative cost conditional on the number of suppliers, despite amounting to a lower increase in the administrative cost equal to 0.044% and 0.054%, respectively. These results reveal the significant role of both management and adjustment costs in the adoption and termination of suppliers.

4 A model of adoption and termination of suppliers

We now develop a model with optimal choices for the adoption and termination of suppliers. The key assumptions of our model —motivated by the evidence in Fact 5— are the adjustment costs in the adoption and termination of suppliers and the management costs.

4.1 Baseline environment and timing

The economy is static, and it is populated by a continuum of final-goods producer $i \in [0, 1]$. Each producer i has an idiosyncratic productivity a_i drawn from a log-normal distribution with zero mean and standard deviation σ_a, which is the only source of heterogeneity in the model. We assume that there is no shock to the idiosyncratic productivity, i.e., a_i is fixed for each producer. The final good market is perfectly competitive, with the price normalized to one. Each producer manufactures goods by assembling intermediate inputs that existing (E) and new (N) suppliers provide. Each vintage $k \in \{E, N\}$ is populated by a continuum of suppliers. Each supplier offers intermediate inputs to different producers.

At the beginning of the period, each producer i starts with the steady-state measure of total suppliers $\bar{V}_i^*$.[13] Each producer optimally sets the mix of existing and new suppliers to maximize profits. The adjustment in the measure of suppliers involves costs for the termination (c^-) and the adoption (c^+) of suppliers. The prices of the intermediate inputs are determined by Nash bargaining between the producer and the suppliers. The producer i manufactures the final good (Y_i) using the supplied inputs from new and existing suppliers at the established price. Summarized in Figure 6 is the timeline in the model.

Figure 6: Timeline

Notes: At the beginning of the period, the final goods producer is endowed with a unitary measure of existing suppliers. Then, it terminates a subset of the existing suppliers and adopts a subset of the new suppliers. Next, it bargains with each of its input suppliers on the price of the intermediate input that splits the surplus of each production line. At the end of the period, the producer manufactures the final output using the inputs from the selected new and existing suppliers.

[13]For each producer i, its measure of active suppliers in the production stage is a function $V_i^*(\bar{V}_i^*, A)$ of the measure of existing suppliers that the producer starts with ($\bar{V}_i^*$) and the aggregate TFP (A). The steady-state measure of suppliers, $\bar{V}_i^*$, is the unique fixed point for the above mapping from $\bar{V}_i^*$ to V_i^* when the aggregate TFP is at the steady-state level $A = \bar{A}$, i.e., $V_i^*(\bar{V}_i^*, \bar{A}) = \bar{V}_i^*$.

4.2 Suppliers

Each supplier provides a distinct input to the producer. Suppliers of each vintage k are indexed by their match-specific efficiency z_k. Within the new vintage, match-specific efficiency is uniformly distributed over the interval $[0, 1]$ with unitary density. Within the existing vintage, match-specific efficiency is uniformly distributed over the interval $[1 - \bar{V}_i^*, 1]$ with unitary density.[14]

4.3 Producers and the bargained price

Each producer i manages a continuum of production lines. Each line of production produces output using the input from one supplier z_k according to the following production technology:

$$y_{i,k}(z_k) = Aa_i z_k, \quad \forall\, k \in \{E, N\}, \forall\, z_k,$$

where A and a_i are aggregate TFP and idiosyncratic productivity, respectively. Aggregate TFP is random and follows a log-normal distribution with zero mean and standard deviation σ_A.

We assume that each supplier manufactures intermediate goods without cost. The total surplus $TS_{i,k}(z_k)$ from the producer-supplier relationship is the output produced by the corresponding production line:

$$TS_{i,k}(z_k) = y_{i,k}(z_k) = Aa_i z_k, \quad \forall\, i \in [0, 1], \forall\, k \in \{E, N\}, \forall\, z_k.$$

The total surplus is split between the producer and the supplier by Nash bargaining over the price charged by the supplier ($p_{i,k}(z_k)$), according to the surplus-sharing condition:

$$p_{i,k}(z_k) = (1 - \alpha) TS_{i,k}(z_k), \quad \forall\, i \in [0, 1], \forall\, k \in \{E, N\}, \forall\, z_k, \tag{2}$$

where $1 - \alpha$ is the supplier's bargaining share.

4.4 Measures of adoption and termination

We denote by $z_{i,k}$ the marginal supplier of vintage k used by producer i. The producer i adopts the new suppliers whose idiosyncratic productivity levels are sufficiently high to generate profits and therefore adopts new suppliers with $z_N \in [z_{i,N}, 1]$. Similarly, the producer i terminates the existing suppliers whose idiosyncratic productivity levels are insufficient to generate profits

[14] We assume that new and existing suppliers have the same maximum match-specific efficiency, which is normalized to one. Allowing different maximum efficiency for new and existing suppliers does not affect the results.

and therefore terminates existing suppliers with $z_E \in [1 - \bar{V}_i^*, z_{i,E})$. The measures of adopted new and terminated existing suppliers are equal to $1 - z_{i,N}$ and $z_{i,E} - 1 + \bar{V}_i^*$, respectively. To retain consistent notation with Section 2, we denote by $s_{i,N}$ and $s_{i,T}$ the rate of adoption (of new suppliers) and the rate of termination (of existing suppliers), respectively, with $s_{i,N} = (1 - z_{i,N}) / \bar{V}_i^*$ and $s_{i,T} = (z_{i,E} - 1 + \bar{V}_i^*) / \bar{V}_i^*$.

4.5 Costs of management, adoption, and termination of suppliers

Costs of managing suppliers. Producers incur costs in managing suppliers, consistent with the *span of control* problem and the "diminishing returns to management" (Coase, 1991; Williamson, 1967). Following Gopinath and Neiman (2014), we assume a quadratic management cost that is a function of the total measure of production lines:

$$G(z_{i,N}, z_{i,E}) = \xi \cdot V_i^2 / 2,$$

where $V_i = 2 - z_{i,N} - z_{i,E}$ is the total measure of active suppliers for each producer i, or the total measure of suppliers whose idiosyncratic productivity levels are above the threshold for selection in each vintage. To simplify our exposition, we assume that the producer pays the management cost before bargaining with suppliers. Hence, the management cost does not enter into the Nash bargaining problem.

Costs of adjusting suppliers. In addition to the costs of managing suppliers, the adoption and termination of suppliers are also costly, and they involve unitary costs of adoption c^+ and of termination c^-. Consistent with the seminal idea in Coase (1991) and several subsequent studies, we assume that the adjustment costs are not contractable and, therefore, outside the bargaining set and paid entirely by producers.

4.6 Optimal choices of adoption and termination

We now describe the optimization of each producer i that chooses the adoption and termination of suppliers to maximize profits. For a given set of marginal suppliers $z_{i,E}$ and $z_{i,N}$, each producer i manufactures final output with the linear production function:

$$Y_i = \int_{z_{i,E}}^{1} y_{i,E}(z_E) dz_E + \int_{z_{i,N}}^{1} y_{i,N}(z_N) dz_N, \tag{3}$$

where the marginal suppliers $z_{i,E}$ and $z_{i,N}$ are optimally chosen to maximize the profit function:

$$\Pi_i = \max_{\{z_{i,E}, z_{i,N}\}} \underbrace{\int_{z_{i,E}}^{1} y_{i,E}(z_E)dz_E + \int_{z_{i,N}}^{1} y_{i,N}(z_N)dz_N}_{\text{Final output}} - \underbrace{\left(\int_{z_{i,E}}^{1} p_{i,E}(z_E)dz_E + \int_{z_{i,N}}^{1} p_{i,N}(z_N)dz_N\right)}_{\text{Input costs}}$$

$$- \underbrace{\left[c^{-}\left(z_{i,E} - 1 + \bar{V}_i^{*}\right) + c^{+}\left(1 - z_{i,N}\right)\right]}_{\text{Adjustment costs}} - \underbrace{\xi \cdot \left(2 - z_{i,N} - z_{i,E}\right)^2 / 2}_{\text{Management cost}}, \tag{4}$$

where the final output from all production lines is diminished by the input costs paid to suppliers, the adjustment costs, and the management cost. The adjustment costs comprise the termination cost ($c^{-}\left(z_{i,E} - 1 + \bar{V}_i^{*}\right)$) and the adoption cost ($c^{+}\left(1 - z_{i,N}\right)$). The quadratic management cost encapsulates the administrative costs for the management of suppliers.

By combining the bargained input price in equation (2) into equation (4), it yields:

$$\Pi_i = \max_{\{z_{i,E}, z_{i,N}\}} \alpha \left\{\int_{z_{i,E}}^{1} A a_i z_E dz_E + \int_{z_{i,N}}^{1} A a_i z_N dz_N\right\} - \left[c^{-}\left(z_{i,E} - 1 + \bar{V}_i^{*}\right) + c^{+}\left(1 - z_{i,N}\right)\right]$$
$$- \xi \cdot \left(2 - z_{i,N} - z_{i,E}\right)^2 / 2.$$

The solution to the above maximization problem yields the optimal conditions for the marginal suppliers $z_{i,E}^{*}$ and $z_{i,N}^{*}$:

$$z_{i,E}^{*} + \frac{c^{-}}{\alpha A a_i} = \frac{\xi V_i^{*}}{\alpha A a_i} \quad , \tag{5}$$

and

$$z_{i,N}^{*} - \frac{c^{+}}{\alpha A a_i} = \frac{\xi V_i^{*}}{\alpha A a_i} \quad , \tag{6}$$

where $V_i^{*} = 2 - z_{i,N}^{*} - z_{i,E}^{*}$ is the total measure of suppliers for producer i in equilibrium.

Equations (5) and (6) outline the distinct roles of the management and adjustment costs for the adoption and termination of suppliers. The management cost increases the marginal costs of using both new and existing suppliers and, therefore, deters expansion in the total measure of suppliers. The cost of adoption (c^{+}) decreases the marginal benefit of using new suppliers, while the cost of termination (c^{-}) increases the marginal benefit of retaining existing suppliers.

Combining equations (5) and (6) yields:

$$z_{i,N}^{*} - z_{i,E}^{*} = \frac{c^{+} + c^{-}}{\alpha A a_i} > 0. \tag{7}$$

Equation (7) shows that the adjustment costs generate the differential in the marginal productivity between new and existing suppliers, such that new suppliers have higher marginal productivity than existing ones in equilibrium. As we discuss in the next section, the productivity differential is critical to the incentives for producers to adopt new suppliers (Lemma 2), and for the different cyclicality in the rate of termination across producers with different idiosyncratic productivity (Proposition 1).

5 Analytical results

In this section, we show that our model based on optimizing producers, distinct management and adjustment costs, and idiosyncratic productivity of producers generates the empirical results in Facts 1-4. We begin by focusing on Facts 1 and 2 that directly result from the model (Section 5.1). We then present the scaling and switching effects (Section 5.2.1), which are the forces that determine the decisions of the adoption, termination, and production by the single producer (Section 5.2.2), and subsequently extend the analysis to the aggregate economy to focus on Facts 3 and 4 (Section 5.2.3).

5.1 Returns from more suppliers and new relationships (Facts 1-2)

Fact 1 and Fact 2 show that the profits and sales of producers increase with the number of suppliers, and the increase is magnified by relationships with new suppliers. Showing that these empirical regularities are consistent with our model is straightforward. By combining equations (5) and (6), the next lemma holds.

Lemma 1. Returns from more suppliers (Fact 1). *Conditional on the rate of adoption $s^*_{i,N}$, the final output increases in the total measure of suppliers, V^*_i.*

$$\frac{\partial \ln Y^*_i}{\partial \ln V^*_i} = \frac{Aa_i V^*_i}{Y^*_i} z^*_{i,E} > 0.$$

Proof: see Appendix E.

Lemma 1 shows that the elasticity of output to the total measure of suppliers is always positive, consistent with the observed positive *returns from more suppliers* established in Fact 1.

The model also generates the *returns from new relationships*, as formalized in the next lemma.

Lemma 2. Returns from new relationships (Fact 2). *When $c^+ > 0$ or $c^- > 0$, the semi-elasticity of final output (Y^*_i) to the adoption rate ($s^*_{i,N}$) is positive and equal to:*

$$\frac{\partial ln Y^*_i}{\partial s^*_{i,N}} = \frac{c^+ + c^-}{\alpha Y^*_i / \bar{V}^*_i} > 0.$$

Proof: see Appendix E.

Lemma 2 shows that the semi-elasticity of output to the rate of adoption is positive when the adjustment costs are positive, consistent with our Fact 2 that establishes positive returns from new relationships. Lemma 2 also reveals that the *return from new relationships* is proportional to the adjustment costs.

5.2 Responses of adoption, termination, and output to changes in aggregate TFP (Facts 3-4)

In this section, we consider the responses of adoption, termination, and output to changes in aggregate TFP to replicate Facts 3 and 4. We first focus on the scaling and switching effects (Section 5.2.1) that determine the response of the single producer to changes in aggregate TFP (Section 5.2.2). Then we extend the analysis to the aggregate economy (Section 5.2.3).

The response of the single producer to aggregate TFP shocks critically depends on the economic relevance of the costs of management, adoption, and termination of suppliers, measured by the costs of management, adoption, and termination of suppliers in units of the idiosyncratic productivity of the producer a_i, and are defined as:

$$\widetilde{\xi}_i \equiv \xi/a_i,\ \widetilde{c}_i^+ \equiv c^+/a_i,\ \widetilde{c}_i^- \equiv c^-/a_i,$$

respectively. A higher $\widetilde{\xi}_i$ indicates that the producer faces a larger management cost relative to its idiosyncratic productivity and, similarly, a higher $\widetilde{c}_i^+$ (vs. $\widetilde{c}_i^-$) indicates that the producer faces a greater adoption (vs. termination) cost relative to its idiosyncratic productivity. For notational convenience, we define the total adjustment costs in units of the idiosyncratic productivity as:

$$\widetilde{c}_i = \widetilde{c}_i^+ + \widetilde{c}_i^-,$$

which provides a measure of the economic relevance of the total adjustment costs.

To study the responses of variables to changes in aggregate TFP, we denote the steady state of a variable x by $\bar{x}$, and the deviation of x from the steady state by $dx \equiv x - \bar{x}$.

5.2.1 Scaling and switching effects

Before focusing on Facts 3 and 4, we show that changes in aggregate TFP exert two distinct scaling and switching effects on the total measure and the composition of suppliers. These forces are critical for the responses of the adoption and termination rates of the single producer to aggregate TFP shocks.

The scaling effect. The higher aggregate TFP leads producers to increase the total measure of suppliers to benefit from the increased aggregate productivity (and profits) relative to the unchanged management costs. To take advantage of the higher productivity and resulting profits, producers increase their adoption of new suppliers and decrease their termination of existing suppliers, which we refer to as the *scaling effect*, as formalized in the next lemma.

Lemma 3. *The producer increases the total measure of new and existing suppliers to expand the scale of production in response to an increase in aggregate TFP.*

$$\textit{Scaling effect} \equiv \frac{d\ln V_i^*}{d\ln A} = \frac{2\widetilde{\xi}_i \bar{V}_i^* + \left(\widetilde{c}_i^+ - \widetilde{c}_i^-\right)}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)\bar{V}_i^*} > 0, \tag{8}$$

which increases in $\widetilde{\xi}_i$ and decreases in a_i.

Proof: see Appendix E.

Lemma 3 shows that the magnitude of the scaling effect increases with the economic relevance of the management cost ($\widetilde{\xi}_i$), which governs the constraints on the producer's scale of production. In particular, producers with higher $\widetilde{\xi}_i$ are more constrained by the burden of management costs and hence reduce the scale of production more strongly in response to a negative aggregate TFP shock. Because $\widetilde{\xi}_i$ is inversely related to the idiosyncratic productivity, the scaling effect decreases with the idiosyncratic productivity.

The scaling effect incentivizes producers to reduce the size of production by terminating existing suppliers in response to negative aggregate TFP shocks, which is critical to generate the countercyclical rate of termination among large producers established in Fact 4 (Figure 4).

The switching effect. The adjustment costs generate a positive co-movement between the rates of adoption and termination and aggregate TFP. For instance, the increase in aggregate TFP reduces the productivity differential between new and existing suppliers (see equation 7), as well as incentivizes the producer to adjust the composition of suppliers by replacing existing with new suppliers, thereby enhancing both rates of termination and adoption of suppliers. We refer to this phenomenon as the *switching effect*, as formalized in the next lemma.

Lemma 4. *For a given measure of suppliers, an increase in aggregate TFP generates the switching from existing to new suppliers. The size of the switching effect is equal to:*

$$\textit{Switching effect} \equiv \frac{\partial s_{i,N}^*}{\partial\ln A} = \frac{\partial s_{i,T}^*}{\partial\ln A} = \frac{\widetilde{c}_i}{2\alpha\bar{A}\bar{V}_i^*} > 0, \tag{9}$$

which increases in $\widetilde{c}_i$ and decreases in a_i.

Proof: see Appendix E.

Because replacing existing with new suppliers involves the simultaneous adoption and termination of suppliers, the switching effect entails equal changes in the rates of adoption ($s^*_{i,N}$) and termination ($s^*_{i,T}$) of suppliers. Lemma 4 shows that the size of the switching effect increases with $\widetilde{c}_i$, which declines in the idiosyncratic productivity a_i. In particular, smaller producers with lower a_i are more prone to a negative aggregate TFP shock than larger producers with higher a_i in their replacement of existing suppliers with new ones. This is because smaller producers endure larger increases in the relevance of the fixed adjustment costs in relation to their decreased profits. Therefore, they are more inclined to refrain from adjusting suppliers and hence display larger declines in the adoption and termination rates (i.e., a larger switching effect).[15]

5.2.2 Effect of aggregate TFP on the producer's decisions

Using the scaling and switching effects discussed above, we examine the responses of the producer's rates of adoption, termination, and output to changes in aggregate TFP.

Response of the producer's adoption rate to changes in aggregate TFP. The response of the rate of adoption for the producer i ($s^*_{i,N}$) to changes in aggregate TFP (A) is a linear combination of the scaling and switching effects:

$$\frac{ds^*_{i,N}}{d\ln A} = \underbrace{\frac{1}{2}\frac{d\ln V^*_i}{d\ln A}}_{\text{Scaling effect on adoption} > 0} + \underbrace{\frac{\partial s^*_{i,N}}{\partial \ln A}}_{\text{Switching effect} > 0}. \tag{10}$$

Because the switching and scaling effects are both positive on the adoption rate, the response of the rate of adoption for the producer is always positive.[16]

Response of the producer's termination rate to changes in aggregate TFP. The response of the rate of termination for the producer i ($s^*_{i,T}$) to changes in aggregate TFP (A) is also a linear

[15] In the extreme case where producers have infinitely large idiosyncratic productivity and almost zero $\widetilde{c}_i$, producers always choose the efficient level of supplier replacement with $s^*_{i,N} = 1/2$ under any level of aggregate TFP. In this case, the switching effect is zero because the replacement of existing suppliers with new ones is so stable, which does not respond to changes in aggregate TFP.

[16] To derive equation (10), we combine equations (5) and (6), and the definition of $s^*_{i,N}$, which yields the producer's rate of adoption: $s^*_{i,N} = \frac{V^*_i}{2V^*_i} - \frac{\widetilde{c}_i}{2\alpha A V^*_i}$.

combination of the scaling and switching effects:

$$\frac{ds^*_{i,T}}{d\ln A} = \underbrace{-\frac{1}{2}\frac{d\ln V^*_i}{d\ln A}}_{\text{Scaling effect on termination} < 0} + \underbrace{\frac{\partial s^*_{i,T}}{\partial \ln A}}_{\text{Switching effect} > 0} . \tag{11}$$

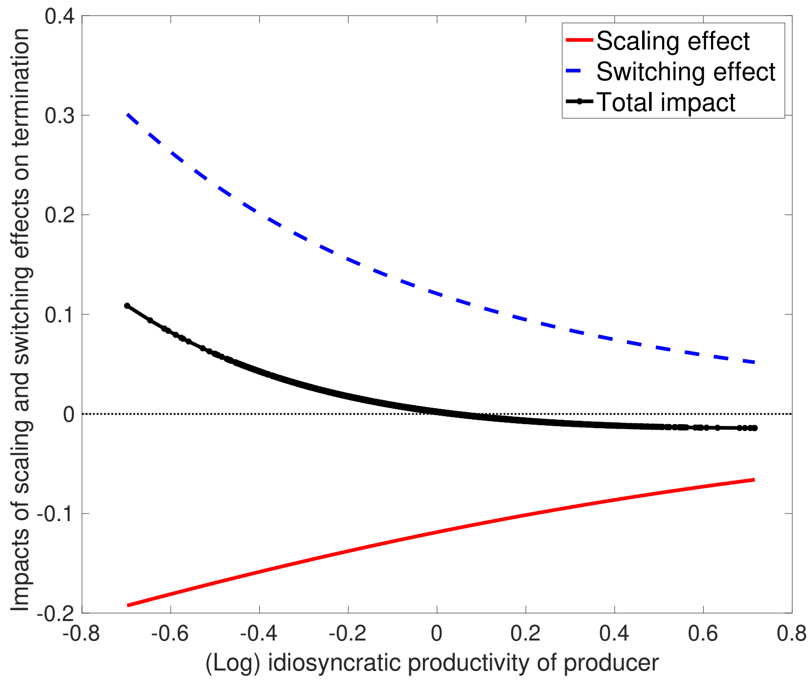


Figure 7: Impacts of scaling and switching effects on termination as functions of a_i

Notes: The figure plots the impacts of scaling (solid red curve) and the switching (dashed blue curve) effects on the response of termination rate to changes in aggregate TFP as functions of the (log) idiosyncratic productivity of the producer, respectively. The solid black curve with circles is the total impact of the two effects.

The scaling effect implies a negative response of the rate of termination to aggregate TFP shocks. This is because the producer achieves an increase in the scale of production by reducing the rate of termination of existing suppliers.[17] In contrast, the switching effect implies a positive response of the rate of termination — consistent with the positive impact of the switching effect on the rate of adoption to enact the replacement of existing suppliers with new ones. Equation (11) shows that the sign of the response of the termination rate to changes in aggregate TFP is determined by the relative strength of the switching and scaling effects.

To examine the countervailing forces of the scaling and switching effects in determining the response of the termination rate of the producer to changes in aggregate TFP, shown in Figure 7

[17] To derive equation (11), we combine equations (5) and (6), and the definition of $s^*_{i,T}$, which yields the producer's rate of termination: $s^*_{i,T} = 1 - \frac{V^*_i}{2\bar{V}^*_i} - \frac{\tilde{c}_i}{2\alpha A \bar{V}^*_i}$.

are the impacts of the scaling (i.e., the solid red curve) and switching (i.e., the dashed blue curve) effects on the responses of termination against the idiosyncratic productivity of the producer, together with the combined effect (i.e., the solid black curve with circles). The calibration of the model is on the U.S. data, as we describe in Section 6. Consistent with equation (11), the scaling (vs. switching) effect exerts negative (vs. positive) impact on the response of termination to changes in aggregate TFP. Moreover, both curves converge towards zero, showing that the magnitudes of both effects decline with the idiosyncratic productivity of the producer, as shown in Lemmas 3 and 4. However, the scaling effect is less sensitive to changes in idiosyncratic productivity than the switching effect, as evinced by the steeper curve associated with the switching effect.[18]

In Figure 7, the solid black curve with circles shows the total impact of the two effects that tracks the cyclicality of the rate of termination. The total impact declines in the idiosyncratic productivity, as the switching effect is highly sensitive to a_i and decreases faster than the scaling effect. Termination becomes acyclical when the total impact reaches zero at the idiosyncratic productivity of 0.04. The switching effect dominates when idiosyncratic productivity is lower than 0.04, implying that the rate of termination increases with aggregate TFP (i.e., $ds^*_{i,T}/dlnA > 0$). In contrast, the scaling effect dominates when idiosyncratic productivity is higher than 0.04, implying that the rate of termination decreases with aggregate TFP (i.e., $ds^*_{i,T}/dlnA < 0$).

Overall, our analysis shows that the different responses of the rate of termination to aggregate TFP shocks across producers are driven by the heterogeneous idiosyncratic productivity a_i, which determines the economic relevance of the adjustment costs faced by each producer, as stated in the next proposition.

Proposition 1. Heterogeneous cyclicality in termination. *When both ξ and $c^+ + c^-$ are sufficiently large, the rate of termination is countercyclical for producers with high idiosyncratic productivity while procyclical for producers with low idiosyncratic productivity.*
Proof: see Appendix E.

Note that the steady-state measure of suppliers ($\bar{V}_i^*$) increases with the idiosyncratic pro-

[18]The low sensitivity of the scaling effect to changes in idiosyncratic productivity is driven by two countervailing forces. On the one hand, lower idiosyncratic productivity (i.e., higher $\widetilde{\xi}_i$) implies more stringent constraints from the management cost that leads to a stronger response of the scale of production to aggregate TFP shocks. On the other hand, a higher $\widetilde{\xi}_i$ also leads to a lower measure of suppliers in the steady state, which relieves some of the constraints from the management cost and partially attenuates the response of the scale of production to aggregate TFP shocks. Mathematically, the above two offsetting forces are reflected by the $\widetilde{\xi}_i$ terms in both the denominator and the numerator of the equation (8), respectively.

ductivity. This is because the management cost is less relevant for the producers with high idiosyncratic productivity, and these producers maintain a large scale of production with a large measure of suppliers. Therefore, Proposition 1 suggests that the rate of termination is countercyclical for producers with many suppliers, but procyclical for producers with a small measure of suppliers. This result is consistent with Fact 4 (Figure 4), which shows that producers with a large (vs. small) measure of suppliers display a countercyclical (vs. procyclical) rate of termination.

Response of the producer's output to changes in aggregate TFP. Management and adjustment costs in units of producers' idiosyncratic productivity determine the cyclicality of the rates of adoption and termination by affecting the strength of scaling and switching effects. We now study how the two distinct costs amplify the effect of aggregate TFP on the output of the single producer.

Lemma 5. *Aggregate TFP has a positive effect on the output of the producer, i.e., $d \ln Y_i^* / d \ln A > 0$. The effect of aggregate TFP is stronger for producers with larger management or adjustment costs in units of idiosyncratic productivity, i.e., $\partial \big(\frac{d \ln Y_i^*}{d \ln A}\big) / \partial \widetilde{c}_i$ and $\partial \big(\frac{d \ln Y_i^*}{d \ln A}\big) / \partial \widetilde{\xi}_i > 0$.*

Proof: see Appendix E.

Lemma 5 shows that the output of the producer declines with a low aggregate TFP. Higher management and adjustment costs (in units of idiosyncratic productivity) amplify the negative TFP shock and generate a larger fall in the output of the producer. The intuition is as follows: producers with higher management costs (in units of idiosyncratic productivity) reduce the scale of production more sharply, as the scaling effect is stronger (Lemma 3). Meanwhile, producers with higher adjustment costs (in units of idiosyncratic productivity) curtail their replacement of existing suppliers with new ones more substantially, as the switching effect is stronger (Lemma 4).

5.2.3 Effect of aggregate TFP on the aggregate economy

We now investigate the effect of aggregate TFP on the rates of adoption and termination of suppliers, and the dynamics of aggregate output. Consistent with the empirical analysis, we define the aggregate measure of suppliers (V^*) and rates of adoption (s_N^*) and termination (s_T^*)

as the weighted average of their counterparts at the producer level:

$$V^* = \sum_i V_i^* \frac{\bar{Y}_i^*}{\bar{Y}^*},\ s_N^* = \sum_i s_{i,N}^* \frac{\bar{Y}_i^*}{\bar{Y}^*},\ \textit{and}\ s_T^* = \sum_i s_{i,T}^* \frac{\bar{Y}_i^*}{\bar{Y}^*},$$

respectively, where $Y^* = \sum_{i'} Y_{i'}^*$ is the aggregate output, and the steady-state share of output for the producer i, $\bar{Y}_i^*/\bar{Y}^*$, is used as the weight.[19]

Effect of aggregate TFP on the aggregate output. An immediate implication of Lemma 5 at the aggregate level is that the aggregate TFP has a positive effect on the aggregate output, and both management and adjustment costs amplify this effect, as summarized in the proposition below.

Proposition 2. Amplified response of aggregate output to aggregate TFP shocks. *Aggregate TFP has a positive effect on the aggregate output, i.e.,* $d \ln Y^*/d \ln A > 0$. *The effect of aggregate TFP is stronger with larger management or adjustment costs, i.e.,* $\partial\left(\frac{d \ln Y^*}{d \ln A}\right)/\partial(c^+ + c^-) > 0$ *and* $\partial\left(\frac{d \ln Y^*}{d \ln A}\right)/\partial\xi > 0$.

Proof: see Appendix E.

The intuition of Proposition 2 follows from Lemma 5. In response to a given negative shock to the aggregate TFP, compared to the case with low management and adjustment costs, higher management costs put more stringent constraints on producers' scale and generate more dramatic scaling down of production (Lemma 3). Furthermore, higher adjustment costs impede the replacement of existing with new suppliers by a larger extent (Lemma 4). As a result, the two forces jointly amplify the fall in aggregate output.

Effect of aggregate TFP on the aggregate measure of suppliers. A direct implication of the positive *scaling effect* established in Lemma 3 is the positive relationship between the total measure of suppliers for the producer and the aggregate TFP. Lemma 3 implies that the aggregate measure of suppliers is positively related to the aggregate TFP, as stated in the following proposition.

Proposition 3. Procyclical aggregate measure of suppliers (Fact 3). *The aggregate measure of suppliers,* V^**, increases in* A.

Proof: see Appendix E.

Proposition 3 shows that our model replicates the procyclical aggregate measure of suppliers in Fact 3.

[19] Because producers share the same Cobb-Douglas production function, output is proportional to the costs of goods sold (COGS), which is used as the weight for aggregations in our empirical exercise.

Effect of aggregate TFP on the aggregate rate of adoption. Because equation (10) implies a positive relationship between the rate of adoption of each producer and the aggregate TFP, the aggregate rate of adoption and the aggregate TFP are positively correlated, as summarized in the proposition below.

Proposition 4. Procyclical aggregate rate of adoption (Fact 4). *The aggregate rate of adoption of suppliers increases with aggregate TFP.*
Proof: see Appendix E.

Proposition 4 shows that our model replicates the procyclical aggregate rate of adoption in Fact 4.

Effect of aggregate TFP on the aggregate rate of termination. The effect of aggregate TFP on the aggregate rate of termination is less definite and depends on several parameters. First, as shown in Proposition 1, the effect of aggregate TFP on the producer's rate of termination is heterogeneous across producers and decreases with the producer's idiosyncratic productivity. Thus, the cyclicality of the aggregate rate of termination depends on the distribution of producers' idiosyncratic productivity.

Second, as shown in equation (11), the effect of aggregate TFP on the rate of termination of each individual producer is determined by the size of the scaling and the switching effects, which depends on the magnitudes of the management and adjustment costs. Hence, the management and adjustment costs are both crucial determinants of the cyclicality of the aggregate rate of termination.

We will show in our quantitative analysis that the aggregate rate of termination is acyclical, consistent with Fact 4 (Panel b of Figure 3), for a realistic calibration of the distribution of idiosyncratic productivity of the different producers and with the management and adjustment costs calibrated to the U.S. data.

Overall, our analysis reveals that our parsimonious model with optimizing producers and distinct costs for the management and adjustment of suppliers (as motivated by Fact 5) replicates the novel empirical findings on the adoption and termination of suppliers.

6 Quantitative analysis

In this section, we calibrate the model on the U.S. data to explore the critical role of adjustment and management costs for: (i) the heterogeneity in the cyclicality of the rate of termination across producers with different measures of suppliers, and (ii) the amplification of aggregate TFP shocks.

6.1 Calibration

We calibrate the standard deviation of the log idiosyncratic productivity of each producer, σ_a, equal to 0.2, which is the middle value between the estimates of 0.15 and 0.24 in Syverson (2004) and Fostera et al. (2015), respectively. The standard deviation of the log aggregate TFP, σ_A, is set to 0.024 to match the standard deviation of the cyclical (HP-filtered) annual log-real gross output in the U.S. data for the period 2003-2019 (2.7%).

We set the bargaining share of the producer (α) equal to 0.36 to match the ratio of the producers' operating surplus to intermediate input costs for the U.S. economy.

We assume symmetric costs of adoption and termination of suppliers, i.e., $c^+ = c^-$. Given the calibrated bargaining share and the average idiosyncratic productivity normalized to one, we jointly calibrate the parameters for the management and adjustment costs, ξ and c^+ (and equivalently, c^-), to match the following two target moments. First, we match the ratio of the adjustment costs to the operating costs, set equal to 0.5 in Caballero and Hammour (1994) on the basis that the yearly adjustment costs in production amount to one-half of the operating costs.[20] The average observed duration of relationships is about 3.5 years, implying that the expected adoption and termination occur every 3.5 years. We calibrate c^+ and c^- to 0.067, so that the ratio of the total adjustment cost ($c^+ + c^-$) to the total operating cost over the expected duration of the relationship (i.e., 3.5$\times$yearly operating cost) is equal to 0.14 (i.e., 0.5/3.5). Second, we calibrate ξ equal to 0.057 to match the ratio of the adjustment costs to the sum of operating surplus and intermediate input costs for the producer, which is equal to approximately 14% (Gopinath and Neiman, 2014). Summarized in Table 5 is the calibration of the model.

We simulate 9,000 producers ($i \in \{1, 2, \cdots, 9,000\}$) with i.i.d. idiosyncratic productivities drawn from the calibrated distribution. Then, we simulate 1,000 economies ($j \in \{1, 2, \cdots, 1,000\}$) for the same 9,000 producers, and draw new i.i.d aggregate TFP shocks in each economy.[21] We use the same set of producers for different economies to examine how the heterogeneity in producers affects the impact of aggregate TFP on the aggregate output.

[20]The operating costs are the intermediate input costs in our model.

[21]Note that our model is static and each economy lasts one period.

Table 5: Calibration of the model

Parameter	Value	Target moment
α	0.36	The ratio of producers' surplus to intermediate input costs.
ξ	0.057	Steady-state share of management costs (Gopinath and Neiman, 2014).
$c^+(c^-)$	0.067	Steady-state share of adjustment costs in operating costs (Caballero and Hammour, 1994).
σ_a	0.2	Middle estimate between Syverson (2004) and Fostera et al. (2015).
σ_A	0.024	The standard deviation of the HP-filtered log real gross output.

Notes: α is the bargaining share of the producer, ξ is the management cost parameter, c^+ (c^-) is the cost of adoption (termination), and σ_a and σ_A are the standard deviations of $log(a_i)$ and $log(A)$, respectively.

6.2 Heterogeneity in the response of the rate of termination across producers

Our empirical analysis in Section 3 shows that the rate of termination is countercyclical for large producers and procyclical for small producers. In this subsection, we show that the model matches this important empirical regularity.

We group the 9,000 simulated producers by the measure of suppliers and divide them into 30 groups of equal size (i.e., each group contains 300 producers), with each group indexed by k. To investigate the heterogeneous responses of the termination rate to changes in the business condition across different groups of producers, we conduct the following panel regression for each k-group of producers separately:

$$s^k_{i,T,j} = a^k + b^k \cdot log(Y^k_{i,j}) + \chi^k_i + \epsilon^k_{i,j}, \tag{12}$$

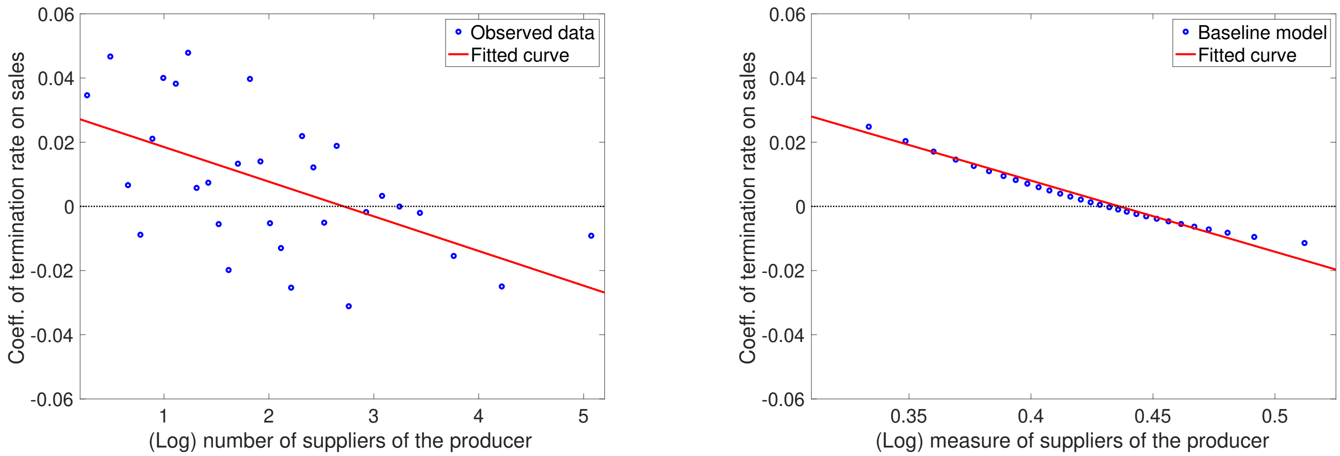
where $s^k_{i,T,j}$ is the termination rate of producer i that belongs to group k in economy j, $Y^k_{i,j}$ is output, and χ^k_i is the producer fixed effect. The coefficient b^k measures the response of the rate of termination to output within the group k. It is the central focus of our analysis; this is because it captures the heterogenous cyclicality of the termination rate for different groups of producers. We then undertake a similar exercise using the observed data by performing the following regression:[22]

$$s^k_{i,T,t} = a^k + b^k \cdot log(Y^k_{i,t}) + \chi^k_i + \epsilon^k_{i,t}. \tag{13}$$

Panel (a) in Figure 8 shows the regression results from equation (13) estimated with the observed data. The blue dots show the point estimates of the different b^k coefficients (y-axis) against the log of the average number of suppliers $V^k \equiv \sum_i \sum_t V^k_{i,t}/N^k_{obs}$ (x-axis), where N^k_{obs} is the total number of observations in group k. The red line is the fitted curve estimated using

[22] Different from the estimation using the simulated data, the observed data has multiple periods t rather than the multiple economies j in the simulated data.

Figure 8: Coefficient of regressing the rate of termination on sales: data vs. baseline model



(a) Data

(b) Baseline model

Note: The coefficient of regressing the termination rate on (log) sales for different producer groups are plotted using the observed data (left panel) and the simulated data from the baseline model (right panel), respectively. In the left (right) panel, we group the 900 (9,000) observed (simulated) producers by the number (measure) of suppliers and then divide them into 30 groups of equal size. Within each group, we run panel regressions of the termination rate on log sales, controlling for the producer fixed effect. For the x-axis, we compute the average number (measure) of suppliers across years (economies) for each producer, which is then averaged across the producers within each group. In the left panel, our sample excludes producers with no more than ten observation years for both the termination rate and the log sales for the panel regression.

OLS. Panel (b) shows the results from equation (12) estimated with the simulated data from the baseline model. In both panels, the correlation between the cyclicality of the termination rate (measured by b^k) and the size of producers (measured by V^k) is negative, showing that the model generates realistic heterogeneity in the cyclicality of the termination rate across the producers with different measures of suppliers. This outcome is also consistent with the theoretical results in Proposition 1.

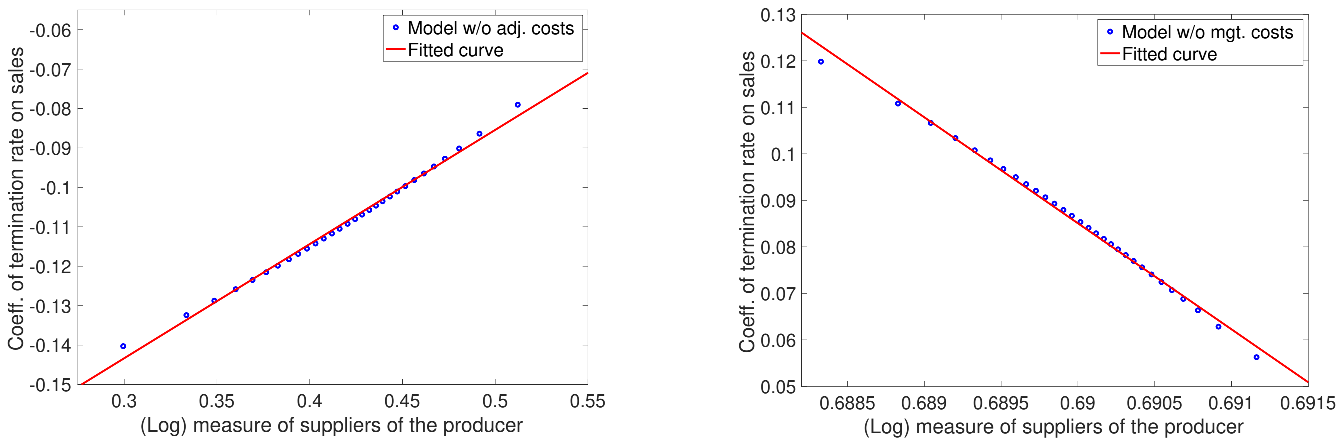
Another important similarity between the observed data and the simulated model that transpires from the figure is the nearly zero cyclicality of the aggregate termination rate. To test formally that the correlation between termination and output is close to zero at the aggregate level, we estimate the following time-series regressions with the simulated and the observed data separately:

$$s_{T,j} = a + b \cdot log(Y_j) + \epsilon_j, \tag{14}$$

$$s_{T,t} = a + b \cdot log(Y_t) + \epsilon_t, \tag{15}$$

where $s_{T,j}$ and $s_{T,t}$ are the aggregate termination rates in economy j (for the simulated data) and period t (for the observed data), and Y_j and Y_t are the aggregate output. The estimated values for the coefficient b are equal to 0.005 and 0.006 for the simulated and the observed data, respectively. Both estimates are close to zero, evincing that the model closely replicates the data. The results show that our model is consistent with the observed acyclical aggregate rate of termination in Panel (b) of Figure 3 (Fact 4).

Figure 9: Coefficient of regressing the rate of termination on sales: Counterfactual analysis



(a) Model without adjustment costs

(b) Model without management costs

Notes: The coefficient of regressing the termination rate on (log) sales for different producer groups are plotted using the simulated data from the models with zero adjustment costs (left panel) and with zero management costs (right panel), respectively. In each panel, we group the 9,000 simulated producers by the measure of suppliers and then divide them into 30 groups of equal size. Within each group, we run panel regressions of the termination rate on log sales, controlling for the producer fixed effect. For the x-axis, we compute the average measure of suppliers across economies for each producer, which is then averaged across the producers within each group.

To clarify the role of adjustment and management costs in the heterogeneous cyclicality of the termination rate across producers, we estimate the cyclicality of the termination rate for each group, b^k, using data simulated with two counterfactual models. One is a model without adjustment costs, and the other is a model without management costs. Shown in Figure 9 are the results in panels (a) and (b), respectively.

When there are no adjustment costs (Panel a), the switching effect is absent (Lemma 4), and the cyclicality of termination is uniquely determined via the scaling effect. These results imply that producers reduce the size of production by terminating existing suppliers in response to a lower aggregate TFP. As a result, the rate of termination is countercyclical for all producers and highly countercyclical for small and low-productivity suppliers, as the scaling effect is stronger for them. This is in stark contrast to the data where the rate of termination is procyclical for small producers and countercyclical for large producers. Without adjustment costs, the aggregate rate of termination is countercyclical: the coefficient of log aggregate output in equation (14) is estimated as -0.11, which is also inconsistent with the data.

When management costs are absent (Panel b), the scaling effect is absent (Lemma 3), and the cyclicality of termination is uniquely determined by the switching effect. This effect induces producers to decelerate the turnover of suppliers in response to a low aggregate TFP. Thus, the rate of termination is procyclical for all producers and more so for smaller and less productive producers, whose switching effect is stronger. Again, these findings are incompatible with the data. Without management costs, the aggregate rate of termination is countercyclical: the coefficient of log aggregate output in equation (14) is estimated as 0.09, which contradicts the data.

6.3 Amplification of aggregate TFP shocks

We now show that adjustment and management costs amplify the response of output to aggregate TFP shocks with the help of the switching and scaling effects.

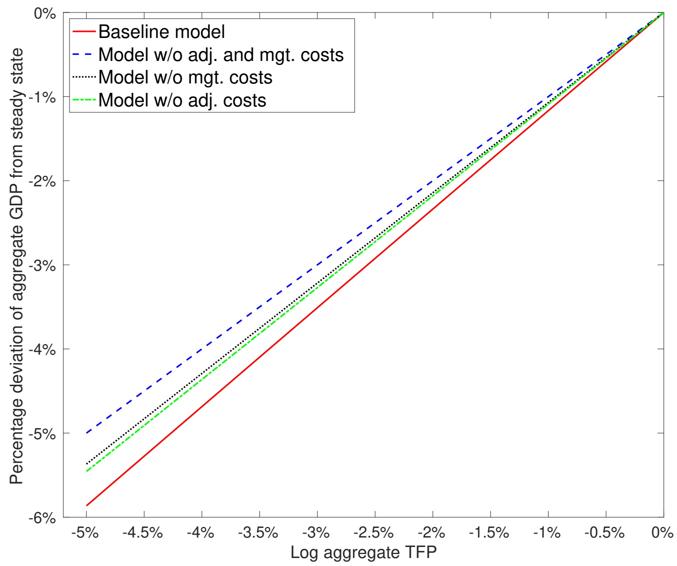
Depicted in Figure 10 is the impact of a 5% negative TFP shock, which generates a 5.9% decline in the aggregate output from the steady state in our baseline model (i.e., the solid red line). We also consider the effect of the shock in the following three alternative specifications of the model: (i) a model without adjustment and management costs ($c^+ = c^- = 0$, and $\xi \approx 0$) in the dashed blue line; (ii) a model without management costs ($\xi \approx 0$) in the dotted black line; and (iii) a model without adjustment costs ($c^+ = c^- = 0$) in the dashed-dotted green line.[23]

As portrayed in Figure 10, a 5% negative shock to aggregate TFP generates a decline in output of approximately 5.9% in our baseline model (i.e., the solid red line). If both the management and adjustment costs are absent (i.e., alternative specification (i), the dashed blue line), the fall in aggregate output is equal to 5% and much smaller compared to other alternative specifications of the model.

As posited in Proposition 2, two forces explain the attenuation in the fall of the aggregate output that is linked to the reduction in management and adjustment cost. First, the reduction in management costs dampens the scaling effect (Lemma 3), attenuating the fall in the scale of production and, therefore, sustaining the measure of suppliers. Second, the decrease in adjustment costs dampens the switching effect (Lemma 4), mitigating the productivity loss for forgoing the replacement of existing with new suppliers. Both forces restrain the fall in the output compared to the baseline model. Overall, the simulation shows that the adjustment and

[23]We set the management cost parameter (ξ) to close to zero (i.e., 1% of the baseline calibration) rather than exactly zero, as zero management cost will induce producers to choose an infinite measure of suppliers.

Figure 10: Response of output to a negative TFP shock under alternative specifications



Note: The figure plots the percentage deviation of the aggregate output from its steady-state level (y-axis) against the log aggregate TFP (x-axis). The solid red line is our baseline model. The dotted black line shows the specification without management costs (and baseline calibration for the adjustment cost). The dash-dotted green line shows the specification without adjustment costs (and baseline calibration for the management cost). Finally, the dashed blue line shows the specification without *both* adjustment and management costs.

management costs jointly amplify the fall in output by approximately 17%.

In the specifications without management costs (i.e., specification (ii), the dotted black line) or without adjustment costs (i.e., specification (iii), the dash-dotted green line), the declines in the aggregate output are equal to 5.4% and 5.5%, respectively, in between the baseline specification (i.e., 5.9%, the solid red line) and the specification without both adjustment and management costs (i.e., 5.0%, specification (i), the dashed blue line). The results indicate that the adjustment and management costs are jointly important for the amplification of aggregate TFP shocks.

7 Conclusion

Our analysis —using newly assembled firm-level data— establishes several novel facts concerning the adoption and termination of suppliers. At the producer level, producer sales and profits positively co-move with the adoption of new suppliers and the expansion in the total number of suppliers. At the aggregate level, the rate of adoption of new suppliers and the total number of suppliers are procyclical, while the termination of existing suppliers is acyclical. The acyclical rate of termination at the aggregate level arises from the different cyclicality in the rate of termination across producers with different numbers of suppliers.

Building on this new evidence, we develop a simple model of producers that optimally adjust the total measure and the composition of new and existing suppliers subject to distinct management and adjustment costs. The model shows the central and separate roles of the costs of managing, adopting, and terminating suppliers in altering the incentives to scale up the measure of suppliers (i.e., scaling effect) and to replace existing with new suppliers (i.e., switching effect) in response to aggregate TFP shocks. The scaling and switching effects are critical to replicate the observed procyclicality in the adoption of new suppliers and the total measure of suppliers. They generate the observed differences in the cyclicality of the rate of termination across producers that result in the acyclical rate of termination at the aggregate level. The calibrated model shows that the management and adjustment costs amplify the response of aggregate output to a negative TFP shock by 17%.

Our study suggests several interesting avenues for future research. First, there is limited empirical evidence that distinguishes between management and adjustment costs, whose differences we find critical to the optimizing decision of producers and the resulting movements in the aggregate rates of adoption and termination of suppliers. Second, the analysis could be extended to consider the intertemporal dimension in the adoption and termination of suppliers, which will link the optimal choices of producers to the discount rate, asset prices, and the expected benefits of the producer-supplier relationship. Third, we find that the heterogeneity in the productivity of producers is important for the adoption and termination of suppliers. Future work could focus on the optimal sorting between producers and suppliers with different productivity levels, which may enhance the cooperation between firms and improve productivity. Finally, though we center on the relationship between a single producer and several suppliers, the analysis could be extended to explore the linkages between producers and suppliers in the context of a network economy. We plan to investigate some of these issues in future work.

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A Data

Our data combine two datasets: the FactSet Revere Supply Chain Relationships data that allows tracking the adoption and termination of suppliers, and the Compustat Fundamentals data that provides the financial statement variables and administrative costs of each producer.

The FactSet Revere Supply Chain Relationships data consists of 784,325 producer-supplier relationship records between 152,119 producers and 95,932 suppliers from 2003 to 2021. Each record includes the start and end dates of the relationship. The database systematically collects producer-supplier relationship information from public sources such as SEC 10-K annual filings, investor presentations, and press releases reported by either the producer or the supplier. Compared to the commonly used Compustat Customer Segment database—which only includes major customers that contribute to more than 10% of a supplier's revenue—FactSet Revere provides a much less truncated set of suppliers.[24] The broader coverage results in more accurate measures of producer-supplier relationships, the number of suppliers, and their adoption and termination. As a result, FactSet Revere captures many supply-chain linkages that would be otherwise missing if the Compustat data were used instead.

To measure the extensive margin, we use the start and end years of each producer-supplier relationship. Based on this information, we calculate the total number of suppliers of producer i in year t and denote it by $v_{i,t}$. We also calculate the number of suppliers adopted and terminated by the producer i in year t and denote them by $v_{i,N,t}$ and $v_{i,T,t}$, respectively, which we employ to construct the rates of adoption and termination.

Then, we further merge the FactSet data with Compustat data using the first six digits of the producer's CUSIP numbers, which uniquely identify a company. With the above merger, we obtain a sample of 3,609 producers with 28,461 producer-year observations spanning from 2003 to 2021, covering 78,193 producer-supplier relationships.

B Derivation of number of suppliers and rates of adoption and termination

We now describe how we derive the number of suppliers and the rates of adoption and termination at both the producer and the aggregate levels.

To compute these aggregate series, we need the share of each producer's intermediate input expenditure in the total intermediate input expenditure of all producers. We denote the share

[24] Public-traded companies are required to report their major customers in accordance with Financial Accounting Standards No. 131, which is the source of Compustat Customer Segments.

of producer i's intermediate input expenditure in the total intermediate input expenditure as $COGS\_share_{i,t}$, which is computed as

$$COGS\_share_{i,t} = \frac{cogs_{i,t}}{\sum_{i'} cogs_{i',t}},$$

where $cogs_{i,t}$ is the *cost of goods sold* (COGS) of producer i documented in Compustat.[25]

With the producers' intermediate input shares defined above, we define the aggregate growth rate of the number of suppliers as

$$\frac{\Delta v_t}{v_{t-1}} \equiv \sum_i \Big(COGS\_share_{i,t} \cdot \frac{\Delta v_{i,t}}{v_{i,t-1}} \Big). \tag{16}$$

The producer-level decomposition of the growth rate of the number of suppliers is

$$\frac{\Delta v_{i,t}}{v_{i,t-1}} = s_{i,N,t} - s_{i,T,t}, \tag{17}$$

where $s_{i,N,t} \equiv v_{i,N,t}/v_{i,t-1}$ and $s_{i,T,t} \equiv v_{i,T,t}/v_{i,t-1}$ are the producer-level rates of adoption and termination, which are defined as the numbers of new/existing suppliers adopted/terminated by the producer i in year t divided by the producer's total number of suppliers in year $t-1$, respectively. Similar to the aggregation of the number of suppliers in equation (16), we use the weighted averages of adoption and termination rates as the aggregate rates of adoption and termination, i.e.,

$$\begin{aligned} \text{aggregate rate of adoption :} \quad & s_{N,t} \equiv \sum_i \Big(COGS\_share_{i,t} \cdot s_{i,N,t} \Big), \\ \text{aggregate rate of termination :} \quad & s_{T,t} \equiv \sum_i \Big(COGS\_share_{i,t} \cdot s_{i,T,t} \Big). \end{aligned}$$

It follows that the growth rate of the aggregate number of suppliers can be decomposed into the aggregate rates of adoption and termination, i.e.,

$$\frac{\Delta v_t}{v_{t-1}} = s_{N,t} - s_{T,t}.$$

Based on equation (17), we compute the variation of the growth rate of the aggregate number of suppliers as

$$\begin{aligned} Var\big(\frac{\Delta v_t}{v_{t-1}}\big) &= Cov\big(\frac{\Delta v_t}{v_{t-1}}, s_{N,t} - s_{T,t}\big) \\ &= Cov\big(\frac{\Delta v_t}{v_{t-1}}, s_{N,t}\big) + Cov\big(\frac{\Delta v_t}{v_{t-1}}, -s_{T,t}\big), \end{aligned}$$

[25] COGS in Compustat is a commonly used measure of the variable cost. According to the Compustat data manual, it "represents all expenses that are directly related to the cost of merchandise purchased or the cost of goods manufactured that are withdrawn from finished goods inventory and sold to customers."

which indicates the following equation showing the percentage contributions of the aggregate rates of adoption and termination to the growth rate of the aggregate number of suppliers

$$\frac{Cov\left(\frac{\Delta v_t}{v_{t-1}}, s_{N,t}\right)}{Var\left(\frac{\Delta v_t}{v_{t-1}}\right)} + \frac{Cov\left(\frac{\Delta v_t}{v_{t-1}}, -s_{T,t}\right)}{Var\left(\frac{\Delta v_t}{v_{t-1}}\right)} = 1,$$

where the first and second terms are the contributions of the aggregate rates of adoption and termination, respectively.

C Panel regressions for the cyclicality of termination

We examine the link between the heterogeneity in the number of suppliers and the heterogeneity in the response of the producer's rate of termination to sales using the following producer-level panel regression:

$$\ln(s_{i,T,t}) = \eta \ln(q_{i,t}) + \beta \left(\ln(max\_v) - \ln(v_i)\right) \times \ln(y_{i,t}) + \alpha_i + \epsilon_{i,t}, \tag{18}$$

where $q_{i,t}$ is the producer's real sales and v_i is the average of the number of suppliers over time for each producer i. The variable $max\_v \equiv \max_i (v_i)$ is the number of suppliers of the producer in our sample with the largest number of suppliers, and the term $(\ln(max\_v) - \ln(v_i))$ captures the percentage difference in the number of suppliers between the producer with the largest number of suppliers and each producer i. Because this term interacts with $ln(y_{i,t})$ in equation (18), the response of the producer's rate of termination to sales is equal to:

$$\frac{\partial \ln(s_{i,T,t})}{\partial \ln(y_{i,t})} = \eta + \beta \left(\ln(max\_v) - \ln(v_i)\right), \tag{19}$$

where η is the response of the rate of termination to sales for the producer with the largest number of suppliers (i.e., when $v_i = max\_v$, and $\ln(max\_v) - \ln(v_i) = 0$). The parameter β encapsulates the heterogeneous responses of the rate of termination to sales for producers with different numbers of suppliers.

To be consistent with **Fact 1** that shows that sales rise with the total number of suppliers, we expect a negative sign for the parameter η so that the fall in the rate of termination increases the total number of suppliers. Analogously, we expect a positive sign for the parameter β to be consistent with our results in Figure 4 that establishes the procyclicality in the rate of termination increases for producers with a low number of suppliers.

Shown in Table 6 are the results of the regression 18. Column (a) shows that the parameter η is insignificant when the regression does not include the interaction term between the number of

Table 6: Response of termination rate to sales under different number of suppliers

	(a)	(b)
VARIABLES	Rate of termination	Rate of termination
Sales (η)	0.006	-0.030**
	(0.004)	(0.013)
Distance from the max number of suppliers $\times$ Sales (β)		0.009**
		(0.004)
Observations	12,812	12,812
Producer number	884	884
Producer fixed effect	Yes	Yes
R^2	0.0104	0.0003

Notes: Data are annual. Rate of termination ($s_{i,T,t}$) is the number of existing suppliers terminated by the producer i in year t divided by its total number of suppliers in year $t-1$. Sales is the log producer's real sales. Distance from the max number of suppliers is the difference between the maximum average number of suppliers among all producers and the average number of suppliers over time of producer i. Producer fixed effect is controlled. We restrict our sample to those whose maximum numbers of suppliers are more than one over time, and exclude producers with no more than ten observation years for both the termination rate and the log sales for the panel regression. Standard errors are clustered at the producer level and are in brackets. ***:significant at 1%; **: significant at 5%.

suppliers and sales. This finding is consistent with Figures 3 and 4, which show that the aggregate rate of termination and the rate of termination for an average producer do not significantly comove with sales.

Shown in Column (b) are the results when we include the interaction term in the regression. The parameter η is negative and significant, and the parameter β is positive and significant. Equation (19) facilitates interpretation of previous findings, showing that the average response of the rate of termination to sales is jointly determined by the parameters η and β and the heterogeneity in the number of suppliers. For the producers with the largest number of suppliers, the rate of termination responds negatively to sales, which is uniquely captured by the negative estimate of the parameter η, as the term $\ln(max\_v) - \ln(v_i)$ in equation (18) is equal to zero. Thus, a negative value for η implies that the termination rate falls with sales for these largest producers. However, for producers with a low number of suppliers, the term $\ln(max\_v) - \ln(v_i)$ in equation (18) is positive, and the parameter β captures the effect of the heterogeneous numbers of suppliers on the response of the rate of termination to sales. The positive estimate for β reveals that producers with a low number of suppliers display a positive response of the rate of termination to sales that counteracts the negative responses in producers with a large number of suppliers. These countervailing effects are consistent with the acyclical rate of termination at the aggregate level that is established in Figure 3.

D A brief literature review of switching costs

This section of the Appendix reviews literature on the switching cost and categorizes its various dimensions into adoption and termination costs. Switching costs are mainly incurred in two types of situations—when consumers/households switch suppliers or retailers and when producers switch suppliers/vendors. Our adoption and termination costs correspond to the switching costs in the second situation.[26]

Most theoretical work on switching costs builds on the switching costs for consumer/household purchasing. However, most of their analyses on the switching costs apply to our situation of producers switching suppliers as well. Among these works, Klemperer (1987, 1995) first provided a taxonomy of switching costs. He classified switching costs into the compatibility of equipment, transaction costs of switching suppliers, learning costs in the use of new brands, uncertainty about the quality of untested brands, loyalty costs for the issuance of discount coupons and similar marketing strategies to adopt producers, contractual costs, and psychological costs. Among these types of switching costs, compatibility of equipment, learning costs in the use of new brands, and uncertainty about the quality of untested brands are purely adoption costs; transaction, contractual, and psychological costs of switching suppliers involve both adoption and termination costs; and loyalty costs are purely termination costs. With the taxonomy of switching costs, Klemperer (1995) used a model to show that switching costs reduce competition and increase prices.

Compared to the theoretical work, empirical studies on switching costs are more recent. Scholars have examined the costs for producers to switch suppliers in an array of vendor industries, such as hardware, computer purchasing, chemical, insurance, and IT outsourcing, with IT outsourcing as the most studied industry. (Barroso and Picón, 2012; Heide and Weiss, 1995; Nielson, 1996; Ping, 1993; Whitten, 2010; Whitten et al., 2010; Whitten and Wakefield, 2006) The focus of their efforts was to identify various dimensions of switching costs. Most of the dimensions uncovered were similar to those in Klemperer (1987, 1995); however, some additional dimensions specific to the producer-supplier relationship environment were revealed. For example, Nielson

[26] Whitten and Wakefield (2006) and Van Deventer (2016) provide comprehensive reviews on the research of switching costs.

(1996), Whitten and Wakefield (2006), Whitten (2010), and Whitten et al. (2010) explored the costs of hiring and retaining skilled workers during switching, which belong to the adoption costs. Whitten and Wakefield (2006), Whitten (2010), and Whitten et al. (2010) investigated the costs of upgrading the management system along vendor switching, which entail both adoption and termination costs. Whitten and Wakefield (2006) and Whitten (2010) explored the sunk costs attendant with vendor switching (i.e., the non-recoverable time/money/effort associated with the existing vendor). The sunk costs are psychological but greatly influence the switching decision. The sunk costs belong to termination costs.

Empiricism on switching costs has also documented the important role of the costs in vendor switching. Whitten and Wakefield (2006) found that switching costs prevented producers from switching from unsatisfactory vendors. Whitten (2010) discerned that high switching costs promoted the continuation of producer-supplier relationships.

Insufficient data concerning the size of switching costs exists. However, Van Deventer (2016) collected recent examples of discontinued IT outsourcing contracts, which provided an approximate size of costs for switching vendors. The share of switching costs in the values of the organizations had a median of 6.6% and were as high as 15%.

E Proofs for propositions

Using equations (5) and (6), we have

$$\begin{aligned} 1-\left(V_i^*-\bar{V}_i^* s_{i,N}^*\right) &= \frac{\xi V_i^*-c^-}{\alpha A a_i \epsilon_i} \\ \iff \left(1+\bar{V}_i^* s_{i,N}^*\right) &= V_i^* + \frac{\xi V_i^*-c^-}{\alpha A a_i}, \end{aligned} \tag{20}$$

and

$$\left(1-\bar{V}_i^* s_{i,N}^*\right) = \frac{\xi V_i^*+c^+}{\alpha A a_i}. \tag{21}$$

Summing equations (5) and (6), we have

$$\begin{aligned} 2 &= V_i^* + \frac{2\xi V_i^*+c^+-c^-}{\alpha A a_i} \\ \iff V_i^* &= \frac{2\alpha A a_i - c^+ + c^-}{\alpha A a_i + 2\xi}. \end{aligned}$$

Taking the difference between equations (20) and (21), we have

$$\begin{aligned}2\bar{V}_i^* s_{i,N}^* &= -\frac{c^- + c^+}{\alpha A a_i} + V_i^* \\ \Longrightarrow s_{i,N}^* &= \frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} - \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right) < \frac{1}{2}\frac{V_i^*}{\bar{V}_i^*},\end{aligned} \tag{22}$$

and

$$\begin{aligned}s_{i,T}^* &= \left[\bar{V}_i^* - \left(V_i^* - \bar{V}_i^* s_{i,N}^*\right)\right] / \bar{V}_i^* \\ &= -\frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} + \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right) + 1,\end{aligned} \tag{23}$$

and

$$\begin{aligned}s_{i,E}^* &= \frac{V_i^*}{\bar{V}_i^*} - \frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} - \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right) \\ &= \frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} + \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right).\end{aligned} \tag{24}$$

In equilibrium, the output of producer i satisfies:

$$\begin{aligned}Y_i^* =& a_i A \frac{\left(2 - \bar{V}_i^* s_{i,E}^*\right) \bar{V}_i^* s_{i,E}^* + \left(2 - \bar{V}_i^* s_{i,N}^*\right) \bar{V}_i^* s_{i,N}^*}{2} \\ \Longleftrightarrow lnY_i^* =& lna_i + lnA + ln\left[\frac{\left(2 - \bar{V}_i^* s_{i,N}^*\right) \bar{V}_i^* s_{i,N}^* + \left(2 - \bar{V}_i^* s_{i,E}^*\right) \bar{V}_i^* s_{i,E}^*}{2}\right] \\ =& lna_i + lnA + ln\left[\frac{\left(2 - \bar{V}_i^* s_{i,N}^*\right) \bar{V}_i^* s_{i,N}^* + \left(2 - V_i^* + \bar{V}_i^* s_{i,N}^*\right)\left(V_i^* - \bar{V}_i^* s_{i,N}^*\right)}{2}\right].\end{aligned} \tag{25}$$

Lemma 1

Proof. Taking the partial derivative of equation (25) wrt. lnV_i^*, we have

$$\frac{\partial lnY_i^*}{\partial lnV_i^*} = \frac{Aa_i V_i^*}{Y_i^*} z_{i,E}^* > 0.$$

□

Lemma 2

Proof. Taking the partial derivative of equation (25) wrt. $s^*_{i,N}$, we have

$$
\begin{aligned}
\frac{\partial ln Y^*_i}{\partial s^*_{i,N}} =& \frac{\left(V^*_i - 2s^*_{i,N}\bar{V}^*_i\right)\bar{V}^*_i}{\frac{(2-\bar{V}^*_i s^*_{i,N})\bar{V}^*_i s^*_{i,N} + (2-V^*_i+\bar{V}^*_i s^*_{i,N})(V^*_i-\bar{V}^*_i s^*_{i,N})}{2}} \\
=& \frac{a_i A V^*_i\left(1 - 2\frac{\bar{V}^*_i s^*_{i,N}}{V^*_i}\right)\bar{V}^*_i}{Y^*_i} \\
=& \frac{(c^- + c^+)}{\alpha Y^*_i/\bar{V}^*_i} > 0,
\end{aligned}
$$

where the last equality comes from equation (22). □

Lemma 3

Proof. Combining equations (20) and (21), we have

$$
2 = V^*_i + \frac{\xi V^*_i - c^-}{\alpha A a_i} + \frac{\xi V^*_i + c^+}{\alpha A a_i}. \tag{26}
$$

Applying the implicit function theorem to equation (26), we have

$$
\begin{aligned}
\frac{dV^*_i}{dlnA} =& \frac{2\xi\bar{V}^*_i + (c^+ - c^-)}{2\xi + \alpha\bar{A}a_i} \\
=& \frac{\alpha\bar{A}a_i\left(z^*_{i,E} + z^*_{i,N}\right)}{2\xi + \alpha\bar{A}a_i} > 0.
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
\frac{d\ln V^*_i}{d\ln A} &= \frac{2\widetilde{\xi}_i\bar{V}^*_i + \left(\widetilde{c}^+_i - \widetilde{c}^-_i\right)}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)\bar{V}^*_i} \\
&= \frac{2\alpha\bar{A}/\bar{V}^*_i - \alpha\bar{A}}{2\widetilde{\xi}_i + \alpha\bar{A}}.
\end{aligned} \tag{27}
$$

When $c^+ = c^-$,

$$
\frac{d\ln V^*_i}{d\ln A} = \frac{2\widetilde{\xi}_i}{2\widetilde{\xi}_i + \alpha\bar{A}}. \tag{28}
$$

□

Lemma 4

Proof. Taking the partial derivative of equation (22) wrt. $\ln A$, we have

$$\frac{\partial s^*_{i,N}}{\partial \ln A} = \frac{\partial s^*_{i,T}}{\partial \ln A} = \frac{\widetilde{c}_i}{2\alpha \bar{A} \bar{V}^*_i} > 0. \tag{29}$$

□

Proposition 1

Proof. Taking the total derivative of equation (23) wrt. $\ln A$, we have

$$\begin{aligned}
\frac{ds^*_{i,T}}{d\ln A} &= \underbrace{-\frac{1}{2}\frac{d\ln V^*_i}{d\ln A}}_{\text{Scaling effect} < 0} + \underbrace{\frac{\widetilde{c}_i}{2\alpha \bar{A} \bar{V}^*_i}}_{\text{Switching effect} > 0} \\
&= -\frac{1}{2}\frac{2\alpha\bar{A}/\bar{V}^*_i - \alpha\bar{A}}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)} + \frac{\widetilde{c}_i/\bar{V}^*_i}{2\alpha\bar{A}}.
\end{aligned}$$

Therefore,

$$\begin{aligned}
\frac{\partial\left(\frac{ds^*_{i,T}}{d\ln A}\right)}{\partial a_i} &= \frac{1}{2}\frac{2\left(2\alpha\bar{A}/\bar{V}^*_i - \alpha\bar{A}\right)}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)^2}\left(-\frac{\widetilde{\xi}_i}{a_i}\right) - \frac{\widetilde{c}_i}{2a_i\alpha\bar{A}\bar{V}^*_i} \\
&\quad - \frac{1}{2}\left[\frac{\widetilde{c}_i}{\alpha\bar{A}} - \frac{2\alpha\bar{A}}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)}\right]\frac{1}{\left(\bar{V}^*_i\right)^2}\frac{\partial\bar{V}^*_i}{\partial a_i} \\
&= -\frac{1}{2a_i}\left[\frac{2\left(2\widetilde{\xi}_i + \left(\widetilde{c}^+_i - \widetilde{c}^-_i\right)/\bar{V}^*_i\right)\widetilde{\xi}_i}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)^2} + \frac{\widetilde{c}_i}{\alpha\bar{A}\bar{V}^*_i}\right] \\
&\quad - \frac{1}{2a_i}\left[\frac{\widetilde{c}_i}{\alpha\bar{A}} - \frac{2\alpha\bar{A}}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)}\right]\frac{1}{\left(\bar{V}^*_i\right)^2}\frac{\partial\bar{V}^*_i}{\partial a_i},
\end{aligned}$$

where the first term is always negative while the second term is negative for small a_i and positive for large a_i. Note that applying the implicit function theorem to equation (26) in the steady state, we have

$$\begin{aligned}
\frac{\partial\bar{V}^*_i}{\partial a_i} &= \frac{2\xi\bar{V}^*_i + (c^+ - c^-)}{a_i\left(2\xi + \alpha\bar{A}a_i\right)} \\
&= \frac{\alpha\bar{A}\left(z^*_{i,E} + z^*_{i,N}\right)}{2\xi + \alpha\bar{A}a_i} > 0.
\end{aligned}$$

Thus, when a_i increases, $ds^*_{i,T}/d\ln A$ first declines and then increases.

Note that

$$\begin{aligned}\frac{ds^*_{i,T}}{d\ln A} &= -\frac{1}{2}\frac{2\alpha\bar{A}/\bar{V}^*_i - \alpha\bar{A}}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)} + \frac{\widetilde{c}_i/\bar{V}^*_i}{2\alpha\bar{A}} \\ &= \frac{1}{2\bar{V}^*_i}\left(\frac{\widetilde{c}_i}{\alpha\bar{A}} - \frac{2\alpha\bar{A}}{2\widetilde{\xi}_i + \alpha\bar{A}}\right) + \frac{1}{2}\frac{\alpha\bar{A}}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)}.\end{aligned}$$

Assume both ξ and $c^+ + c^-$ are sufficiently large. When a_i approaches zero, $2\alpha\bar{A}/\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)$ goes to zero and $\widetilde{c}_i/(\alpha\bar{A})$ becomes extremely positive. Therefore, $ds^*_{i,T}/d\ln A$ is positive. When a_i approaches positive infinite, $\widetilde{\xi}_i$ and $\widetilde{c}_i$ both go to zero, and

$$\frac{ds^*_{i,T}}{d\ln A} = -\frac{2}{2\bar{V}^*_i} + \frac{1}{2} = -\frac{2-\bar{V}^*_i}{2\bar{V}^*_i} < 0.$$

Given that $ds^*_{i,T}/d\ln A$ is continuous in a_i, $ds^*_{i,T}/d\ln A$ is positive when a_i is small, and negative when a_i is large. In other words, the rate of termination is countercyclical for producers with high idiosyncratic productivity, but procyclical for producers with low idiosyncratic productivity.

When $c^- = c^+ = 0$, we have

$$\begin{aligned}\frac{ds^*_{i,N}}{d\ln A} &= \frac{1}{2}\frac{d\ln V^*_i}{d\ln A} > 0, \\ \frac{ds^*_{i,T}}{d\ln A} &= -\frac{1}{2}\frac{d\ln V^*_i}{d\ln A} < 0,\end{aligned}$$

i.e., procyclical adoption and countercyclical termination (Schumpeterian cleansing) for all producers. □

Lemma 5

Proof. Taking the total derivative of equations (22) and (24) wrt. $\ln A$, we have

$$\begin{aligned}\frac{ds^*_{i,N}}{d\ln A} &= \frac{1}{2}\frac{d\ln V^*_i}{d\ln A} + \frac{1}{2}\frac{\widetilde{c}_i}{\alpha\bar{A}\bar{V}^*_i}, \\ \frac{ds^*_{i,E}}{d\ln A} &= \frac{1}{2}\frac{d\ln V^*_i}{d\ln A} - \frac{1}{2}\frac{\widetilde{c}_i}{\alpha\bar{A}\bar{V}^*_i}.\end{aligned}$$

Taking the total derivative of equation (25) wrt. $\ln A$, we have

$$\frac{d\ln Y_i^*}{d\ln A} = 1 + \frac{\left(1-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}}\frac{ds_{i,N}^*}{d\ln A}$$
$$+\frac{\left(1-\bar{V}_i^*\bar{s}_{i,E}^*\right)\bar{V}_i^*}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}}\frac{ds_{i,E}^*}{d\ln A}$$
$$=1+\frac{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,E}^*-\bar{V}_i^*\bar{s}_{i,N}^*\right)}{2}\bar{V}_i^*}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}}\frac{d\ln V_i^*}{d\ln A}$$
$$+\frac{1}{2}\frac{\widetilde{c}_i}{\alpha\bar{A}\bar{V}_i^*}\frac{\left(\bar{s}_{i,E}^*-\bar{s}_{i,N}^*\right)\bar{V}_i^{*2}}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}} > 0.$$

Further taking the cross-derivative wrt. $\widetilde{c}_i$ and $\widetilde{\xi}_i$, respectively, we have

$$\frac{\partial\left(\frac{d\ln Y_i^*}{d\ln A}\right)}{\partial\widetilde{c}_i} = \frac{1}{2}\frac{1}{\alpha\bar{A}\bar{V}_i^*}\frac{\left(\bar{s}_{i,E}^*-\bar{s}_{i,N}^*\right)\bar{V}_i^{*2}}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}} > 0,$$
$$\frac{\partial\left(\frac{d\ln Y_i^*}{d\ln A}\right)}{\partial\widetilde{\xi}_i} = \frac{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,E}^*-\bar{V}_i^*\bar{s}_{i,N}^*\right)}{2}\bar{V}_i^*}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}}\frac{\partial\left(\frac{d\ln V_i^*}{d\ln A}\right)}{\partial\widetilde{\xi}_i}$$
$$=\frac{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,E}^*-\bar{V}_i^*\bar{s}_{i,N}^*\right)}{2}\bar{V}_i^*\alpha\bar{A}}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}}\left[-2\frac{2/\bar{V}_i^*-\alpha}{\left(2\widetilde{\xi}_i+\alpha\bar{A}\right)^2}-\frac{2}{\bar{V}_i^{*2}\left(2\widetilde{\xi}_i+\alpha\bar{A}\right)}\frac{\partial\bar{V}_i^*}{\partial\widetilde{\xi}_i}\right]$$
$$=\frac{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,E}^*-\bar{V}_i^*\bar{s}_{i,N}^*\right)}{2}\bar{V}_i^*\alpha\bar{A}}{\frac{\left(2-\bar{V}_i^*\bar{s}_{i,N}^*\right)\bar{V}_i^*\bar{s}_{i,N}^*+\left(2-\bar{V}_i^*+\bar{V}_i^*\bar{s}_{i,E}^*\right)\left(\bar{V}_i^*-\bar{V}_i^*\bar{s}_{i,E}^*\right)}{2}}\frac{2\alpha\bar{V}_i^*}{\bar{V}_i^*\left(2\widetilde{\xi}_i+\alpha\bar{A}\right)^2} > 0.$$

□

Proposition 2

Proof. Immediately following Lemma 5, we have

$$\frac{\partial\left(\frac{d\ln Y^*}{d\ln A}\right)}{\partial(c^++c^-)} = \sum_i \frac{\partial\left(\frac{d\ln Y_i^*}{d\ln A}\right)}{\partial\widetilde{c}_i}\frac{\bar{Y}_i^*}{a_i\bar{Y}^*} > 0,$$

and

$$\frac{\partial\left(\frac{d\ln Y^*}{d\ln A}\right)}{\partial\xi} = \sum_i \frac{\partial\left(\frac{d\ln Y_i^*}{d\ln A}\right)}{\partial\widetilde{\xi}_i}\frac{\bar{Y}_i^*}{a_i\bar{Y}^*} > 0.$$

□

Proposition 3

Proof. Immediately following Lemma 3, we have

$$\frac{dV^*}{d\ln A} = \sum_i \frac{dV_i^*}{d\ln A}\frac{\bar{Y}_i^*}{\bar{Y}^*} > 0.$$

□

Proposition 4

Proof.

$$\frac{ds_{i,N}^*}{d\ln A} = \frac{1}{2}\frac{d\ln V_i^*}{d\ln A} + \frac{1}{2}\frac{\widetilde{c}_i}{\alpha\bar{A}\bar{V}_i^*} > 0.$$

Therefore,

$$\frac{ds_N^*}{d\ln A} = \sum_i \frac{ds_{i,N}^*}{d\ln A}\frac{\bar{Y}_i^*}{\bar{Y}^*} > 0.$$

□