The Adoption and Termination of Suppliers over the Business Cycle[†]

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Abstract

We assemble a firm-level dataset to study the adoption and termination of suppliers over business cycles. We document that the aggregate number and rate of adoption of suppliers are procyclical. The rate of termination is acyclical at the aggregate level, and the cyclicality of termination encompasses large differences across producers. To account for these new facts, we develop a model with optimizing producers that incur separate costs for management, adoption, and termination of suppliers. These costs alter the incentives to scale up production and to replace existing with new suppliers. Sufficiently high convexity in management relative to adjustment costs is crucial to replicating the observed cyclicality in the adoption and termination rates at the producer and aggregate levels. We study the welfare implications of credit injections and subsidies on new inputs—the two main classes of supply-chain policies adopted in the U.S. since the COVID-19 pandemic. Credit injections generally outperform subsidies on new inputs, except when aggregate TFP is exceptionally high.

Keywords: management and adjustment costs, adoption and termination of suppliers, business cycles.

JEL: E32, L14, L24.

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1. Introduction

Production of final output in modern economies requires inputs from multiple suppliers, so the adoption, termination, and management of suppliers are important decisions in 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] Consequently, 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 forces explain the empirical regularities? What are the different welfare effects of the main classes of supply-chain policies adopted in the U.S.?

We study these questions, combining different datasets and providing novel facts regarding the adoption and termination of suppliers at the producer and aggregate levels. To account for our new evidence, we develop a model of optimizing producers that manufacture output using both new and existing suppliers. The model shows the central roles of the costs of managing and adjusting suppliers in accounting for the empirical patterns. We extend the baseline model by adding credit constraints on producers to study the welfare impacts of the policies of credit injection and subsidies for inputs from new suppliers—implemented by the U.S. government since the COVID-19 pandemic. In the extended model, the inefficiencies arising from management and adjustment costs (due to incomplete contracting) and credit constraints generate *under*-adjustments in the number of suppliers. The two policies enhance welfare by directly relaxing credit constraints and promoting the adjustment of suppliers, respectively. Moreover, credit injections generally outperform subsidies to new inputs, except when aggregate TFP is exceptionally high. The convexity in the cost functions plays a critical role in replicating the empirical patterns of adoption and termination and determining the welfare effects of the supply-chain policies.

Our new evidence on the adoption and termination of suppliers is obtained via merging two datasets: the FactSet Revere Supply Chain Relationships data—which record producer-supplier relations, including adoption and termination of suppliers—and CompuStat Fundamentals—which provide information on producers' output, financial positions, and administrative costs. 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 three novel facts.

Fact 1 studies the dynamics of adoption and termination of suppliers at the aggregate level over the business cycle. It decomposes the procyclical changes in the aggregate number of suppliers into the rates of adoption and termination of suppliers, establishing that the aggregate rate of adoption is procyclical and that the aggregate rate of termination is acyclical. This fact differs from the churning of jobs in the labor market. Though job creation is procyclical (as is supplier adoption), job destruction is countercyclical

[1] See Feenstra, Heizer et al. (2016), and Stevenson (2018) for a summary of the literature on supply chain management.

(unlike acyclical supplier termination).

Fact 2 shows that the acyclical aggregate rate of termination conceals large heterogeneity in the cyclicality of the termination rate across producers having different numbers of suppliers. The termination rate is countercyclical for producers with a large number of suppliers but procyclical for producers with a small number of suppliers; this is in stark contrast to the more countercyclical job destruction for larger than smaller establishments in the labor market. The aggregate acyclicality in the rate of termination results from the countervailing adjustments in the termination of suppliers across producers with different numbers of suppliers.

Fact 3 uses instrumental variable regressions to study the link between the sales of producers and the adjustments in the total number of suppliers, the adoption of new suppliers, and the termination of existing suppliers. It shows the distinct positive returns from *more* and *new* relationships for producers when adopting and terminating suppliers.

To account for Facts 1-3, we develop a model with producers that use a continuum of intermediate inputs supplied by two vintages of suppliers—the existing and new ones. Producers have different idiosyncratic productivities, and they incur separate costs for the management, adoption, and termination of suppliers. Due to the decreasing returns to scale in each production line and the adjustment costs that increase the marginal product of new suppliers compared to existing suppliers, our model encompasses distinct returns from more and new relationships, consistent with Fact 3.

Management and adjustment costs have different implications for changes in the adoption and termination of suppliers. *Management costs* constrain the scale of operations through decreasing the adoption of new suppliers and increasing the termination of existing suppliers. *Adjustment costs* discourage both the adoption of new and the termination of existing suppliers and influence the composition of suppliers. Accordingly, the two separate costs lead to two distinct effects of the aggregate TFP on the adoption and termination of suppliers. One is the *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 the *switching effect*: the higher TFP reduces the relevance of adjustment costs for the producer's profits, engendering greater churning of suppliers. This effect induces a rise in both the rates of adoption and termination of suppliers. Scaling and switching effects jointly generate a positive correlation between the adoption of new suppliers and aggregate TFP, consistent with Facts 1 and 2. In contrast, the two forces exert countervailing effects on the correlation between the rate of termination and TFP.

The model reveals that producers' different measures of suppliers—determined by their idiosyncratic productivities in the model—are critical to the heterogeneous responses of the termination rates 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 2, producers with a large (vs. a small) measure of suppliers display a negative (vs. a positive) response of the termination rate to changes in aggregate TFP—which is driven by the dominating scaling (vs. switching) effect.

At the aggregate level, the cyclicality of the *aggregate* rates of adoption and termination depends on producers' distribution of idiosyncratic productivity and the size of management and adjustment costs that determine the relative strength of the scaling and switching effects. We calibrate the model to U.S. data and show that it replicates the heterogeneous cyclicality in the adoption and termination rates across producers, as well as the procyclical aggregate rate of adoption and the acyclical aggregate rate of termination, consistent with our Facts 1 and 2.

We show that adopting *strictly convex* management costs and *linear* adjustment costs—in contrast to the standard assumptions of *linear* management costs in the network literature (e.g., Huneeus, 2018; Lim, 2018) and *strictly convex* adjustment costs in the labor literature (e.g., Zanetti, 2008)—is critical for replicating the empirical patterns of the cyclicality in the termination of suppliers. In the counterfactual economy with linear management and strictly convex adjustment costs, producers—particularly large ones—use limited resources to cover the adjustment costs, and the switching effect is homogeneous across different producers. The scaling effect dominates and is more significant for small than for large producers. This results in a countercyclical aggregate rate of termination and more countercyclical rate of termination for small than large producers. These findings are in contrast to the cyclicality of supplier termination but consistent with the cyclicality of job destruction in Facts 1 and 2.

We use an enriched version of our model with credit constraints on producers to study two main classes of supply-chain policies that the U.S. government implemented in the aftermath of the COVID-19 pandemic: (i) credit injection policy that alleviates credit constraints of producers, and (ii) subsidies for new inputs that promote the replacement of existing with new suppliers.[2]

Credit injections improve welfare by reducing the inefficiencies arising from financial frictions and promoting both scale of production and the replacement of existing with new suppliers. However, the welfare improvement declines with the aggregate TFP as fewer producers face credit constraints. In contrast, the subsidies on new inputs uniformly increase the aggregate welfare across different levels of aggregate TFP. This is because they reduce the inefficiency arising from the adjustment costs among all producers.

[2]Section 7.1 reviews the recent U.S. policies and legislation to support the resilience of the supply chain from the outset of the COVID-19 pandemic.

The government should adopt the policy of credit injection that generally outperforms subsidies on new inputs—given the magnitudes of financial frictions and management and adjustment costs calibrated from the data—except when the aggregate TFP is exceptionally high. Credit injections generate the largest output improvement in medium-sized producers that are more financially constrained than small or large producers. Specifically, compared to large producers, their external financing is more constrained; compared to small producers, they need more external financing to pay for the management costs that are strictly convex. These results hinge on our estimated convexity of management costs and linear adjustment costs. In a counterfactual economy with linear management costs and strictly convex adjustment costs, credit injections always outperform subsidies on new inputs, and the smallest producers experience the highest output improvement.

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. Related work primarily focuses on the network structure of producer-supplier relations (Atalay, 2017; Acemoglu and Tahbaz-Salehi, 2023; Grassi, 2017; Huneeus, 2018; Qiu et al., 2024) and the cyclical rate of relationship creation (Fernández-Villaverde et al., 2019, 2021).[3] Instead, we document new empirical facts on the vintage structure of producer-supplier relations and the acyclical rate of relationship separation (i.e., termination of suppliers), focusing on the critical role of management and adjustment costs in replicating these facts and the welfare implications of the major classes of U.S. government policies since the COVID-19 pandemic.

Our study also contributes to literature that documents cyclical reallocation of productive factors such as labor (e.g., Burstein et al., 2020; Caballero and Hammour, 1994), intermediate inputs (e.g., Baqaee and Burstein, 2021; Burstein et al., 2024), and capital (Lanteri et al., 2023). Our management costs that generate the scaling effect are similar to fixed costs in the network literature (e.g., Huneeus, 2018; Lim, 2018). Our adjustment costs that generate the switching effect are similar to adjustment costs in the labor literature (e.g., Caballero and Hammour, 1994; Mumtaz and Zanetti, 2015; Zanetti, 2008). We show that the degrees of convexity in these two costs are critical to replicate the differences in the cyclicality of the rate of termination across producers with different suppliers. While Caballero and Hammour (1994) document countercyclical destruction of jobs (i.e., "the cleansing effect"), we document that the cleansing effect is absent for the aggregate termination of suppliers, which is acyclical in the data. We are the first study to show the critical role of convexity in management and adjustment costs for replicating the cyclical adoption and termination of suppliers—as opposed to the creation and destruction of jobs in the labor churning literature—and for determining the impacts of different supply-chain policies.

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

[3] A notable exception is Baqaee et al. (2023), who quantify the causal effect of the addition and separation of suppliers on producers' marginal costs using Belgian data and their impacts on aggregate productivity.

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 provides policy analyses as applications to the model. Section 8 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 producer and supplier firms report. The data comprise a record of 784,325 producer-supplier relationships that include the beginning and ending 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 producers' financial variables (i.e., sales, profits, and administrative costs). Described in Appendix A are 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.

Using the above data, we first define our main variables of interest. We denote by variable $v_{i,t}$ the number of suppliers that are in partnerships with the producer i in year t. 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). In the data, 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. Shown in Table A.3 in Appendix A are the summary statistics of the rates of adoption and termination at the producer level.

To study the economy-wide changes in the total number and churning 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 expenditures to construct the aggregate 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, respectively. By construction, we have $\Delta v_t/v_{t-1} = s_{N,t} - s_{T,t}$.

3. Empirical results on adoption and termination of suppliers

In this section, we establish three novel facts on producer-supplier relations. Fact 1 shows that the aggregate adoption of new suppliers is procyclical, while the aggregate termination of existing suppliers is acyclical. Fact 2 studies the cross-sectional patterns of adoption and termination and reveals the dispersion in their cyclicalities across producers with different sizes. Fact 3 shows that the output of producers increases with the total number, the adoption, and the termination of producer-supplier relationships.

Fact 1: Procyclical adoption and acyclical termination of suppliers

We focus on aggregate adoption and termination rates that jointly determine the aggregate number of suppliers. Figure 1 decomposes the growth rate of the aggregate index of the number of suppliers (i.e., $\Delta v_t / v_{t-1}$, solid green line with circles) into the following metrics: (i) the aggregate rate of adoption (i.e., $s_{N,t}$, solid red line with circles), and (ii) the aggregate rate of termination (i.e., $s_{T,t}$, dash-dotted blue line) of suppliers, according to $\Delta v_t / v_{t-1} = s_{N,t} - s_{T,t}$. 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. In general, the level of the aggregate adoption rate is higher than the aggregate termination rate, generating an upward trend in the aggregate number of suppliers. This is consistent with the increasingly denser input-output networks (Acemoglu and Azar, 2020; Ghassibe, 2023).

To study the co-movements between aggregate rates of adoption and termination and aggregate economic activity, Figure 1 also shows the growth rate of real output (i.e., solid black line). The aggregate rate of adoption closely co-moves with the growth rate of real output, evincing a strong procyclical pattern. The correlation between these two series is 0.69 and is significant at the 1% level. The aggregate rate of adoption increases from 11% in 2009 to 45% in 2011, concomitant to a period of significant economic expansion. In contrast, the aggregate rate of termination is largely acyclical, with a correlation of -0.26 with the growth rate of output, which is not significant at the 10% level.[4]

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

$$\frac{Cov\big(\Delta v_t / v_{t-1}, s_{N,t}\big)}{Var\big(\Delta v_t / v_{t-1}\big)} + \frac{Cov\big(\Delta v_t / v_{t-1}, -s_{T,t}\big)}{Var\big(\Delta v_t / v_{t-1}\big)} = 1. \tag{1}$$

The derivation of equation (1) is described in Appendix A. The decomposition establishes that the contribution of aggregate adoption rate to changes in the aggregate number of suppliers (i.e., the first term in equation 1) equals 83%, and the contribution of the aggregate termination rate equals 17%. Together with the results shown in Figure 1, our analysis consistently reveals that the aggregate adoption rate is the main driver of fluctuations in the aggregate number of suppliers, but the aggregate termination rate plays a subsidiary role.

[4] Figure A.9 in Appendix A shows that the cyclical patterns of aggregate rates of adoption and termination are very similar under alternative methods of aggregation, particularly with constant weights over time.

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 study of 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.

Fact 2: Heterogeneous cyclicality in the adoption and termination of suppliers among producers

In Fact 2, we link procyclicality of aggregate adoption and acyclicality of aggregate termination (established in Fact 1) to differences in the cyclicalities in the adoption and termination rates across producers with different numbers of suppliers. Additionally, we compare these patterns to the labor market cyclicality of job creation and destruction across establishments with different numbers of employees.

Figure 2 shows in panels (a) and (b) the scatter plots of the logarithm of the number of suppliers (x-axis) against the cyclicality of the rates of adoption and termination (y-axis) for the producers in our sample. To reduce noise at the producer level, we categorized all producers into 10 groups according to their average numbers of suppliers over the years. Each red circle on the graph represents one of these groups. For each group, we computed the annual group-wise adoption and termination rates, which were used to calculate the cyclicality of these rates on the y-axis.

Panel (a) in Figure 2 shows that the adoption rate is procyclical across all producers, consistent with the procyclical aggregate rate of adoption shown in Figure 1. Moreover, the adoption rate is more procyclical for producers with fewer suppliers compared to those with more suppliers, as evinced by the downward-sloping fitted line (blue). Similarly, panel (b) in the figure shows that the termination rate is also more procyclical for producers with fewer suppliers than for those with more suppliers, as manifested by the downward-sloping fitted line (blue). However, the termination rate is *procyclical* only for producers with fewer suppliers that are likely to terminate existing suppliers during economic expansions but retain them during downturns. In contrast, the termination rate is *countercyclical* for producers with more suppliers that retain existing suppliers during economic expansions but terminate them during economic downturns. Interestingly, panel (b) also shows that the shares of producers with procyclical and countercyclical termination rates are roughly equal, resulting in an overall acyclical rate of termination. This result is consistent with the acyclical rate of termination at the aggregate level as documented in Figure 1 of Fact 1.

For comparison, Figure 3 shows in panels (a) and (b) the scatter plots of the employment of establishments (x-axis) against the cyclicality of the job creation and destruction rates in the labor market (y-axis) for establishments with different numbers of employees.[5] Panel (a) in Figure 3 shows that the cyclicality of job creation closely mirrors the cyclicality of supplier adoption in panel (a) of Figure 2: establishments uni-

[5]The U.S. Bureau of Labor Statistics publishes the annual rates of job creation and destruction for ten groups of establishments categorized by employee count: "1 to 4," "5 to 9," "10 to 19," "20 to 99," "100 to 499," "500 to 999," "1000 to 2499," "2500 to 4999," "5000 to 9999," and "10000+."

formly entail procyclical job creation (with small establishments displaying more pronounced procyclicality than big ones).

In contrast, panel (b) in Figure 3 shows that the cyclicality of job destruction differs significantly from the cyclicality of supplier termination in panel (b) of Figure 2. In particular, all establishments display countercyclical job destruction, with smaller ones showing more pronounced countercyclicality than larger ones, as indicated by the upward-sloping fitted line (blue). This finding stands in stark contrast to the more procyclical termination rates observed for smaller producers in panel (b) of Figure 2.

Fact 3: Returns from more and from new relationships

Motivated by the comovements between adoption and termination rates and the aggregate output documented in Fact 2, we use instrumental variable regressions to study the link between the real sales of producers and the total number of suppliers, the adoption of new suppliers, and the termination of existing suppliers. Our analysis aims to quantify the separate returns from *more* and *new* relationships. Specifically, we estimate the following panel regressions:

$$d\ln(sale_{i,t}) = \beta_0 + \beta_1 d\ln(v_{i,t}) + \beta_2 x_{i,t} + \beta_3 \ln(v_{i,t-1}) + \beta_4 \ln(sale_{i,t-1}) + \alpha_i + \gamma_t + \epsilon_{i,t}, \qquad (2)$$
$$\text{where} \quad x_{i,t} \in \{s_{i,N,t}, s_{i,T,t}, s_{i,CH,t}\},$$

where the dependent variable is the growth rate of the producer's real sales ($d\ln(sale_{i,t})$). On the right-hand side of regression (2), $d\ln(v_{i,t})$ is the growth rate of the total number of suppliers. $x_{i,t}$ includes producer i's adoption rate ($s_{i,N,t}$), termination rate ($s_{i,T,t}$), and the churning rate that is defined as the minimum of the adoption and termination rates (i.e., $s_{i,CH,t} = \min\{s_{i,N,t}, s_{i,T,t}\}$). The terms α_i and γ_t are the producer and year fixed-effects, respectively. We control for the total number of suppliers and sales of producer i in the previous year, as they may influence the sales in the current year. A positive β_1 indicates the returns from more relationships, while a positive β_2 reflects the returns from new relationships. This is because the adoption of new suppliers, the termination of existing suppliers, and the churning of suppliers all contribute to a newer portfolio of suppliers for the producer.

A potential endogeneity issue arises because both sales and the number of suppliers (as well as the adoption, termination, and churning rates) are influenced by changes in producers' productivity and other business conditions that are missing in our regression, thus making the OLS estimates potentially biased. To address this issue, we construct Bartik-type instrumental variables. These instrumental variables aim to capture exogenous changes in each producer's $v_{i,t}$ and $x_{i,t}$ by leveraging variations in the number of suppliers at the sectoral level. Specifically, we define:

$$\widehat{s}_{i,N,t} = \sum_j \omega_{i,t_0(i)}(j) \cdot s_{N,t}(j) \quad \text{and} \quad \widehat{s}_{i,T,t} = \sum_j \omega_{i,t_0(i)}(j) \cdot s_{T,t}(j), \qquad (3)$$

where $\omega_{i,t_0(i)}(j)$ is the share of producer i's suppliers in sector j at the initial period $t_0(i)$ of producer

i's appearance in the sample. $s_{N,t}(j)$ and $s_{T,t}(j)$ are the sectoral rates of adoption and termination for sector j.[6] The key idea of the instrumental variable is that neither $s_{N,t}(j)$ (vs. $s_{T,t}(j)$) nor $\omega_{i,t_0(i)}(j)$ is endogenously determined by changes in producer i's productivity and other business conditions between t_0 and t. Intuitively, $\omega_{i,t_0(i)}(j)s_{N,t}(j)$ and $\omega_{i,t_0(i)}(j)s_{T,t}(j)$ serve as natural predictions of producer i's rates of adoption and termination of suppliers from sector j. Thus, $\widehat{s}_{i,N,t}$ and $\widehat{s}_{i,T,t}$ predict producer i's adoption and termination rates, and consequently predict churning and growth rates of the number of suppliers. Table B.4 in Appendix B shows the first-stage results, verifying that $\widehat{s}_{i,N,t}$ and $\widehat{s}_{i,T,t}$ predict the foregoing variables.

Table 1 presents the estimation results of regression (2), where the growth rate of the number of suppliers, as well as the rates of churning, adoption, and termination, are instrumented using Bartik-type IVs, as specified in equation (3).[7] Column (1) shows that an increase in the number of suppliers raises the sales of producers, as evidenced by the positive coefficients for the growth rate of the number of suppliers. This finding indicates a positive *return from more relationships*, corroborating the central tenet of the "returns from more varieties" in models of varieties (Hamano and Zanetti, 2017). Using the constructed instrumental variables, our results establish *causal effects* of the number of suppliers on sales, contributing to the existing literature focused on the correlation between the number of suppliers on sales (e.g., Lim 2018 for the U.S., Bernard et al. 2019 for Japan, and Arkolakis et al. 2023 for Chile). A notable exception is Baqaee et al. (2023); they study the causal effect of the number of suppliers on producers' marginal costs in Belgium, using an alternative instrumental variable.[8]

Column (2) shows that supplier churning also enhances sales growth. Specifically, a 1% increase in churning rate is associated with a 1.3% rise in the growth rate of sales, which is economically significant and indicates a positive *return from new relationships*. This *return from new relationships* echoes the "creative destruction," as documented in Baqaee et al. (2023). Columns (3)-(5) further investigate the effects of adopting new suppliers and terminating existing ones on sales growth. The positive coefficients for the rates of adoption and termination indicate that both actions raise the producer's sales, conditional on the growth rate of the number of suppliers. Therefore, both adoption and termination contribute to the positive *return from new relationships* documented in column (2).[9]

[6]Specifically, $\omega_{i,t_0(i)}(j) \equiv v_{i,t_0(i)}(j)/v_{i,t_0(i)}$, where $v_{i,t_0(i)}(j)$ is the number of producer i's suppliers in sector j, while $v_{i,t_0(i)}$ is the total number of producer i's suppliers. We classify sectors according to one-digit NAICS industries. $s_{N,t}(j) \equiv v_{N,t}(j)/v_{t-1}(j)$ and $s_{T,t}(j) \equiv v_{T,t}(j)/v_{t-1}(j)$. $v_{t-1}(j)$, $v_{N,t}(j)$, and $v_{T,t}(j)$ are the total number, the adoption, and the termination of sector j suppliers, respectively. The sectoral rates of adoption and termination of suppliers are regressed on the year and sector fixed effects, and we use the residuals as the shocks in the sectoral rates of adoption and termination for the construction of the Bartik-type instrumental variables. We also define $s_{CH,t}(j) \equiv \min\{s_{N,t}(j), s_{T,t}(j)\}$ and construct $\widehat{s}_{i,CH,t} = \sum_j \omega_{i,t_0(i)}(j) \cdot s_{CH,t}(j)$ as the Bartik-type instrumental variable for the rate of churning.

[7]Tables B.5 in Appendix B presents the OLS regression results for regressions in Table 1. The coefficients in the OLS regressions have similar signs as those in the 2SLS IV regressions. However, they are less significant both economically and statistically due to the strong reverse causality between the sales and the total number of suppliers, adoption, and termination.

[8]Baqaee et al. (2023) use the restricted subsets of birth and death of upstream suppliers of the producer to instrument the addition and separation of suppliers by the producer.

[9]Notably, we include only one of $s_{i,N,t}$ and $s_{i,T,t}$ in columns (3)-(4) because including two of them is colinear with $d\ln(v_{i,t})$ as $d\ln(v_{i,t}) = s_{i,N,t} - s_{i,T,t}$. Also note that the coefficient of the growth rate of the total number of suppliers is negative and

4. A model of adoption and termination of suppliers

We now develop a model with optimal choices for the costly adoption, termination, and management of suppliers, which allows us to replicate Facts 1-3 documented in the previous section.

4.1. Baseline environment and timing

The economy is static, and it is populated by a continuum of final-goods producers $i \in [0, 1]$. Each producer i has an idiosyncratic productivity a_i drawn from a log-normal distribution with zero mean and standard deviation σ_a; this is the only source of heterogeneity in the model.[10] We assume that there is no shock to 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 $\bar{V}_i^*$.[11] Each producer optimally sets the mix of existing and new suppliers to maximize profits. The adjustment in the measure of suppliers involves costs for termination (c^-) and adoption (c^+) of suppliers. Prices of intermediate inputs are determined by Nash bargaining between the producer and suppliers. Producer i manufactures the final good (Y_i) using the supplied inputs from new and existing suppliers at the established price. Summarized in Figure H.11 in Appendix H is the model's timeline.

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.[12]

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less significant in column (3) than in the other columns, as the changes in the total number of suppliers are mainly driven by the adoption of new suppliers. Controlling for the rate of adoption, the rate of termination—which is negatively associated with the total number of suppliers—increases the producer's sales by replacing existing suppliers with new ones, thus making the coefficient of the total number of suppliers negative.

[10] In our stylized model, the heterogeneity in the number of suppliers across different producers is uniquely determined by the producer's idiosyncratic productivity. In the data, however, the number of suppliers of individual producers can be influenced by several factors other than productivity (e.g., the management cost parameter (ξ_i), capital stock, and employment).

[11] 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 with which the producer starts $(\bar{V}_i^*)$ 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., $V_i^*(\bar{V}_i^*, \bar{A}) = \bar{V}_i^*$.

[12] 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.

4.3. *Producers and the bargained input 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:

$$y_{i,k}\left(z_k\right) = A a_i z_k, \quad \forall\, k \in \{E, N\}, \, \forall\, z_k,$$

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, $y_{i,k}\left(z_k\right)$, which 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:

$$p_{i,k}(z_k) = (1-\alpha) TS_{i,k}(z_k), \quad \forall\, i \in [0,1], \, \forall\, k \in \{E, N\}, \, \forall\, z_k, \tag{4}$$

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. Specifically, 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, producer i terminates existing suppliers whose idiosyncratic productivity levels are insufficient to generate profits and therefore terminates existing suppliers with $z_E \in [1-\bar{V}_i^*, z_{i,E})$. 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 $s_{i,N} = \left(1-z_{i,N}\right)/\bar{V}_i^*$ and $s_{i,T} = \left(z_{i,E}-1+\bar{V}_i^*\right)/\bar{V}_i^*$.

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 (Lucas Jr, 1978) and the "diminishing returns to management" (Coase, 1991). Following Gopinath and Neiman (2014), we assume a quadratic management cost that is a function of the total measure of production lines: $G\left(z_{i,N}, z_{i,E}\right) = \xi \cdot V_i^2/2$, 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.[13]

[13] In Appendix C, we use the indirect inference method in Gourieroux et al. (1993) and follow the identification strategy of Arkolakis et al. (2023) to estimate the curvature of the management cost function to be 2.2 approximately, which is close to our calibration.

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^{-}. We defer the discussion on the functional form of management and adjustment costs to Section 5.2.1.

Consistent with the seminal idea in Coase (1991) and subsequent studies, we assume that both management and adjustment costs are not contractable and, therefore, are paid entirely by producers—in consequence to asset specificity and appropriability problems, as studied in Caballero and Hammour (1996).[14]

Inefficiencies associated with the costs. We assume that the *whole* costs of managing and adjusting suppliers are labor income of hired households that contributes to consumption and welfare rather to social costs. In our context of producer-supplier relationships, two sources of inefficiency naturally emerge from the producers' costs of managing and adjusting suppliers: first, since the producers earn a fraction of α of output while bearing the *entire* costs of managing and adjusting suppliers, the private benefits of managing and adjusting suppliers perceived by the producers are lower than the social benefits. Second, since all producers' private costs are the labor income of hired households that contributes to consumption and welfare rather than social costs, the private costs of managing and adjusting suppliers are higher than the social costs. Both sources of inefficiency lead producers to under-adjust the total measure of suppliers and the adoption of new suppliers, requiring the adoption of subsidies on the producers' management and adjustment costs to retain efficiency. The policy of subsidies on inputs from new suppliers that we will study in Section 7 partially offsets the inefficiency associated with the adjustment costs.

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:[15]

$$Y_i = \int_{z_{i,E}}^{1} y_{i,E}(z_E)dz_E + \int_{z_{i,N}}^{1} y_{i,N}(z_N)dz_N, \tag{5}$$

[14]Specifically, if a complete contract cannot be written and enforced on sharing the management and adjustment costs that are specific assets for the producer, the quasi-rents from these specific assets are potentially appropriable, so the producer will incur the entire costs.

[15]We assume separable production lines from different suppliers—particularly new versus existing suppliers—to retain the tractability of the model and obtain transparent analytical results. If we aggregate production lines using a CES aggregator, the degree of complementarity between suppliers rises—which increases the returns from new relationships and generates a stronger switching effect (as described in Section 5.2)—resulting in a greater heterogeneity in the cross-sectional cyclicality of termination.

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

$$\Pi_i = \max_{\{z_{i,E}, z_{i,N}\}} \underbrace{\int_{z_{i,E}}^{1} y_{i,E}(z_E) dz_E + \int_{z_{i,N}}^{1} y_{i,N}(z_N) dz_N}_{\text{Final output}} - \underbrace{\left(\int_{z_{i,E}}^{1} p_{i,E}(z_E) dz_E + \int_{z_{i,N}}^{1} p_{i,N}(z_N) dz_N \right)}_{\text{Input costs}}$$
$$- \underbrace{\left[c^- \left(z_{i,E} - 1 + \bar{V}_i^* \right) + c^+ \left(1 - z_{i,N}\right) \right]}_{\text{Adjustment costs}} - \underbrace{\xi \cdot \left(2 - z_{i,N} - z_{i,E}\right)^2 / 2}_{\text{Management cost}}, \tag{6}$$

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

Combining the bargained input price in equation (4) with equation (6) 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 $z_{i,N}^*$:

$$z_{i,E}^* + \frac{c^-}{\alpha A a_i} = \frac{\xi V_i^*}{\alpha A a_i}, \tag{7}$$
$$z_{i,N}^* - \frac{c^+}{\alpha A a_i} = \frac{\xi V_i^*}{\alpha A a_i}, \tag{8}$$

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

Equations (7) and (8) 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, and the cost of termination (c^-) increases the marginal benefit of retaining existing suppliers. Combining equations (7) and (8) yields:

$$z_{i,N}^* - z_{i,E}^* = \frac{c^+ + c^-}{\alpha A a_i} > 0. \tag{9}$$

Equation (9) shows that the adjustment costs generate the differential in 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 incentive 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 1-3. We begin by presenting the returns from more and new relationships that directly result from the model and generate Fact 3 (Section 5.1). We then analyze the cross-sectional cyclicality of termination across producers with different productivity to study Fact 2 (Section 5.2.1). We conclude by extending the analysis to the aggregate economy to study Fact 1 (Section 5.2.2).

5.1. Returns from more relationships and new relationships (Fact 3)

Our model directly generates returns from more relationships and from new relationships, i.e., the sales of producers increase with the number of suppliers, and the increase is magnified by relationships with new suppliers. These returns—which replicate Fact 3—are the fundamental forces behind the cyclical movements in the total measure, the adoption, and the termination of suppliers and, therefore, are critical for replicating Facts 1 and 2. We start by deriving analytical expressions for the returns from more and new relationships in our model. Combining equations (7) and (8), the next lemma holds.

Lemma 1. Returns from more relationships (Fact 3). *Conditional on the rate of adoption $s^*_{i,N}$, the final output increases in the total measure of suppliers, V^*_i.*

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

The proof of Lemma 1 can be found in Appendix H. This lemma shows that the elasticity of output to the total measure of suppliers is always positive, which is consistent with Fact 3 and the *returns from more relationships* documented in Baqaee et al. (2023).

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

Lemma 2. Returns from new relationships (Fact 3). *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:*

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

The proof of Lemma 2 can be found in Appendix H. This lemma shows that the semi-elasticity of output to the rate of adoption is positive when the adjustment costs are positive, establishing the positive return from new relationships that is consistent with our empirical finding in Fact 3. Lemma 2 also reveals that this *return from new relationships* is proportional to the adjustment costs, which is a driving force behind the cyclical adjustments in the adoption and termination that we document in Facts 1 and 2.

5.2. Responses of adoption, termination, and output to changes in aggregate TFP (Facts 1-2)

In this section, we consider the responses of adoption, termination, and output to changes in aggregate TFP to replicate Facts 1 and 2. We first introduce the scaling and switching effects that determine the response of the single producer to changes in aggregate TFP—which jointly replicate the cross-sectional cyclicality of termination across different producers in Fact 2, particularly when the convexity of management costs is sufficiently high relative to that of adjustment costs (Section 5.2.1). Then, we extend the analysis to the aggregate economy to study Fact 1 (Section 5.2.2).

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

5.2.1. Effect of aggregate TFP on the producer's decisions

The changes in aggregate TFP exert two distinct *scaling* and *switching* effects on the producers' rates of adoption and termination of suppliers. The *scaling* effect embeds a positive (vs. negative) response of producers' adoption of new suppliers (vs. termination of existing suppliers) to a higher aggregate TFP (i.e., $dlnV_i^*/dlnA > 0$) (Lemma 3 in Appendix D), since producers increase the total measure of suppliers to benefit from the increased aggregate productivity (and profits) relative to the unchanged management costs. The *switching* effect embeds positive responses of both producers' adoption and termination to a higher aggregate TFP (i.e., $\partial s_{i,N}^*/\partial lnA = \partial s_{i,T}^*/\partial lnA > 0$) (Lemma 4 in Appendix D), since producers replace more existing suppliers with new ones to benefit from the increased aggregate productivity (and profits) relative to the unchanged adjustment costs.

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

Response of the producer's adoption rate to changes in aggregate TFP. The response of the adoption rate 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 adoption rate to a positive aggregate TFP shock is always positive for the producer.[16]

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

[16]To derive equations (10) and (11), we combine equations (7) and (8), and the definitions of $s_{i,N}^*$ and $s_{i,T}^*$, which yields the producer's rates of adoption and termination: $s_{i,N}^* = \frac{V_i^*}{2V_i^*} - \frac{c^+ + c^-}{2\alpha A a_i V_i^*}$ and $s_{i,T}^* = 1 - \frac{V_i^*}{2V_i^*} - \frac{c^+ + c^-}{2\alpha A a_i V_i^*}$.

switching effects:

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

The scaling effect implies a negative response of the termination rate to a positive aggregate TFP shock. This is because the producer achieves an increase in the scale of production by reducing the rate of termination of existing suppliers. 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 termination 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.

Cross-sectional responses of the termination rate across different producers (Fact 2). 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, as well as how the forces vary across different producers, we show in Figure 5 the impacts of the scaling (i.e., solid red curve) and switching (i.e., dashed blue curve) effects on the responses of termination against the producer's idiosyncratic productivity, together with the combined total impact (i.e., solid black curve with circles) implied by the calibrated model.

Consistent with equation (11), the scaling (vs. switching) effect exerts a negative (vs. positive) impact on the response of termination to changes in aggregate TFP. Both curves converge towards zero, showing that the magnitudes of both effects decline with the producer's idiosyncratic productivity, as shown in Lemmas 3 and 4 of Appendix D. Intuitively, facing a negative aggregate TFP shock, smaller producers—those that have smaller idiosyncratic productivity a_i—experience larger increases in the relevance of the fixed management and adjustment costs in relation to their decreased profits. Therefore, they are more inclined to refrain from expanding and adjusting suppliers, and hence display larger scaling and switching effects.

Moreover, 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.[17] As a result, the total impact, shown by the solid-black curve with circle markers, follows the switching effect to decline with idiosyncratic productivity. Termination becomes acyclical when the total impact reaches zero at the (log) idiosyncratic productivity of -0.01. When log idiosyncratic productivity is lower than -0.01, the switching effect dominates, implying that the rate of termination increases with aggregate TFP (i.e., $ds_{i,T}^*/dlnA > 0$). In contrast, when log idiosyncratic productivity is higher than -0.01, the scaling effect dominates, implying that the rate of termination decreases with aggregate TFP (i.e., $ds_{i,T}^*/dlnA < 0$).

[17] The low sensitivity of the scaling effect to changes in idiosyncratic productivity relies on our assumption of quadratic management cost and linear adjustment cost functions, which we discuss below in the next paragraph of this subsection on the convexity of cost functions.

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

Proposition 1. Heterogeneous cyclicality in termination (Fact 2). *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.*

The proof of Proposition 1 can be found in Appendix H. Note that the steady-state measure of suppliers ($\bar{V}_i^*$) increases with the idiosyncratic productivity. This is because the management cost is less relevant for the producers with higher 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 smaller measure of suppliers. This result is consistent with Fact 2 (Figure 2), which shows that producers with a large (vs. small) measure of suppliers display a countercyclical (vs. procyclical) rate of termination.

Convexity of the cost functions. The degrees of convexity of the management and adjustment cost functions are important for replicating the heterogeneous responses in the rate of termination across producers with a different number of suppliers, as in our Fact 2. More specifically, we show that the degree of convexity of the management cost function must be sufficiently high relative to that of the adjustment cost function for the model to be consistent with Fact 2 in Figure 2, which displays a negative correlation between the procyclicality of termination and the size of the producer.

Our benchmark model assumes quadratic management costs and linear adjustment costs. This differs from the conventional formulation in the literature, which typically assumes linear management costs for suppliers (e.g., Lim, 2018; Huneeus, 2018) and strictly convex adjustment costs for labor inputs (e.g., Caballero and Hammour, 1994; Mumtaz and Zanetti, 2015; Zanetti, 2008). We show in Panel (b) of Figure I.12 in Appendix I that linear management costs and convex adjustment costs—the standard assumption in the labor literature—generate a positive correlation between the procyclicality of termination and producer size, which is inconsistent with our Fact 2 but consistent with that of job destruction in the labor market (Panel b in Figure 3).

As equation (11) shows, the management cost—similar to the fixed overhead cost in the network literature—generates the negative scaling effect and makes the rate of termination countercyclical, and the adjustment cost—similar to the adjustment cost in the labor literature—generates the switching effect and makes the rate of termination procyclical. Our analysis in Appendix I shows that the scaling effect is invariant to producer size, and the switching effect significantly decreases with producer size when the convexity of the management cost is sufficiently high relative to that of the adjustment cost (as in our baseline model). Thus, the (pro)cyclicality of termination—which equals the sum of the switching effect and the negative scaling effect, as shown in equation (11)—decreases with producer size, as evinced in Figure 2 of Fact 2.

We illustrate this result quantitatively in Figure I.14 of Appendix I, where we extend our model to allow for flexible combinations of the degree of convexity in the management and adjustment costs (i.e., flexible combinations that nest linear and quadratic specifications for those costs).

5.2.2. Effect of aggregate TFP on the aggregate rates of adoption and termination

We now investigate the effect of aggregate TFP on the aggregate rates of adoption and termination. 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:

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

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.

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 2. Procyclical aggregate rate of adoption (Fact 1). *The aggregate rate of adoption of suppliers, s_N^*, increases in A.*

The proof of Proposition 2 can be found in Appendix H. This proposition shows that our model replicates the procyclical aggregate rate of adoption in Fact 1.

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 sizes of the scaling and the switching effects, which depend 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 1 (Figure 1)—for a realistic calibration of the distribution of idiosyncratic productivity of 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 replicates the novel empirical findings on the adoption and termination of suppliers.

6. Quantitative analysis

In this section, we calibrate the model on U.S. data to explore the critical role of management and adjustment costs for the heterogeneity in the cyclicality of the rate of termination across producers with different measures of suppliers.

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 adjustment and management costs, c^+ (and equivalently, c^-) and ξ, to match 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 (i.e., intermediate input costs in our model). 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 0.077, 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×yearly operating cost) is equal to 0.14 (i.e., 0.5/3.5). Second, we calibrate ξ equal to 0.081 to match the ratio of the management costs to the sum of operating surplus and intermediate input costs for the producer, which is equal to approximately 9% (Gopinath and Neiman, 2014). Summarized in Table 2 is the calibration of the model.

We simulate 3,000 producers ($i \in \{1, 2, \cdots, 3000\}$) with i.i.d. idiosyncratic productivities drawn from the calibrated distribution. Then, we simulate 1,000 economies ($j \in \{1, 2, \cdots, 1000\}$) for the same 3,000 producers, and draw new i.i.d aggregate TFP shocks in each economy. We use the same set of producers for different economies to examine how the heterogeneity in producers affects the cyclicality of the aggregate rate of termination.

6.2. Heterogeneity in the cyclicality of the rates of adoption and termination across producers

Our empirical analysis in Section 3 shows that the termination rate is countercyclical for larger producers and procyclical for smaller producers, and the adoption rate is also more pro-cyclical for smaller than larger producers. In this subsection, we show that the model matches this important empirical regularity.

We divide the 3,000 simulated producers into 10 equal-interval groups according to the (log) measure of suppliers, 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 using our simulated data:

$$s_{k,p,j} = a_{p,k} + b_{p,k} \cdot dlog(Y_j) + \epsilon_{k,j},\ p \in \{N, T\}, \tag{12}$$

where $s_{k,N,j}$ (vs. $s_{k,T,j}$) is the group-wise adoption (vs. termination) rate of the group k in economy j, which equals the ratio of the group-wise number of adopted new (vs. terminated existing) suppliers to the steady-state number of suppliers in group k. $dlog(Y_j)$ is the percentage deviation of the aggregate output from the steady state in economy j. The coefficients $b_{N,k}$ and $b_{T,k}$ measure the responses of the rates of adoption and termination to aggregate output for the group k, respectively. They are the central focus of our analysis, as they capture the heterogenous cyclicality of the adoption and termination rates for different groups of producers, respectively. We perform a similar analysis using the observed data by estimating the following regression:[18]

$$s_{k,p,t} = a_{p,k} + b_{p,k} \cdot dlog(Y_t) + \epsilon_{k,t},\ p \in \{N, T\}. \tag{13}$$

Panels (a) and (c) in Figure 4 show the regression results for equation (13) estimated with the observed data. Blue dots show the point estimates of the different $b_{N,k}$ (vs. $b_{T,k}$) coefficients (y-axis) against the log of the average number of suppliers $V_k \equiv \sum_{i\in k} \sum_t V_{i,t}/N_{k,obs}$ (x-axis), where $N_{k,obs}$ is the total number of observations in group k. The red line is the fitted line, estimated using OLS. Panels (b) and (d) show the results for equation (12) estimated with the simulated data from our baseline model. In all panels, the correlations between the cyclicality of the adoption and termination rates (measured by $b_{N,k}$ and $b_{T,k}$, respectively) and the size of producers (measured by V_k) are negative. This shows that the model generates empirically congruous heterogeneity in the cyclicality of the adoption and termination rates across the producers with different measures of suppliers. This result is also consistent with the theoretical findings in Proposition 1.[19]

Another important similarity between the observed data and the simulated model that emerges from Figure 4 is the nearly zero cyclicality of the termination rate on average. To test formally that the correlation between termination and output is close to zero on average, we estimate the following time-series regressions with the simulated and the observed data separately:

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

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

[18]Different from the estimation from the simulated data, the observed data have multiple periods t rather than the multiple economies j in the simulated data, and $dlog(Y_t)$ is the growth rate of the real gross output.

[19]The magnitudes of the coefficients $b_{N,k}$ and $b_{T,k}$ are larger in the data than in the simulated data because the log number of suppliers has a larger range in the observed data than in the simulated data (about 2.5 vs. 0.25), which leads to larger within-group standard deviations of the adoption and termination rates in the data than in the simulated data.

where $s_{T,j}$ and $s_{T,t}$ are the average 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 0.004 and 0.06 for the simulated and the observed data, respectively. Both estimates are close to zero, evincing that the model is consistent with the observed acyclical aggregate rate of termination in Figure 1. Appendix E illustrates the crucial role of the existence of *both* management *and* adjustment costs for the observed patterns of adoption and termination rates at both the aggregate and the cross-sectional levels.

7. Policy analysis

In this section, we examine the effect of recent U.S. government supply chain policies on social welfare. To contextualize our analysis, we begin by reviewing the recent U.S. policies and legislation to support the resilience of the supply chain during and after the advent of the COVID-19 pandemic. Subsequently, we extend our baseline model outlined in Section 4 to study the welfare implications of those policies.

7.1. Supply-chain-related policies in the aftermath of the COVID-19 pandemic

The resilience of the supply chain has become central to U.S. government policies and legislation in the aftermath of the COVID-19 pandemic.[20] Several policies and legislative measures were targeted at small and medium-sized enterprises (SMEs), largely implemented through the federal agency the Small Business Administration (SBA) during the pandemic. These initiatives primarily consisted of *loan policies* aimed at alleviating the financial constraints that SMEs faced.[21] For example, In December 2020, the U.S. Congress approved the "Economic Aid to Hard-Hit Small Businesses, Nonprofits, and Venues Act" as an amendment to the "Small Business Act," in which *supplier costs* were—for the first time—included as eligible expenses for the Paycheck Protection Program (PPP) loan. The Trump administration then reopened the PPP in January 2021 as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act.[22]

After COVID-19, the U.S. government has continued to strengthen the diversity and resilience of the supply chain through various policies and acts, including the establishment of the "White House Council on Supply Chain Resilience." Most of these initiatives aimed to rebuild the production and innovation capabilities of the U.S. supply chain by *subsidizing* the adoption and production of *inputs with new technologies*,

[20] Bai et al. (2024) and references therein provide an overview of the severity of global supply disruptions for the U.S. economy.

[21] Major policies and legislation managed by the SBA during COVID-19 included the "Paycheck Protection Program" (PPP) and the "Economic Injury Disaster Loan (EIDL) Program", established under the "Coronavirus Aid, Relief, and Economic Security (CARES) Act" and the "American Rescue Plan Act of 2021." In Congressional testimony on August 2, 2022, titled "Oversight of SBA's COVID Economic Injury Disaster Loan Program," Patrick Kelley, the Associate Administrator for the Office of Capital Access at the SBA, stated "The SBA's core lending programs are supporting this dynamic cohort of new businesses through the tailwinds and headwinds of today's economy. *Small manufacturers*, which are *key to the President's goal of tackling supply chain bottlenecks* head-on by increasing domestic production, benefit uniquely from the *504 Loan Program*."

[22] Other loan policies to support supply chains included the "American Rescue Plan Act" of 2021 by the Biden administration, in which the State Small Business Credit Initiative (SSBCI) provided nearly $10 billion in funds to help small businesses access the capital through loans and investments facing "*a lack of resiliency and security in supply chains*." The White House report "Two Years of Building Stronger Supply Chains and a More Resilient Economy" summarized the efforts of the Biden administration in building more resilient supply chains.

such as semiconductors, electric vehicles (EVs), batteries, and pharmaceuticals. For example, as part of the "Inflation Reduction Act" that was enacted to combat inflation that global supply chain disruptions caused, the U.S. Treasury provided tax credits to support the production and adoption of new clean-energy technologies.

7.2. An extended model with credit constraints and supply chain policies

To evaluate the economic and welfare implications of the aforementioned supply-chain-related policies, we extend our baseline model in Section 4 with a representative household whose utility serves as a measure of welfare, and include credit constraints that require loan policies to improve welfare. Besides the financial friction, the extended model inherits from the baseline model the other source of inefficiency associated with management and adjustment costs due to an incomplete contract between producers and suppliers, thus resulting in a higher cost-to-profit ratio for private producers than for society (Section 4.5).

The government implements two major classes of policies to support the resilience of input-output relations and reduce inefficiency: (1) credit injection policy that alleviates producers' credit constraints and reduces inefficiency from financial frictions, and (2) subsidies for new inputs that promote the replacement of existing suppliers with new ones and reduce inefficiency from adjustment costs.

Credit constraints and policies. We extend the production sector described in Section 4 to incorporate financial frictions in the form of credit constraints, following Jermann and Quadrini (2012) and Lian and Ma (2021). At the beginning of the period, producers borrow from a competitive financial intermediary to cover working capital. These loans are repaid within the period after producers receive revenues. The working capital, denoted by wc_i, comprises the sum of input, management, and adjustment costs, i.e.,

$$\begin{aligned} wc_i \equiv & \left(\int_{z_{i,E}}^1 p_{i,E}(z_E) dz_E + (1-\tau_N) \int_{z_{i,N}}^1 p_{i,N}(z_N) dz_N \right) + \left[c^- \left(z_{i,E} - 1 + \bar{V}_i^* \right) + c^+ \left(1 - z_{i,N} \right) \right] \\ & + \xi \cdot \left(2 - z_{i,N} - z_{i,E} \right)^2 / 2, \end{aligned} \tag{16}$$

which is subject to the following constraint:

$$wc_i \leq \theta_i A^{\eta_{A,i}} \Pi_i^{ss} + \tau_L(A) \max\{ wc_i^* - \theta_i A^{\eta_{A,i}} \Pi_i^{ss}, 0 \}. \tag{17}$$

The first term on the RHS of equation (17) — $\theta_i A^{\eta_{A,i}} \Pi_i^{ss}$— represents the external financing obtained from the financial intermediary linked to the net worth of the producer, which is a function of the aggregate TFP, A, and the steady-state profits of the producer i, Π_i^{ss}.[23] The parameter θ_i captures the tightness of

[23] In the external financing of the credit constraint, we use the steady-state profit of the producer, which is pre-determined and exogenous to the choices of suppliers of the producer, for two reasons: (i) Lian and Ma (2021) document that borrowing constraints commonly rely on a specific measure of cash flows, where a firm's total debt or interest expenses cannot exceed a

the credit constraints, and $\eta_{A,i}$ is the elasticity of the net worth of the producer i to the aggregate TFP. A positive $\eta_{A,i}$ indicates that producers face tighter credit constraints during economic downturns. We set $\theta_i = 4.1 + 1.5 ln(V_i^{ss})$ and $\eta_{A,i} = 1.6 - 6.1 ln(V_i^{ss}/median(V_i^{ss}))$ based on the estimates from producer-level panel regressions of the debt-to-profit ratio on the number of suppliers and real aggregate output.[24]

To replicate the central aspect of government programs that supply loans to SMEs proportionally to the severity of individual financial constraints, the second term on the RHS of equation (17)—$\tau_L(A)\max\{wc_i^* - \theta_i A^{\eta_{A,i}}\Pi_i^{ss}, 0\}$—captures the amount of government's credit injection to producers at the state-contingent rate $\tau_L(A)$, which increases with the gap between the producer's demand for loans—i.e., the working capital in the baseline model without credit constraints, denoted by wc_i^*—and the amount of external financing $\theta_i A^{\eta_{A,i}}\Pi_i^{ss}$. The injected credit is financed by lump-sum taxes and repaid to the government within the period after producers receive revenues. These funds are then rebated to the representative household as lump-sum subsidies. The credit injection rate is positive and uniform for financially constrained producers that voluntarily solicit for the credit injection, and it is zero for unconstrained producers.

The producers solve the following optimality problem, subject to the credit constraint in equation (17):

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

$$- \underbrace{\left[c^-\left(z_{i,E} - 1 + \bar{V}_i^*\right) + c^+\left(1 - z_{i,N}\right)\right]}_{\text{Adjustment costs}} - \underbrace{\xi \cdot \left(2 - z_{i,N} - z_{i,E}\right)^2/2}_{\text{Management costs}}. \tag{18}$$

In addition to the credit constraint, the optimization problem in equation (18) differs from the analogous problem in the benchmark model (equation 6) for the presence of government subsidies (τ_N) given to producers for the purchases of input from new suppliers. The new formulation captures the essence of U.S. policies that encourage the adoption of new technologies. The subsidies on new inputs increase the total surplus of the production lines that have new suppliers, i.e., $TS_{i,N}(z_N) = y_{i,N}(z_N) + \tau_N p_{i,N}(z_N)$, and this surplus is split between producer and supplier according to the Nash-bargaining rule in equation (4). The extended model nests the baseline version without credit constraints and policies, by setting $\theta_i = +\infty$ and $\tau_L(A) = \tau_N = 0$.

We set the credit injection rate $\tau_L(A)$ to have the ratio of the amount of credit injection on producers to the aggregate output in the model equal to 0.72% for any level of aggregate TFP, A, which matches the observed ratio during the COVID-19 year of 2020.[25] We set the rate of input subsidies $\tau_N = 2.6\%$, such that

multiple of EBITDA (i.e., earnings before interest, taxes, depreciation, and amortization) from the previous 12 months; and (ii) in our static model, if the constraint is not pre-determined, it will be proportional to the producer's sales, making the constraint less responsive to economic conditions.

[24] See Appendix F.2 for the estimates of the panel regressions and the calibration of the parameters.

[25] Appendix F.2 describes how we calibrate the rates of credit injection and input subsidies to match the observed data.

the steady-state ratio of input subsidies to aggregate output matches that of the credit injection, at 0.72%. Notably, our calibration ensures that both policies incur the same cost, making them directly comparable in the subsequent welfare analysis.

Government, representative household, and welfare. The government finances both the credit injection and input subsidies using lump-sum taxes on households. Each unit of tax incurs an efficiency cost of $\delta = 0.1\%$, consistent with Gertler and Karadi (2011). This deadweight loss reflects the observed costs of raising funds via government debt. The economy consists of a representative household with the logarithmic utility function $U(C) = log(C)$, where C denotes aggregate consumption. The economic resource constraint is:

$$C(A) = Y(A) - \delta \left(\int_0^1 \tau_N \int_{z_{i,N}}^1 p_{i,N}(z_N) dz_N di + \int_0^1 \tau_L(A) \max\{wc_i^* - \theta_i A^{\eta_{A,i}} \Pi_i^{ss}, 0\} di \right),$$

where the aggregate consumption equals the total output minus the efficiency costs associated with providing input subsidies and credit injections.[26]

The credit injection policy improves welfare by alleviating the credit constraints that restrict the producers' scale of production and hinders the replacement of existing suppliers with new, high-productivity ones. Subsidies on new inputs improve welfare by promoting the replacement of existing with new suppliers and reducing the inefficiency from adjustment costs—which lead to under-adjustment in the adoption of new suppliers. In Appendix F.1, we present the optimality condition of the producers and discuss how they are affected by the credit constraints and the two policies.

7.3. Simulation of the extended model

We simulate 100 economies, each composed of 300 producers, and study three key policy questions: First, how do credit constraints, credit injections, and subsidies on new inputs influence welfare? Second, how should the government choose between the policies of credit injection and subsidies on new inputs? Third, how do different producers benefit from the two policies and contribute to welfare enhancement?

Panel (a) in Figure 6 shows the welfare loss (in units of percent of steady-state consumption) of the extended economy with credit constraints relative to the efficient case without any frictions (y-axis) against the (log) aggregate TFP (x-axis) for three distinct cases: (i) without any policies (dashed black line), (ii) with credit injection policy (solid red line), and (iii) with subsidies on new inputs (dash-dotted blue line). We also plot the welfare loss without credit constraints (dashed green line) to disentangle the different welfare losses from credit constraints and from adjustment costs, respectively.

[26]As we assumed in Section 4.5, all management and adjustment costs are paid to the household as labor income, thereby are part of the aggregate consumption.

The effect of credit constraints. Credit constraints generate welfare loss relative to both the efficient case and the case without credit constraints, as shown by the dashed black line (case i) being below both zero and the dashed green line. Intuitively, binding credit constraints increase the effective management and adjustment costs due to the higher marginal cost of financing the working capital. This restricts both the scale of production and the replacement of existing suppliers with new ones, thereby reducing output and welfare. The welfare loss linked with credit constraints diminishes with the increase of aggregate TFP, as indicated by the upward-sloping dashed black curve that converges to the dashed green curve for a higher level of aggregate TFP that relaxes the financial constraints of more producers.

The effect of credit injections. Credit injection improves welfare by relaxing the credit constraints, thereby increasing both the scale of production and the replacement of existing suppliers with new ones, as evinced by the solid red line that is above the dashed black line. When aggregate TFP is high, the welfare loss due to financial constraints is low, and credit injection results in a smaller welfare improvement, as indicated by the solid red line converging towards the dashed black line toward the right side of the graph.

The effect of input subsidies. Subsidies on new inputs almost uniformly improve the welfare across different levels of aggregate TFP, as exhibited by the dash-dotted blue line being above and parallel to the dashed black line. Intuitively, subsidies on new inputs increase the profits from new production lines and reduce the effective costs of adopting new suppliers, thereby encouraging the replacement of existing suppliers with new ones and reducing the welfare loss associated with the adjustment costs.

Policy comparison. Given the same costs of financing credit injections and input subsidies in our calibration, the relative effectiveness of the two policies depends on the level of the TFP, resulting in a state-dependent optimal policy. Specifically, the welfare improvement from input subsidies is generally less powerful than credit injection for several levels of aggregate TFP. Consequently, the government is more effective in increasing welfare by adopting a policy of subsidies on new inputs *only when* the aggregate TFP is exceptionally high (i.e., when the detrended log aggregate output is above 0.05, which is close to the level in the year 2007), such that the financial constraints are not binding for most producers and credit injection can hardly improve welfare, as shown by the dash-dotted blue line that is above both the solid red and dashed green lines towards the right side of panel (a) in Figure 6. Otherwise, the government should adopt the policy of credit injection to enhance welfare. The dominant role of credit injection is primarily because of the sizable financial frictions implied by the empirical distribution of producers' debt-to-profit ratios, while adjustment costs—following the calibration of Caballero and Hammour (1994)—account for a limited fraction of GDP.

The role of convex management costs and linear adjustment costs. To study the role of convex management costs and linear adjustment costs—which is a central theme of our analysis—panel (b) in Figure 6 presents the results for the welfare analysis in an economy with counterfactual linear management costs and convex adjustment costs. This setup implies a cross-sectional cyclicality of terminations that is consistent with the pattern in the labor market (as shown in Figure 3b), but it is inconsistent with the pattern in the producer-supplier market (as shown in Figure 2b).

Credit constraints result in a more significant welfare loss compared to the benchmark economy, as shown by the larger gap between the dashed green and black lines in Panel (b) relative to Panel (a). Credit injection that alleviates the credit constraints leads to similar welfare improvement as in the benchmark economy, as evinced by the similar gap between the solid red and dashed black lines in panels (a) and panel (b). In contrast, input subsidies lead to smaller welfare improvements than in the benchmark economy, which are also smaller than the welfare improvement from credit injection across all levels of aggregate TFP, as evinced by the dash-dotted blue line that consistently lies below the solid red line. As a result, in the counterfactual economy, input subsidies lead to smaller welfare improvement than that by credit injection, and the government should always prioritize credit injection over subsidies on new inputs, unlike in the benchmark case where the input subsidies should be adopted under sufficiently strong economic conditions.

Intuitively, the strictly convex adjustment costs in the counterfactual economy imply that producers replace fewer existing suppliers with new ones compared to the benchmark economy, thus incurring lower adjustment costs. As a result, credit injections—which primarily enhance welfare by alleviating financial constraints and expanding the scale of production—lead to greater welfare improvement than subsidies on new inputs—which primarily enhance welfare by reducing the inefficiency from adjustment costs.

The heterogeneous impacts of credit injections and input subsidies. In the previous Section 6.2, we show that the convex management costs and the linear adjustment costs are crucial for generating the heterogeneous cyclicality of adoption and termination across different producers in Figure 2 of Fact 2, which is one of our key empirical findings. An important issue is whether the convexity in management and adjustment costs makes different producers benefit differently from the policies by generating cross-sectional heterogeneity in the adoption and termination. Panel (a) in Figure 7 shows the output improvement of producers from credit injection (solid red line, y-axis) against their (log) idiosyncratic productivities (x-axis) in the benchmark economy when the detrended log aggregate output is at the 2020 level of -0.044 and many producers face tight financial constraints. As expected, credit injections increase the output of low- and medium-productivity (i.e., small-and medium-sized) producers who initially were financially constrained, but they do not affect the output of high-productivity producers. Interestingly, medium-sized producers benefit more from credit injections than the smallest ones, as indicated by the upward-sloping segment of the line. Intuitively, although the smallest producers have small net worth, they incur much lower management costs due to the convexity of the management cost function. Consequently, they experience less tightness in credit constraints compared to larger producers and, therefore, receive inferior benefits from the credit injections. In contrast, in the counterfactual economy with linear management costs (panel b), output improvement (weakly) decreases in the productivity and size of producers, as evinced by the downward-slopping solid red line.

The dash-dotted blue lines show the improvement in producers' output resulting from subsidies on new inputs. For smaller producers, input subsidies result in significantly lower output improvements compared to credit injections. This is because financial constraints are a major friction for those producers, thus making credit injections more effective in enhancing welfare. Conversely, input subsidies yield positive output improvements for larger producers that are not financially constrained by promoting the churning of suppliers.

8. Conclusion

Our analysis establishes several novel facts concerning the adoption and termination 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. At the producer level, producer sales positively co-move with the churning of suppliers and the expansion in the total number of suppliers.

To account for 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.

We extend our baseline model to include financial friction to study the welfare effects of two major classes of supply-chain policies—credit injection and subsidies for new suppliers—implemented in the U.S. in the aftermath of the COVID-19 pandemic. We find that credit injections generally outperform subsidies on new inputs, except when aggregate TFP is exceptionally high.

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 (Fernández-Villaverde et al., 2023). Finally, though we focus 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 (Baqaee et al., 2023), and the endogenous changes in the structure of the network (Ghassibe, 2023). We plan to investigate some of these issues in future work.

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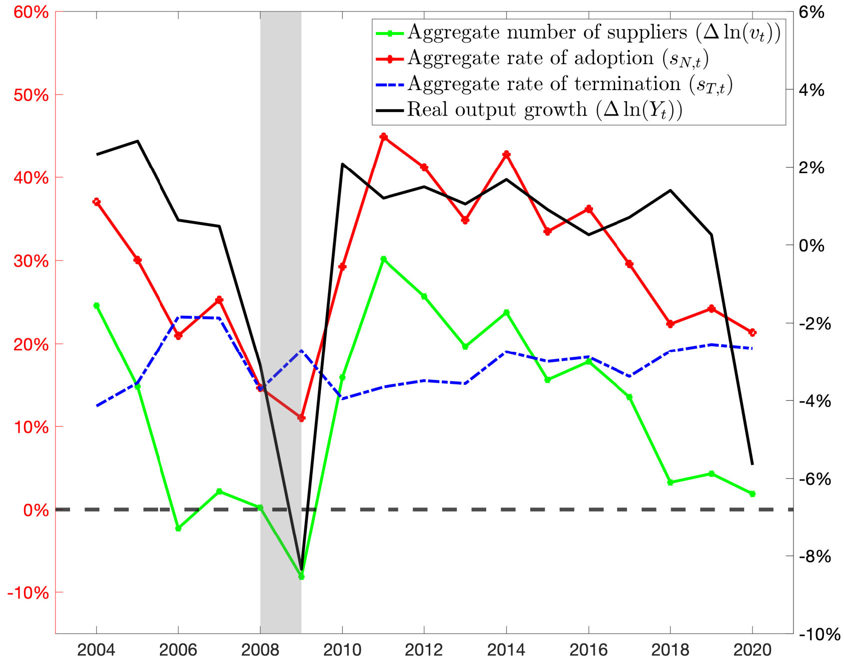
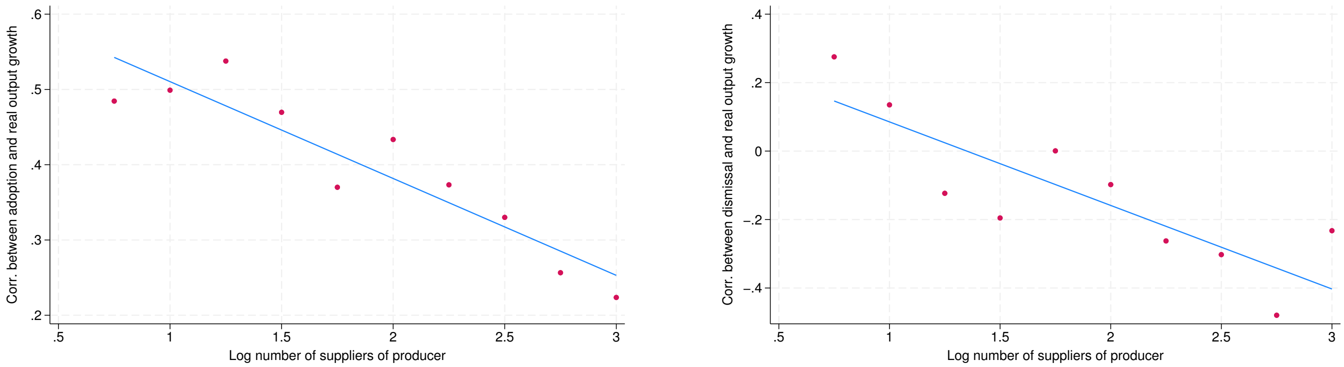
Figure 1: Procyclical adoption and acyclical termination of suppliers



Notes: The figure shows the growth rate of the aggregate number of suppliers (i.e., solid green line with circles), the aggregate rates of adoption (i.e., solid red line with circles) and termination (i.e., dash-dotted blue line), and the growth rate of real output (i.e., 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 real output is the BEA chain-type quantity index of gross output of private industries. Aggregate number of suppliers is the aggregate index of the number of suppliers. 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 demeaned. Shaded areas indicate NBER-defined recession years. The samples whose adoption and termination rates are among the top and bottom 2.5% of the sample or larger than one are winsorized.

Figure 2: Cyclicality of adoption and termination of suppliers for producers with different numbers of suppliers

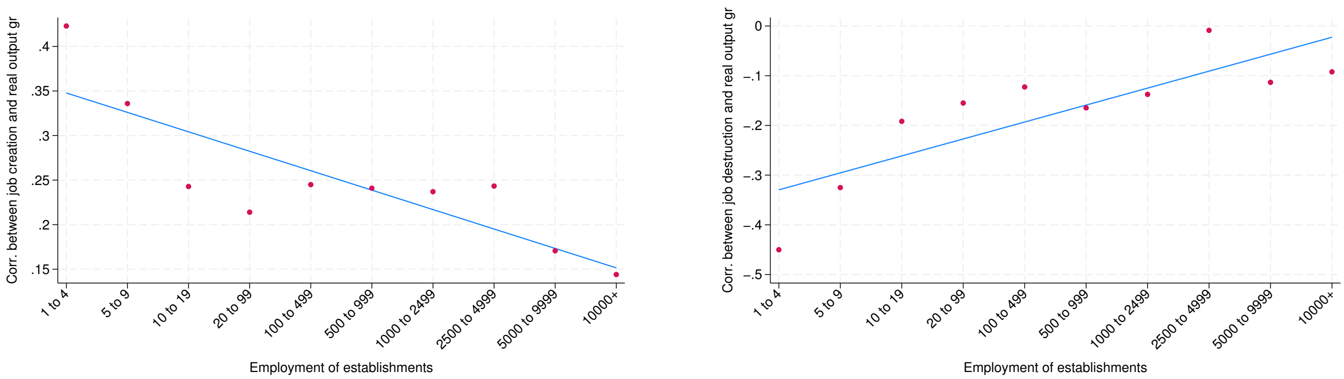


(a) Cyclicality of adoption

(b) Cyclicality of termination

Notes: The scatter plot in Panel (a) (vs. (b)) shows the (log) average number of suppliers per producer (x-axis) against the correlation between the adoption (vs. termination) rate and the real aggregate output growth (y-axis) for different groups of producers in our sample. Producers were divided into 10 groups according to their (log) average numbers of suppliers, and for each group in each year, we computed the aggregate adoption (vs. termination) rate of the group. Then, for the y-axis, we computed the correlation between the group-wise rate of adoption (vs. termination) and the economy-wise real output growth over the years for each group (red circle). For the x-axis, we computed the average number of suppliers per producer across the years for each group. The solid blue line is a linear fit of the cyclicality of adoption (vs. termination) on the (log) number of suppliers. The real aggregate output is the BEA chain-type quantity index of gross output of private industries.

Figure 3: Cyclicality of job creation and destruction for establishments with different numbers of employees

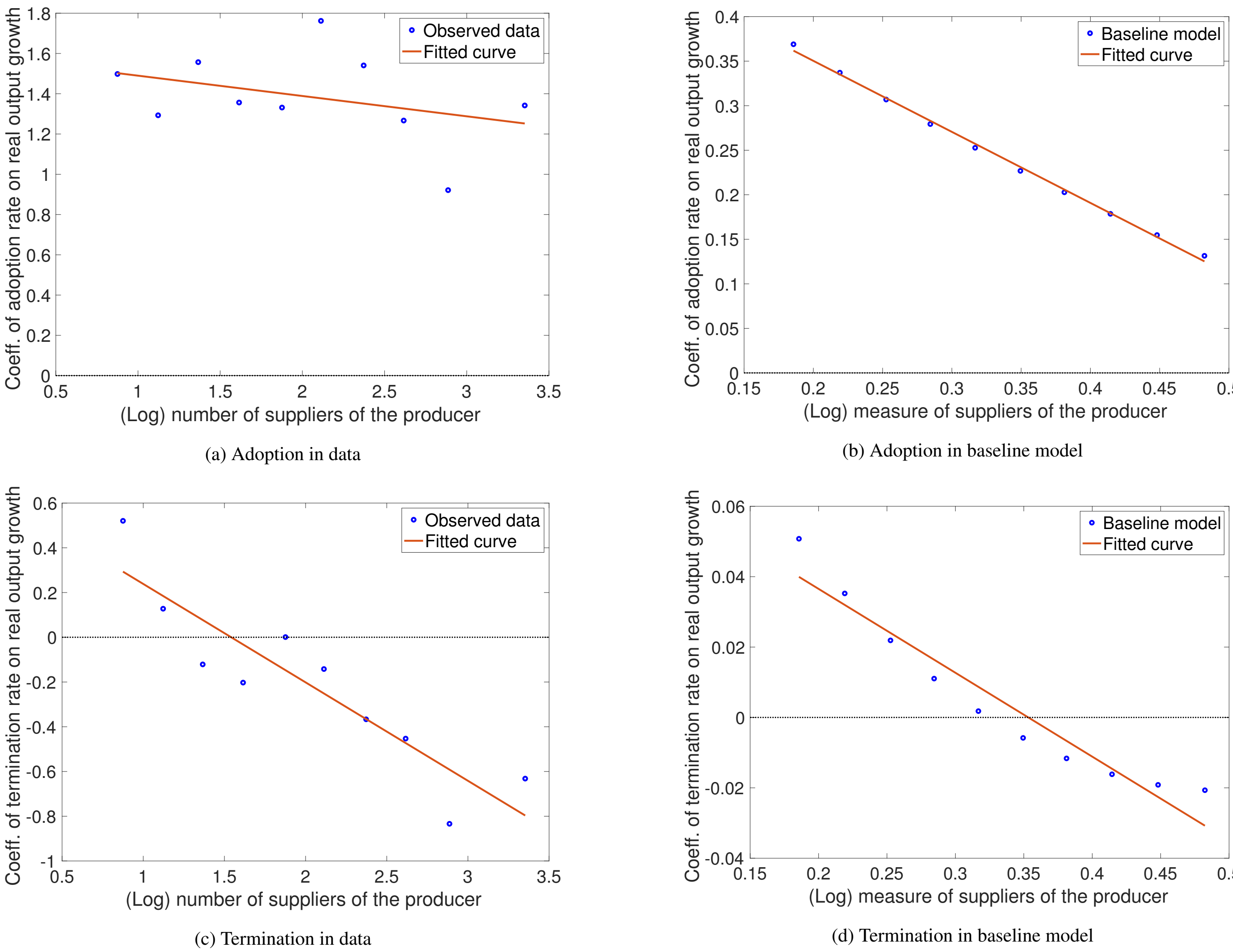


(a) Cyclicality of job creation

(b) Cyclicality of job destruction

Notes: The scatter plot in Panel (a) (vs. (b)) shows the number of employees of the establishment (x-axis) against the correlation between the job creation (vs. destruction) rate and the real output growth (y-axis) for different groups of establishments in our sample. Establishments were divided into 10 groups by the BLS according to their numbers of employees, and for each group in each year, the BLS reports the job creation (vs. destruction) rate. Then, for the y-axis, we computed the correlation between the rate of job creation (vs. destruction) and the economy-wise real output growth over the years for each group (red circle). The solid blue line is a linear fit of the cyclicality of creation (vs. destruction) on the x-axis. The real output is the BEA chain-type quantity index of gross output of private industries.

Figure 4: Coefficient of regressing the rate of termination on sales: Data vs. baseline model



(a) Adoption in data

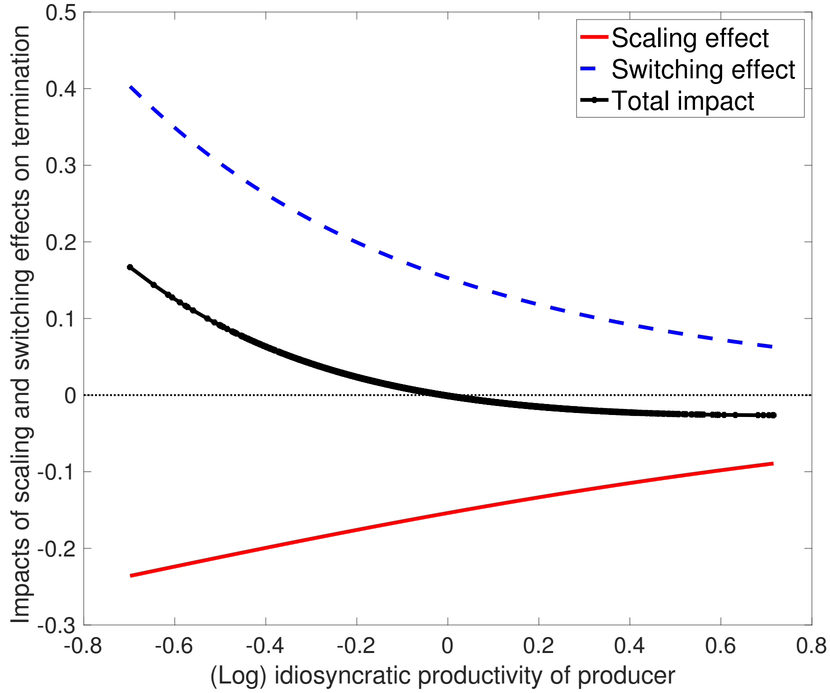
(b) Adoption in baseline model

(c) Termination in data

(d) Termination in baseline model

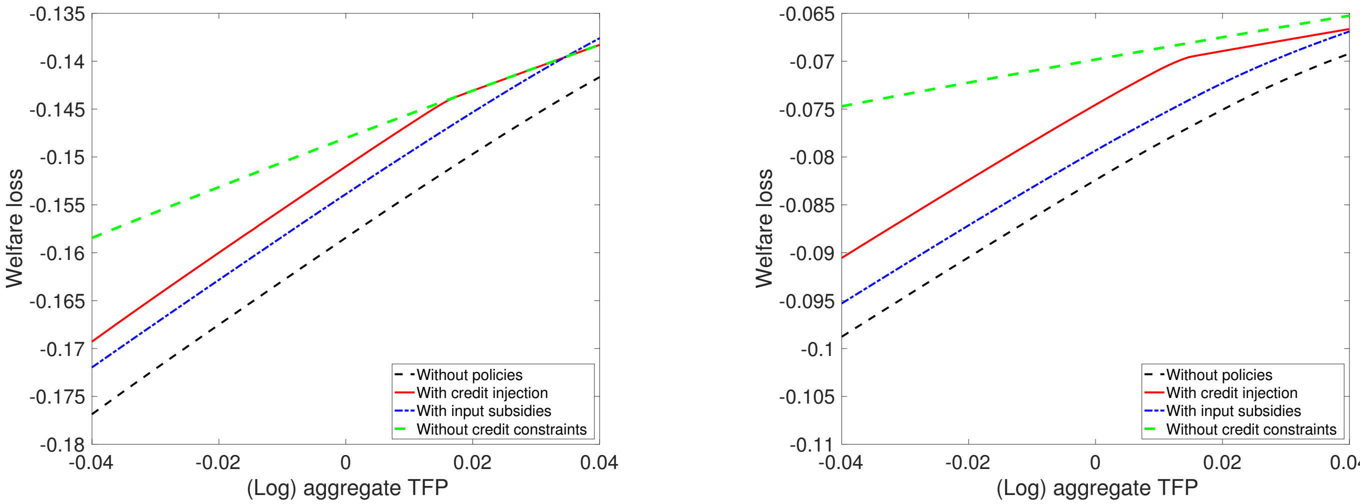
Note: Panels (a) and (b) (vs. c and d) plot the coefficients of regressing the adoption (vs. termination) rate on real output growth for different producer groups using the observed data (Panels a and c) and the simulated data from the baseline model (Panels b and d), respectively. In Panel (a) and (c) (vs. Panels b and d), we divided the 2,988 (3,000) observed (simulated) producers into 10 groups according to the log number (measure) of suppliers. Within each group, we calculated the group-wise adoption and termination rates and regress them on real output growth. For the x-axis, we computed the average number (measure) of suppliers across years (economies) for each producer, which was then averaged across the producers within each group. In Panels (a) and (c), the samples whose adoption and termination rates were among the top and bottom 2.5% of the sample or larger than one were winsorized. The real output is the BEA chain-type quantity index of gross output of private industries.

Figure 5: 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.

Figure 6: Welfare loss under different levels of TFP

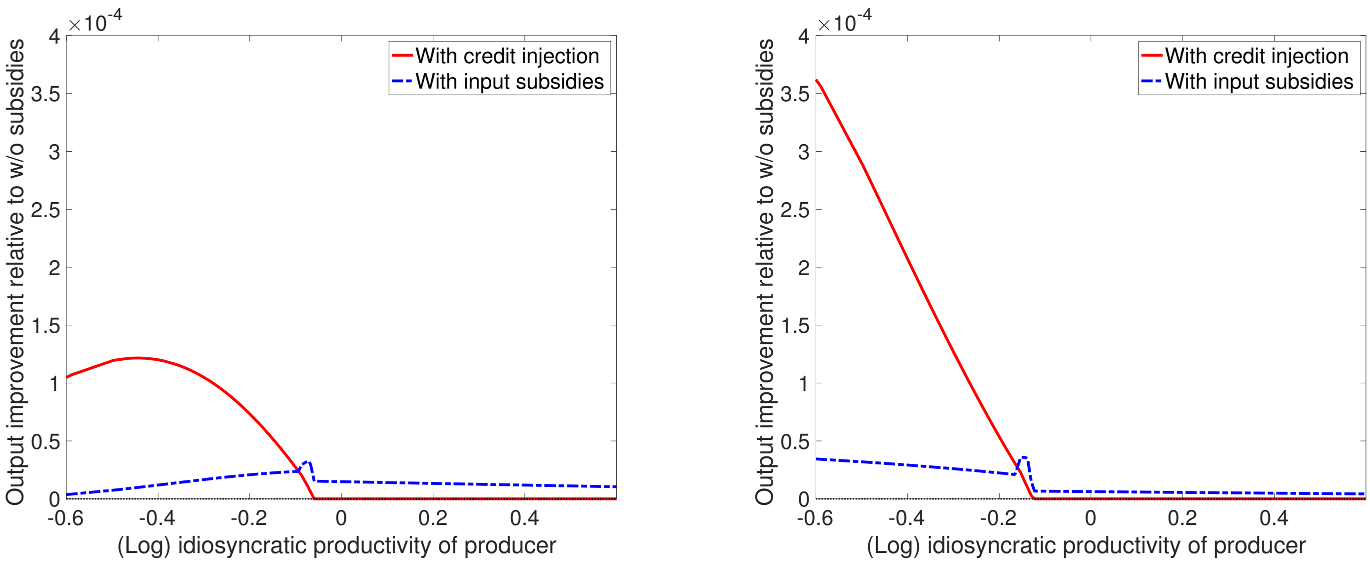


(a) Convex mgt. and linear adj. costs (benchmark)

(b) Linear mgt. and convex adj. costs (counterfactual)

Notes: The figure plots the welfare loss with credit constraints relative to the efficient case without any frictions (y-axis) against the (log) aggregate TFP (x-axis) for three distinct cases: (i) without any policies (dashed black curve), (ii) with credit injection (solid red curve), and (iii) with subsidies on new inputs (dash-dotted blue curve). The dashed green curve plots the economy with no financial constraints and policies. Panels (a) and (b) are for the benchmark economy with convex management costs and linear adjustment costs, and in the counterfactual economy with linear management costs and convex adjustment costs, respectively. The welfare loss is in units of percentage of steady-state consumption.

Figure 7: Output improvement by policies under low TFP



(a) Convex mgt. and linear adj. costs (benchmark)

(b) Linear mgt. and convex adj. costs (counterfactual)

Notes: The figure plots the improvement in output—weighted by the output share of the producer in the steady state without policies—relative to the case without policies (y-axis) against the (log) idiosyncratic productivity of the producer (x-axis) when the detrended log aggregate output is at the 2020 level of -0.044. The solid red and dash-dotted blue curves show the output improvement by credit injection and input subsidies, respectively. Panels (a) and (b) are for the benchmark economy with convex management costs and linear adjustment costs and in the counterfactual economy with linear management costs and convex adjustment costs, respectively.

Table 1: Responses of sales to the total number and churning of suppliers

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Sales growth		
Supplier no. growth rate	0.453***	0.090***	-0.473*	0.377***	
	(0.137)	(0.035)	(0.282)	(0.121)	
Rate of churning		1.299***			
		(0.415)			
Rate of adoption			0.648***		0.288***
			(0.233)		(0.094)
Rate of termination				0.850***	0.473*
				(0.289)	(0.272)
Sales of last year	-0.237***	-0.226***	-0.222***	-0.226***	-0.224***
	(0.031)	(0.030)	(0.031)	(0.031)	(0.031)
Supplier no. of last year	0.123***	-0.008	0.030	0.017	0.023
	(0.043)	(0.015)	(0.039)	(0.038)	(0.040)
First-stage F-stat	34.9	11.8	12.8	18.1	18.7
Observations	14,828	14,828	14,828	14,828	14,828
Number of producers	1,831	1,831	1,831	1,831	1,831
Producer Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes

Notes: Annual data for the sample period 2003 to 2020. The dependent variable is the producer's real sales growth rate. Column (1) uses $\widehat{s}_{i,N,t}$ to instrument the growth rate of the number of suppliers. Column (2) uses $\widehat{s}_{i,N,t}$, $\widehat{s}_{i,T,t}$, and $\widehat{s}_{i,CH,t}$ to instrument the growth rate of the number of suppliers and the rate of churning. Column (3)-(5) use $\widehat{s}_{i,N,t}$ and $\widehat{s}_{i,T,t}$ to instrument the growth rate of the number of suppliers and the rates of adoption and termination. The top and bottom 2.5% of the sample for adoption and termination rates were winsorized. The sample was restricted to producers whose maximum number of suppliers exceeded one over time. Standard errors were clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The first-stage F-stat is the Kleibergen-Paap (KP) statistic.

Table 2: Calibration of the model

Parameter	Value	Target moment
α	0.36	The ratio of producers' surplus to intermediate input costs.
ξ	0.081	Steady-state share of management costs (Gopinath and Neiman, 2014).
$c^{+}(c^{-})$	0.077	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.

Online Appendix

The Adoption and Termination of Suppliers over the Business Cycle

(Le Xu, Yang Yu, and Francesco Zanetti)

Appendix 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 (e.g., the dataset used by Lim, 2018)—which only includes major customers who contribute to more than 10% of a supplier's revenue—FactSet Revere provides a much less truncated set of suppliers.[27] 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 starting and ending 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.

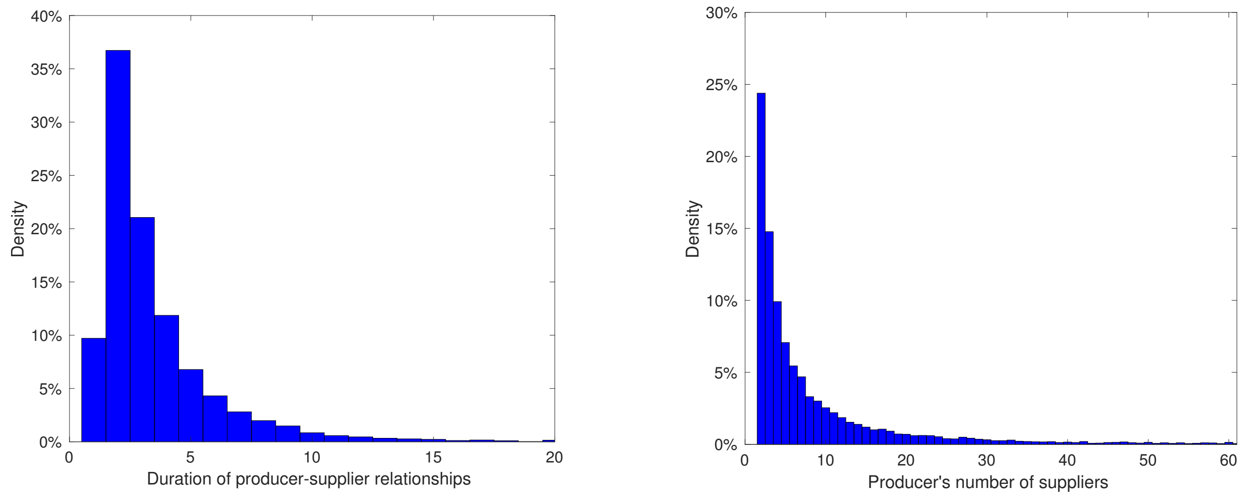
Summary statistics of the supply-chain relationship data.

Table A.3: 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 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.

Figure A.8: 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 of the producer's number of suppliers, respectively. The height of each bar equals the percentage of samples within the bin in all samples.

Derivation of number of suppliers and rates of adoption and termination. We 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 the 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 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.[28]

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

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

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

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

[27]Publicly-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.

[28]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."

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 suppliers adopted and existing suppliers terminated by 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 (A.1), we use the weighted averages of adoption and termination rates as the aggregate rates of adoption and termination, i.e.,

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

It follows that the growth rate of the aggregate number of suppliers can be decomposed into the aggregate rates of adoption and termination:

$$\frac{\Delta v_t}{v_{t-1}} = s_{N,t} - s_{T,t}. \tag{A.2}$$

Based on equation (A.2), we compute the variation of the growth rate of the aggregate number of suppliers as

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

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

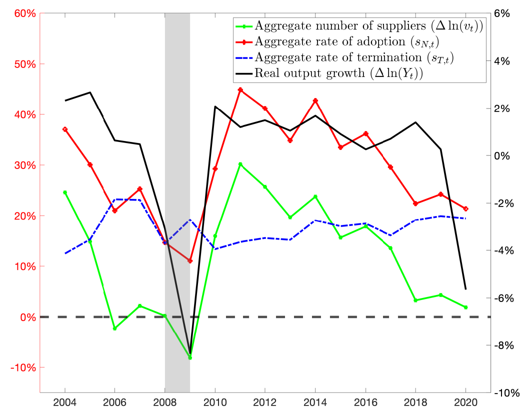
$$\frac{Cov\big(\frac{\Delta v_t}{v_{t-1}}, s_{N,t}\big)}{Var\big(\frac{\Delta v_t}{v_{t-1}}\big)} + \frac{Cov\big(\frac{\Delta v_t}{v_{t-1}}, -s_{T,t}\big)}{Var\big(\frac{\Delta v_t}{v_{t-1}}\big)} = 1,$$

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

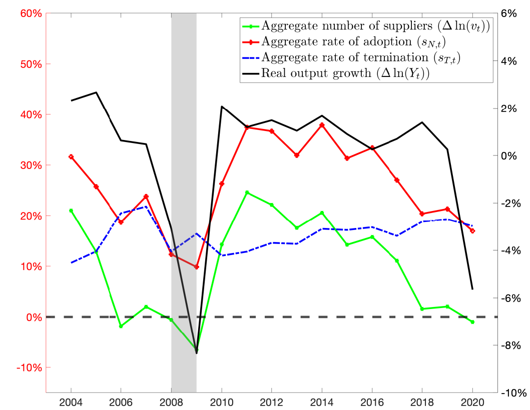
Alternative ways of aggregating adoption and termination rates. To check the robustness of Figure 1 in Fact 1, particularly to control for the changes in the weights, we reproduce Figure 1 with the following three alternative ways of aggregating producer-level adoption and termination rates: (i) we weigh producer-level rates of growth in the number of suppliers, the adoption, and the termination using the time-average share of costs of goods sold of the producer that is constant over time, i.e., we replace $COGS\_share_{i,t} = (\sum_{t'} cogs_{i,t'})/(\sum_{t'} \sum_{i'} cogs_{i',t'})$ in equation (A.1) (Panel b in Figure A.9); (ii) we compute the unweighted aggregate number of suppliers, aggregate number of adopted new suppliers, and aggregate number of terminated existing suppliers in each year, and use them to compute the growth rate of aggregate number of suppliers, aggregate rate of adoption, and aggregate rate of termination (Panel c in

Figure [A.9](#));[29] (iii) we weigh producer-level rates of growth in the total number of suppliers, the adoption, and the termination using the time-average share of supplier numbers of the producer that is constant over time, i.e., we replace $COGS\_share_{i,t} = (\sum_{t'} v_{i,t'})/(\sum_{t'} \sum_{i'} v_{i',t'})$ in equation (A.1) (Panel d in Figure A.9).

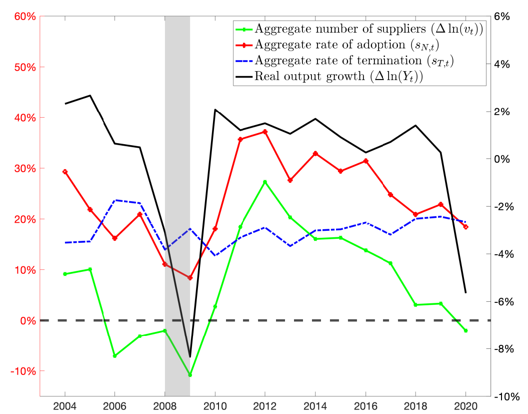
Figure A.9: Aggregate number of suppliers, rates of adoption and termination under alternative aggregation methods



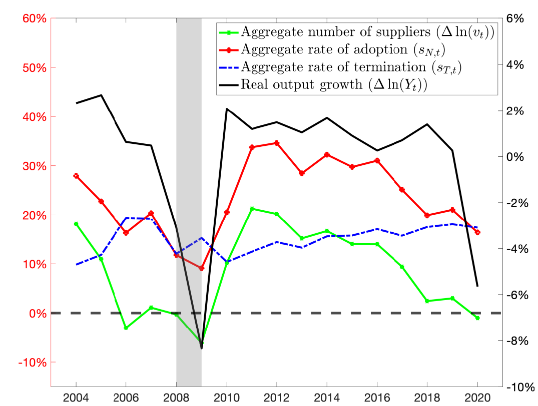
(a) Weight: time-varying costs of goods sold (Baseline)



(b) Weight: constant costs of goods sold



(c) Unweighted



(d) Weight: constant supplier no.

Notes: The figure shows the growth rate of the aggregate number of suppliers (i.e., solid green line with circles), the aggregate rates of adoption (i.e., solid red line with circles) and termination (i.e., dash-dotted blue line), and the growth rate of real output (i.e., solid black line) under four alternative ways of aggregation. Real output growth is demeaned. Shaded areas indicate NBER-defined recession years. The samples whose adoption and termination rates are among the top and bottom 2.5% of the sample or larger than one are winsorized.

[29] We normalize aggregate number of suppliers, aggregate number of adopted new suppliers, and aggregate number of terminated existing suppliers in each year by the total number of producers in that year to avoid higher adoption and termination rates that are due to more producers. This is not a concern for other ways of aggregation, in which the aggregate rates are the weighted averages of producer-level rates in each year.

Appendix B. Positive returns from more and new relationships

Table B.4: Responses of sales to the total number and churning of suppliers (First stages of IV regressions)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Supplier no. gr	Supplier no. gr	Adopt. rate	Term. rate	Supplier no. gr	Churn. rate
Bartik IV adopt. rate	0.344***	0.286***	0.457***	0.061**	1.664***	0.083***
	(0.056)	(0.056)	(0.068)	(0.027)	(0.089)	(0.030)
Bartik IV term. rate		-0.475***	-0.112	0.370***	1.089***	0.127***
		(0.113)	(0.124)	(0.058)	(0.131)	(0.048)
Bartik IV churn rate					-3.090***	0.035
					(0.141)	(0.045)
Sales of last year	0.067***	0.067***	0.072***	-0.007	0.058***	0.011***
	(0.010)	(0.010)	(0.010)	(0.004)	(0.010)	(0.002)
Supplier no. of last year	-0.304***	-0.304***	-0.289***	0.098***	-0.323***	0.016***
	(0.010)	(0.010)	(0.011)	(0.004)	(0.010)	(0.002)
Observations	14,828	14,828	14,828	14,828	14,828	14,828
R-squared	0.188	0.189	0.183	0.085	0.233	0.054
Number of producers	1,831	1,831	1,831	1,831	1,831	1,831
Producer Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Annual data for the sample period 2003 to 2020. Sales growth and Supplier number growth rate are the growth rates of the producer's real sales and its total number of suppliers, respectively. Rate of churning is the minimum of the adoption and termination rates. Producer and year fixed effects are controlled. The top and bottom 2.5% of the sample for adoption and termination rates are winsorized. In all columns, we control for the log real sales and the total number of suppliers of the producer of last year. We restrict our sample to producers whose maximum numbers of suppliers exceed one over time. Standard errors are clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table B.5: Responses of sales to the total number and churning of suppliers (OLS)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Sales growth		
Supplier no. growth rate	0.021***	0.020***	0.013	0.031***	
	(0.008)	(0.008)	(0.010)	(0.009)	
Rate of churning		0.027*			
		(0.015)			
Rate of adoption			0.009		0.019**
			(0.011)		(0.008)
Rate of termination				0.032**	-0.004
				(0.015)	(0.012)
Sales of last year	-0.208***	-0.208***	-0.208***	-0.208***	-0.208***
	(0.028)	(0.029)	(0.028)	(0.028)	(0.028)
Supplier no. of last year	-0.009	-0.010	-0.009	-0.009	-0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	14,828	14,828	14,828	14,828	14,828
R-squared	0.145	0.145	0.145	0.145	0.145
Number of producers	1,831	1,831	1,831	1,831	1,831
Producer Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes

Notes: Annual data for the sample period 2003 to 2020. Sales growth and Supplier number growth rate are the growth rates of the producer's real sales and its total number of suppliers, respectively. Rate of churning is the minimum of the adoption and termination rates. Producer and year fixed effects are controlled. The top and bottom 2.5% of the sample for adoption and termination rates are winsorized. In all columns, we control for the log real sales and the total number of suppliers of the producer of last year. We restrict our sample to producers whose maximum numbers of suppliers exceed one over time. Standard errors are clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix C. Estimation of the curvature of management costs

We follow the identification strategy of Arkolakis et al. (2023) to determine the curvature of the management cost function in our model. Arkolakis et al. (2023) assume a random search of producers for suppliers, which allows the log total number of suppliers to be linearly related to the log sales of the producer and unaffected by the individual productivity of any supplier. As a result, they can directly estimate the curvature of the management cost function using this linear relationship. In contrast, in our specification, the idiosyncratic productivity of the marginal supplier—equal to the marginal cost of management—declines in the number of suppliers of the producer, which is critical for our analysis of the adoption and termination of suppliers. Our specification generates a non-linear relationship between the log total number of suppliers and the log sales of the producer, which prevents us from directly estimating this relationship to calibrate the curvature of the management cost function as Arkolakis et al. (2023) do. Therefore, instead of precisely following Arkolakis et al. (2023), we follow their identification strategy and use an indirect inference method to estimate the curvature of the management cost function.

First, we generalize the management cost function in our baseline model to allow flexible curvature η, i.e., $G\left(z_{i,N}, z_{i,E}\right) = \xi \cdot V_i^{\eta}/\eta$. Then, we use the indirect inference method following Gourieroux et al. (1993) to estimate η. Specifically, we conduct panel regressions of the log number of suppliers on the log real sales of the producer, controlling for producer fixed effects, using both data and model-simulated data under different values of η:[30]

$$\ln(V_{i,t}) = \beta_0 + \beta_1^{data} \ln(Y_{i,t}) + \alpha_i + \epsilon_{i,t}, \tag{C.1}$$

$$\ln(V_{i,j}) = \beta_0 + \beta_1^{model} \ln(Y_{i,j}) + \alpha_i + \epsilon_{i,j}, \tag{C.2}$$

where $V_{i,t}$ (vs. $V_{i,j}$) and $Y_{i,t}$ (vs. $Y_{i,j}$) are the number of suppliers and real sales of producer i in data year t (vs. simulated economy j), respectively, and α_i is the producer fixed effect. β_1^{data} and β_1^{model} are the estimated coefficients of the log real sales of the producer in the data and in the model-simulated data, respectively. According to the indirect inference method, the curvature of the management cost function η is estimated such that β_1^{model} is equal to β_1^{data} (0.237). Notably, our identification strategy of the curvature of the management cost function—viz., using β_1^{model} to identify the curvature—is akin to the method used by Arkolakis et al. (2023) to identify the curvature of their search cost function.

Our estimated curvature of the management cost function is equal to 2.2 when $\beta_1^{model} = \beta_1^{data} = 0.237$, evincing that calibrating curvature to 2 is empirically reasonable.

Appendix D. Scaling and switching effects

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

[30] We simulate 100 economies, each composed of 300 producers as in Section 7.3.

termination rates of the single producer to aggregate TFP shocks.

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, which are 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; 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 measures the economic relevance of total adjustment costs.

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. The size of the scaling effect is equal to:*

$$\textit{Scaling effect} \equiv \frac{d\ln V_i^*}{d\ln A} = \frac{2\widetilde{\xi}_i \bar{V}_i^* + \left(\widetilde{c}_i^+ - \widetilde{c}_i^-\right)}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)\bar{V}_i^*} > 0, \tag{D.1}$$

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

Proof: In Appendix H.

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, when $\widetilde{c}_i^+ - \widetilde{c}_i^-$ is close to zero and $\bar{V}_i^*$ is positive. 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 idiosyncratic productivity, the scaling effect decreases with idiosyncratic productivity.

The scaling effect incentivizes producers to reduce the size of production by terminating existing suppliers in response to negative aggregate TFP shocks and, therefore, is critical to generate the countercyclical rate of termination among large producers established in Fact 2 (Figure 2).

The switching effect. Adjustment costs generate a positive co-movement between 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 9) and, therefore, incentivizes the producer to adjust the composition of suppliers by replacing existing with new suppliers. This incentive of switching suppliers enhances 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:*

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

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

Proof: In Appendix H.

Because replacing existing with new suppliers involves 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 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 adoption and termination rates (i.e., a larger switching effect).

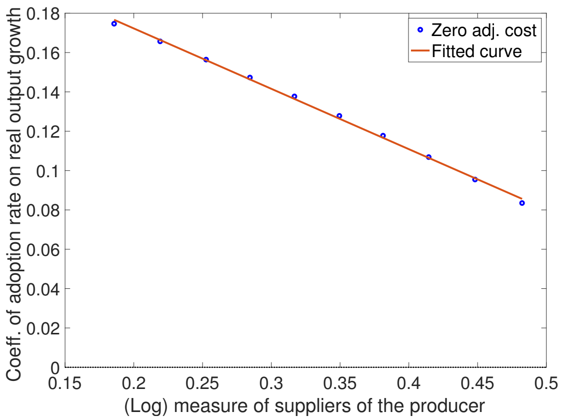
Appendix E. The role of the existence of both management and adjustment costs

To clarify the role of management and adjustment costs in the heterogeneous cyclicality of the termination rate across producers, we estimate the cyclicality of the adoption and termination rates for each group, $b_{N,k}$ and $b_{T,k}$, using data simulated with two counterfactual models. One is a model without adjustment costs (Panels a and c in Figure E.10), and the other is a model without management costs (Panels b and d in Figure E.10).

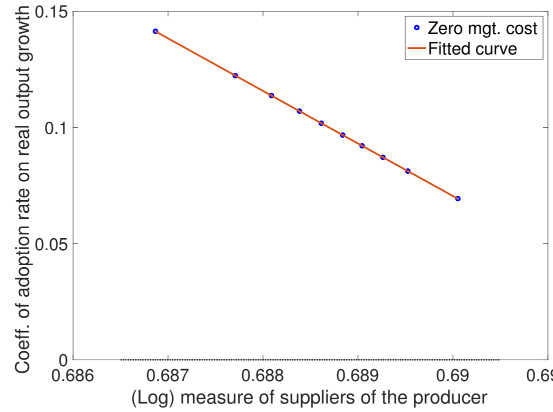
When there are no adjustment costs (Panels a and c), the switching effect is absent (Lemma 4), and the cyclicality of termination is uniquely determined by the scaling effect. These results imply that producers reduce the size of production by terminating existing suppliers in response to a lower aggregate TFP. As a result, the rate of termination is countercyclical for all producers and highly countercyclical for smaller and lower-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 smaller producers and countercyclical for larger producers. Without adjustment costs, the aggregate rate of termination is countercyclical: the coefficient of log aggregate output in equation (14) is estimated as -0.14, which is also inconsistent with the data.

When management costs are absent (Panels b and d), the scaling effect is absent (Lemma 3), and the cyclicality of termination is uniquely determined by the switching effect that induces producers to decelerate the churning of suppliers in response to a low aggregate TFP. Thus, the termination rate is procyclical for all producers and more so for smaller and less productive producers whose switching effect is stronger. Again,

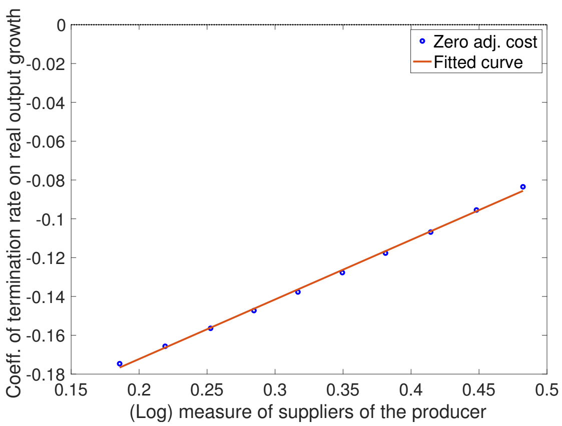
Figure E.10: Coefficients of regressing the adoption and termination rates on sales: counterfactual models



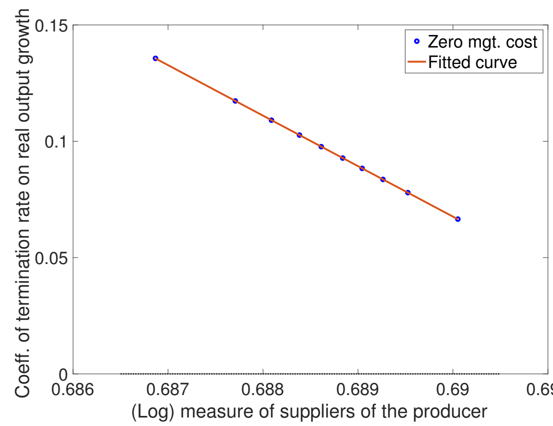
(a) Counterfactual model without adjustment costs (Adoption)



(b) Counterfactual model without management costs (Adoption)



(c) Counterfactual model without adjustment costs (Termination)



(d) Counterfactual model without management costs (Termination)

Notes: Panels (a) and (b) (vs. c and d) plot the coefficients of regressing the adoption (vs. termination) rate on real output growth for different producer groups using the simulated data from the counterfactual model with zero adjustment costs (Panels a and c) and the simulated data from the counterfactual model with zero management costs (Panels b and d), respectively. In all panels, we divide the 3,000 simulated producers into 10 groups according to the log measure of suppliers. Within each group, we calculate the group-wise adoption and termination rates and regress them on real output growth. 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.

these findings are incompatible with the data. Without management costs, the aggregate termination rate is procyclical: the estimated coefficient of log aggregate output in equation (14) is 0.1, contradicting the data.

Appendix F. Optimality conditions and empirical discipline of the extended model

Appendix F.1. Optimality conditions of the extended model

The optimality conditions of the producer with respect to $z_{i,E}$ and $z_{i,N}$ for the constrained maximization problem in equation (18) yield:

$$z^*_{i,E} + \frac{(1+\lambda_i)\, c^-}{[\alpha - \lambda_i (1-\alpha)]\, Aa_i} = \frac{(1+\lambda_i)\, \xi V_i^*}{[\alpha - \lambda_i (1-\alpha)]\, Aa_i}, \tag{F.1}$$

$$z^*_{i,N} - \frac{(1+\lambda_i)\, c^+}{[\alpha - (\lambda_i - (1+\lambda_i)\widetilde{\tau}_N)(1-\alpha)]\, Aa_i} = \frac{(1+\lambda_i)\, \xi V_i^*}{[\alpha - (\lambda_i - (1+\lambda_i)\widetilde{\tau}_N)(1-\alpha)]\, Aa_i}, \tag{F.2}$$

where λ_i is the Lagrange multiplier of the credit constraint for producer i, which captures the shadow cost of borrowing. The multiplier is strictly positive when the credit constraint binds and zero when it does not. The effective rate of subsidies on new inputs to the producer, $\widetilde{\tau}_N \equiv \alpha\tau_N/\left[1-(1-\alpha)\,\tau_N\right]$, due to sharing of the subsidies between producers and suppliers, strictly increases with τ_N. Subsidies on inputs from new suppliers increase the marginal benefits of using new inputs, thereby lowering the effective costs of adopting new suppliers relative to the marginal benefits, as evinced by the denominator in equation (F.2) that increases with $\widetilde{\tau}_N$.

A tighter credit constraint—reflected by a higher λ_i—raises the effective marginal costs of inputs, management, and adjustment costs in two ways: (i) it directly increases the marginal costs of management and adjustment, as reflected by $(1+\lambda_i)$ in the numerators; and (ii) it increases the marginal costs of inputs and reduces the profits, thereby increasing the ratio of management and adjustment costs to the profits of the producer, reflected by the $-\lambda_i\,(1-\alpha)$ in the denominator. A positive rate of credit injection $\tau_L(A)$ relaxes the credit constraint and reduces λ_i, implicitly increasing the effective costs of management and adjustment and affecting the adoption and termination of suppliers. The first-order conditions in equations (F.1) and (F.2) nest the first-order conditions in equations (7) and (8) of our baseline model by setting $\tau_N = \tau_L(A) = 0$.

Appendix F.2. Empirical evidence to discipline the extended model with credit constraints

In this subsection, we document empirical facts on the relationship between the financial friction, the size of the producer, and the aggregate economic conditions, and then use these facts to discipline the model in Section 7.2.

Specifically, we follow Lian and Ma (2021) to measure the profits and debts of the producer using CompuStat earnings before interest, taxes, depreciation, and amortization (EBITDA) and the sum of Long-term Debts (DLTT) and Debt in current Liabilities (DLC), deflate them using the GDP deflator, and denote them by $b_{i,t}$ and $\pi_{i,t}$, respectively, for each producer i in each year t. We further denote the average profit of producer i over time by $\bar{\pi}_i \equiv (\sum_{t=1}^{T}\pi_{i,t})/T$, and use the ratio of debt to average profit $b_{i,t}/\bar{\pi}_i$ to measure the corresponding debt-to-profit ratio in the model—viz., the ratio of the LHS of equation (17) to the steady-state profit Π_i^{ss} on the RHS.[31]

Merging the debt-to-profit ratio from CompuStat with the number of suppliers from FactSet supply chain data, we examine the relationship between the tightness of the credit constraint and the number of suppliers of the producer by running the following panel regression:

$$b_{i,t}/\bar{\pi}_i = \beta_0 + \beta_1 \ln(\bar{v}_i) + \gamma_t + \epsilon_{i,t}, \tag{F.3}$$

where $\bar{v}_i \equiv (\sum_{t=1}^{T} v_{i,t})/T$ is the average number of suppliers of producer i over time. A positive coefficient

[31] Because our model is static and has no capital, we can only model the credit constraint based on the profits rather than the asset value of the producer. However, all our empirical results are robust to using the debt-to-asset ratio (i.e., the ratio of the debt to the average asset over the years of the firm, with the asset measured by the total asset (AT) in CompuStat) instead of the debt-to-profit ratio. As a result, the RHS of our credit constraint in equation (17) can be alternatively specified as a multiplier of the long-term value of asset of the producer in a dynamic model.

of β_1 indicates that small producers with fewer suppliers have a tighter credit constraint than large producers with more suppliers. We also examine the cyclicality in the tightness of the credit constraint and the heterogeneity in the cyclicality varies across different producers by running the following panel regression:

$$d\ln(b_{i,t}/\bar{\pi}_i) = \beta_0 + \beta_1 d\ln(Y_t) + \beta_2 \ln(\bar{v}_i/med(\bar{v}_i)) \cdot d\ln(Y_t) + \alpha_i + \epsilon_{i,t}, \tag{F.4}$$

where Y_t is the growth rate of real gross output in year t. We are interested in the coefficients β_1 and β_2, which capture the cyclicality of the tightness of the credit constraint and the relationship between this cyclicality and the number of suppliers, respectively.[32] A positive coefficient of β_1 indicates that the credit constraints are tighter in recessions than in booms, and a negative β_2 indicates that the increase in the tightness of credit constraints is more severe for small producers with fewer suppliers.

Table F.6: Relationship between producer's debt-to-profit ratio and supplier no. and real GDP growth

VARIABLES	(1) Debt-to-profit ratio	(2) Debt-to-profit ratio growth
Supplier no.	0.174***	
	(0.051)	
Real output growth		1.576***
		(0.253)
Supplier no. * Real output growth		-0.701***
		(0.220)
Observations	19,347	14,980
R-squared	0.082	0.002
Number of producers	2,427	2,107
Producer Fixed Effect	No	Yes
Year Fixed Effect	Yes	No

Notes: Data are annual. Producer's supplier number is the log average number of suppliers across years for the producer. The producer's supplier number in column (2) is divided by the sample median. Real output growth is the growth rate of the BEA quantity index of gross output. Year and producer-fixed effects are controlled in columns (1) and (2), respectively. The top and bottom 2.5% of the sample for adoption and termination rates are winsorized. We restrict our sample to producers whose maximum numbers of suppliers exceed one over time. Standard errors are clustered at the producer level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Column (1) in Table F.6 shows the estimation results of the regression in equation (F.3). The positive and significant coefficient of the number of suppliers indicates that small producers with fewer suppliers have a tighter credit constraint than large producers with more suppliers, implying that the producer-specific multiplier in the credit constraint of equation (17), θ_i, increases in the size of the producer. Column (2) shows the estimation results of the regression in equation (F.4). The positive and significant coefficient of the growth rate of real gross output indicates that the tightness in the credit constraints is countercyclical, viz., recessions are accompanied by tighter constraints. The negative and significant coefficient of the interaction term between the number of suppliers and the growth rate of real output indicates that the increase in the tightness of credit constraints during recessions is more severe for small producers with fewer suppliers than

[32] $\bar{v}_i$ is divided by the sample-median $med(\bar{v}_i)$ so that β_1 captures the cyclicality of the tightness of the credit constraint for the producer with the median number of suppliers.

large producers with more suppliers.

Calibration of the parameters. We use the estimation of coefficient β_1 in equation (F.3) to calibrate θ_i. Specifically, we assume that $\theta_i = \theta_{i0} + \beta_\theta \ln(V_i^{ss})$ is a linear function of the number of suppliers. Because the range of the log number of suppliers in the data is larger than that in the model-simulated data (3.5 vs. 0.4), we calibrate β_θ to be $0.174 * 3.5/0.4 \approx 1.5$, which is 8.75 times the coefficient of the number of suppliers in Column (1) of Table F.6. Given the calibrated β_θ, we then calibrate θ_{i0} so that one-third of all producers have binding credit constraints in the steady state.[33] We further use the estimation results of equation (F.4) to calibrate $\eta_{A,i}$. Specifically, we assume that $\eta_{A,i} = \eta_{A,i0} + \beta_\eta \ln(V_i^{ss}/med(V_i^{ss}))$ is a linear function of the number of suppliers, where $med(V_i^{ss})$ is the number of suppliers of the median producer. We calibrate $\eta_{A,i0}$ to be 1.6, consistent with the coefficient of the real output growth in Column (2) of Table F.6. Because the range of the log number of suppliers in the data is larger than that in the model-simulated data (3.5 vs. 0.4), we calibrate β_η to be $-0.7 * 3.5/0.4 \approx -6.1$, which is 8.75 times the coefficient of the interaction term in Column (2) of Table F.6.

We calibrate the credit injection rate $\tau_L(A)$ and the rate of input subsidies τ_N to match the model-implied shares of credit injection and input subsidies in the aggregate output to the shares in the observed data. Specifically, by the time the program concluded in mid-2021, the PPP provided around $800 billion dollars in loans, among which $342 billion had a maturity of two years and the remaining $458 billion had a maturity of five years. Thus, the annualized ratio of PPP loans in the U.S. gross output in 2020 ($36.6 trillion dollars) is around 0.72% (i.e., $(342/2 + (800 - 342)/5)/(36.6 * 1000)) \approx 0.0072$), resulting in a calibrated annual rate of credit injection of 0.42 when the detrended log aggregate output is at the year 2020 level of -0.044. We set the credit injection rate $\tau_L(A)$ to have the ratio of the amount of credit injection on producers to the aggregate output in the model equal to 0.72% for any level of aggregate TFP. We set the rate of input subsidies $\tau_N = 2.6\%$, such that the steady-state ratio of input subsidies to aggregate output is also 0.72%.

Appendix G. 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.[34]

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

[33] In the FEDS Notes by Perez-Orive and Timmer (2023), the authors use data from S&P Global, Compustat, and Wharton Research Data Services to calculate the shares of financially-distressed firms in the U.S. since the 1970s, which range from 10% to 50% and average around 30%.

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

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. (Ping, 1993; Heide and Weiss, 1995; Nielson, 1996; Whitten and Wakefield, 2006; Whitten, 2010; Whitten et al., 2010; Barroso and Picón, 2012) 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 (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%.

Appendix H. Model timeline and proofs for propositions

Timeline of the model.

Figure H.11: Timeline

Notes: At the beginning of the period, the final goods producer is endowed with a continuum 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.

Proofs for propositions.

Using equations (7) and (8), we have

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

and

$$\left(1-\bar{V}_i^* s_{i,N}^*\right) = \frac{\xi V_i^*+c^+}{\alpha A a_i}. \tag{H.2}$$

Summing equations (7) and (8), we have

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

Therefore, the steady-state total measure of suppliers of producer i equals

$$\begin{aligned} \Longleftrightarrow \bar{V}_i^* &= \frac{2\alpha \bar{A} a_i-c^++c^-}{\alpha \bar{A} a_i+2\xi} \\ &= \frac{2\alpha \bar{A}-\widetilde{c}^++\widetilde{c}^-}{\alpha \bar{A}+2\widetilde{\xi}}. \end{aligned} \tag{H.3}$$

Taking the difference between equations (H.1) and (H.2), we have

$$\begin{aligned} 2\bar{V}_i^* s_{i,N}^* &= -\frac{c^-+c^+}{\alpha A a_i}+V_i^* \\ \Longrightarrow s_{i,N}^* &= \frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*}-\frac{c^-+c^+}{\alpha A a_i \bar{V}_i^*}\right) < \frac{1}{2}\frac{V_i^*}{\bar{V}_i^*}, \end{aligned} \tag{H.4}$$

and

$$
\begin{aligned}
s_{i,T}^* &= \left[\bar{V}_i^* - \left(V_i^* - \bar{V}_i^* s_{i,N}^*\right)\right] / \bar{V}_i^* \\
&= -\frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} + \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right) + 1,
\end{aligned} \tag{H.5}
$$

and

$$
\begin{aligned}
s_{i,E}^* &= \frac{V_i^*}{\bar{V}_i^*} - \frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} - \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right) \\
&= \frac{1}{2}\left(\frac{V_i^*}{\bar{V}_i^*} + \frac{c^- + c^+}{\alpha A a_i \bar{V}_i^*}\right).
\end{aligned} \tag{H.6}
$$

In equilibrium, the output of producer i satisfies:

$$
\begin{aligned}
Y_i^* =& a_i A \frac{\left(2 - \bar{V}_i^* s_{i,E}^*\right) \bar{V}_i^* s_{i,E}^* + \left(2 - \bar{V}_i^* s_{i,N}^*\right) \bar{V}_i^* s_{i,N}^*}{2} \\
\Longleftrightarrow ln Y_i^* =& ln a_i + ln A + ln \left[\frac{\left(2 - \bar{V}_i^* s_{i,N}^*\right) \bar{V}_i^* s_{i,N}^* + \left(2 - \bar{V}_i^* s_{i,E}^*\right) \bar{V}_i^* s_{i,E}^*}{2}\right] \\
=& ln a_i + ln A + ln \left[\frac{\left(2 - \bar{V}_i^* s_{i,N}^*\right) \bar{V}_i^* s_{i,N}^* + \left(2 - V_i^* + \bar{V}_i^* s_{i,N}^*\right)\left(V_i^* - \bar{V}_i^* s_{i,N}^*\right)}{2}\right].
\end{aligned} \tag{H.7}
$$

Lemma 1

Proof. Taking the partial derivative of equation (H.7) wrt. lnV_i^*, we have

$$
\frac{\partial ln Y_i^*}{\partial ln V_i^*} = \frac{A a_i V_i^*}{Y_i^*} z_{i,E}^* > 0.
$$

□

Lemma 2

Proof. Taking the partial derivative of equation (H.7) wrt. $s_{i,N}^*$, we have

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

where the last equality comes from equation (H.4).

□

Lemma 3

Proof. Combining equations (H.1) and (H.2), we have

$$2 = V_i^* + \frac{\xi V_i^* - c^-}{\alpha A a_i} + \frac{\xi V_i^* + c^+}{\alpha A a_i}. \tag{H.8}$$

Applying the implicit function theorem to equation (H.8), 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,

$$\begin{aligned}\frac{d\ln V_i^*}{d\ln A} &= \frac{2\widetilde{\xi}_i\bar{V}_i^* + \left(\widetilde{c}_i^+ - \widetilde{c}_i^-\right)}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)\bar{V}_i^*} \\ &= \frac{2\alpha\bar{A}/\bar{V}_i^* - \alpha\bar{A}}{2\widetilde{\xi}_i + \alpha\bar{A}}.\end{aligned} \tag{H.9}$$

When $c^+ = c^-$,

$$\frac{d\ln V_i^*}{d\ln A} = \frac{2\widetilde{\xi}_i}{2\widetilde{\xi}_i + \alpha\bar{A}}. \tag{H.10}$$

□

Lemma 4

Proof. Taking the partial derivatives of equations (H.4) and (H.5) wrt. $\ln A$, we have

$$\frac{\partial s_{i,N}^*}{\partial\ln A} = \frac{\partial s_{i,T}^*}{\partial\ln A} = \frac{\widetilde{c}_i}{2\alpha\bar{A}\bar{V}_i^*} > 0. \tag{H.11}$$

□

Proposition 1

Proof. Taking the total derivative of equation (H.5) wrt. $\ln A$, we have

$$\begin{aligned}\frac{ds_{i,T}^*}{d\ln A} &= \underbrace{-\frac{1}{2}\frac{d\ln V_i^*}{d\ln A}}_{\text{Scaling effect} < 0} + \underbrace{\frac{\widetilde{c}_i}{2\alpha\bar{A}\bar{V}_i^*}}_{\text{Switching effect} > 0} \\ &= -\frac{1}{2}\frac{2\alpha\bar{A}/\bar{V}_i^* - \alpha\bar{A}}{\left(2\widetilde{\xi}_i + \alpha\bar{A}\right)} + \frac{\widetilde{c}_i/\bar{V}_i^*}{2\alpha\bar{A}}.\end{aligned} \tag{H.12}$$

Therefore,

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

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 (H.8) in the steady state, we have

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

Thus, when a_i increases from zero, $ds^*_{i,T}/d\ln A$ 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 $\widetilde{c}_i/\left(\alpha\bar{A}\right)$ 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

$$\frac{ds_{i,N}^*}{d\ln A}=\frac{1}{2}\frac{d\ln V_i^*}{d\ln A}>0,$$
$$\frac{ds_{i,T}^*}{d\ln A}=-\frac{1}{2}\frac{d\ln V_i^*}{d\ln A}<0,$$

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

Proposition 2

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,

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

□

Appendix I. Extended model with flexible convexity in management and adjustment costs

Appendix I.1. Flexible combination of convexity in management and adjustment costs

We extend our model to allow for flexible combinations of the degree of convexity in the management and adjustment costs (i.e., flexible combinations that nest linear and quadratic specifications for those costs). The management cost becomes

$$G\left(z_{i,N},z_{i,E}\right)=\xi_0V_i+\xi_1\cdot V_i^2/2, \tag{I.1}$$

where parameter ξ_0 governs the size of the linear component and ξ_1 governs the size of the quadratic (i.e., strictly convex) component. The share of the quadratic component in the entire management cost, denoted by $\hat{\xi}_1\equiv\xi_1/(\xi_0+\xi_1)$, captures the degree of convexity in the management cost function.

We allow for similar flexible combinations in the degree of convexity in adjustment costs. Particularly, we assume symmetric functions of the adoption and termination costs, which are written as

$$c^{+}\left(V_{i,N}\right)*V_{i,N}=c_0V_{i,N}+c_1V_{i,N}^2/2, \tag{I.2}$$
$$c^{-}\left(V_{i,T}\right)*V_{i,T}=c_0V_{i,T}+c_1V_{i,T}^2/2, \tag{I.3}$$

where $V_{i,N}\equiv\bar{V}_i^*s_{i,N}=1-z_{i,N}$ and $V_{i,T}\equiv\bar{V}_i^*s_{i,T}=z_{i,E}-1+\bar{V}_i^*$ are the measures of adopted new suppliers and terminated existing suppliers, respectively. Parameter c_0 governs the size of the linear component, and

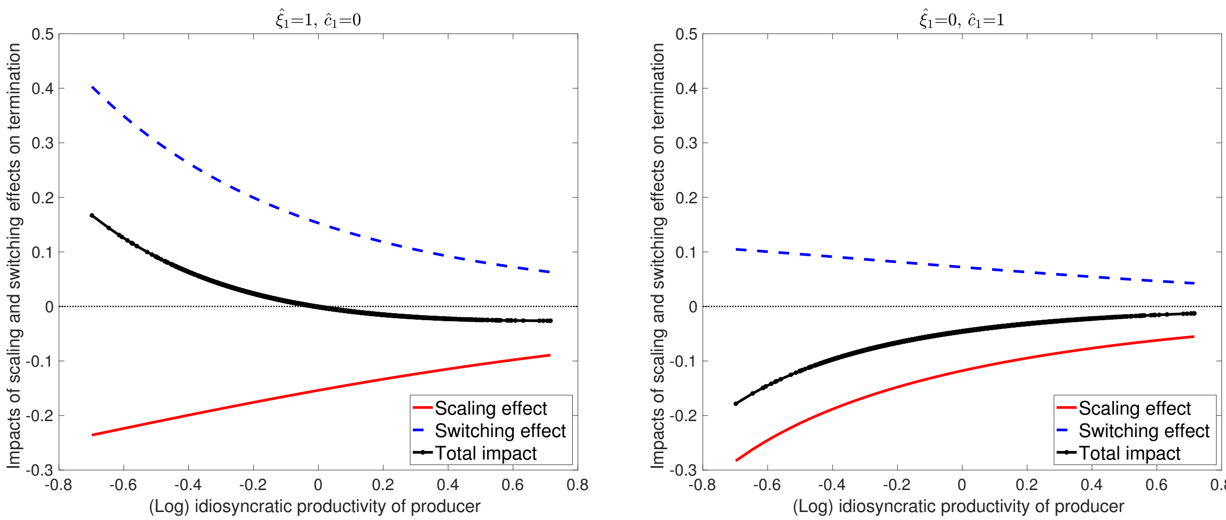
c_1 governs the size of the quadratic (i.e., strictly convex) component. The share of the quadratic component in the entire adoption (vs. termination) cost, denoted by $\hat{c}_1 \equiv c_1/(c_0 + c_1)$, captures the degree of convexity in the adoption (vs. termination) cost function.

In our baseline model of Sections 4 and 5, we have $\hat{\xi}_1 = 1$ and $\hat{c}_1 = 0$ such that the management cost is quadratic and the adoption and termination costs are linear (i.e., $G(z_{i,N}, z_{i,E}) = \xi_1 \cdot V_i^2/2$ and $c^+(V_{i,N}) = c^-(V_{i,T}) = c_0$).

Appendix I.2. Convexity of costs and cross-sectional scaling and switching effects for the termination rate

In this section, we experiment with different degrees of convexity in the management and adjustment costs. We fix $\xi_0 + \xi_1$ and $c_0 + c_1$ to the baseline values that are consistent with the acyclical aggregate termination rate. Then, we change the degree of convexity of the management cost by varying the share of the quadratic component in the management cost (i.e., $\hat{\xi}_1$). Similarly, we change the degree of convexity of the adjustment cost by varying the share of the quadratic component in the adoption and termination costs (i.e., $\hat{c}_1$).

Figure I.12: Convexity in management and adjustment costs and the scaling and switching effects



(a) Baseline model

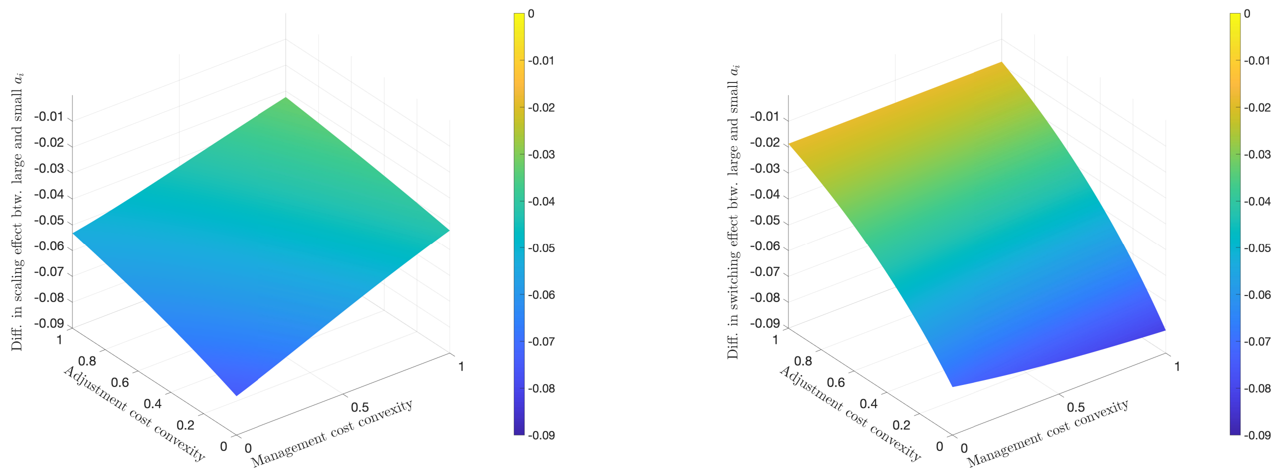
(b) Counterfactual model

Notes: The figure plots the impacts of scaling (dotted 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, which indicates the (pro)cyclicality of the rate of termination. Panel (a) is the baseline model with quadratic management cost and linear adjustment costs (i.e., $\hat{\xi}_1 = 1$ and $\hat{c}_1 = 0$), and Panel (b) is the counterfactual model with linear management cost and quadratic adjustment costs (i.e., $\hat{\xi}_1 = 0$ and $\hat{c}_1 = 1$).

Panel (a) of Figure I.12 shows our baseline model that has quadratic management costs (i.e., $\hat{\xi}_1 = 1$) and linear adoption and termination costs (i.e., $\hat{c}_1 = 0$). In the baseline model, the switching effect significantly declines with the idiosyncratic productivity of the producer, while the size (i.e., the absolute value) of the scaling effect is insensitive to the idiosyncratic productivity. Thus, the total impact (i.e., the procyclicality of termination)—which equals the sum of the switching effect and the negative scaling effect, as shown in equation (11)—decreases with the producer's idiosyncratic productivity, generating countercyclical termination for large producers and procyclical termination for small producers that are consistent with Figure 2 of Fact 2.

Panel (b) of Figure I.12 shows the counterfactual specification of the model where the management cost is linear as in the network literature (i.e., $\hat{\xi}_1 = 0$ and therefore less convex than in the baseline model, e.g., Lim, 2018; Huneeus, 2018), and the adjustment cost is quadratic as in the labor literature (i.e., $\hat{c}_1 = 1$ and more convex than in the baseline model, e.g., Caballero and Hammour, 1994; Bloom, 2009; Zanetti, 2008). In this counterfactual specification of the model, the switching effect hardly changes with the idiosyncratic productivity of the producer, while the size (i.e., the absolute value) of the scaling effect significantly diminishes with the idiosyncratic productivity. Thus, the total impact (i.e., the procyclicality of termination)—which equals the sum of the switching effect and the negative scaling effect, as shown in equation (11)—is negative for all producers and increases with the producer's idiosyncratic productivity, generating countercyclical termination for small producers as well as *less* countercyclical termination for large producers, against the empirical results in Figure 2 of Fact 2.

Figure I.13: Diff. in the size of scaling/switching effect btw. large and small producers vis-à-vis convexity of costs



(a) Diff. in the size of scaling effect

(b) Diff. in the size of switching effect

Notes: Panel (a) plots the difference in the size (i.e., the absolute value) of the scaling effect (for the termination rate) between the two producers with (log) idiosyncratic productivity equal to 0.2 and -0.2 (vertical axis) *vis-à-vis* the convexity in the management and the adjustment costs (horizontal axes). The size of the scaling effect equals the minus of the scaling effect because the scaling effect is negative for the termination rate. Panel (b) plots the difference in the size of the switching effect (for the termination rate) between the two producers with (log) idiosyncratic productivity equal to 0.2 and -0.2 (vertical axis) *vis-à-vis* the convexity in the management and the adjustment costs (horizontal axes). The convexity in the management and adjustment costs are measured by $\hat{\xi}_1$ and $\hat{c}_1$, respectively.

Comparing Panels (a) and (b) in Figure I.12, we can conclude that the *sensitivity* of the scaling (vs. switching) effect to the producer's idiosyncratic productivity—defined as the *semi-elasticity* of the size (i.e., the absolute value) of the scaling (vs. switching) effect to a_i—declines with the degree of convexity of the management (vs. adjustment) costs. This pattern is verified by Figure I.13, where the difference in the size of the scaling (vs. switching) effect between the larger and the smaller producers—measuring the *sensitivity* of the scaling (vs. switching) effect to a_i—is plotted against broader combinations of the degree of convexity in management (vs. adjustment) costs.[35] Panel a (vs. Panel b) in Figure I.13 shows that the difference in the size of the scaling (vs. switching) effect between the larger and the smaller producers is always negative, evincing that the size of the scaling (vs. switching) effect diminishes with the idiosyncratic productivity of the producer, consistent with Lemmas 3 and 4, and Figure I.12. Moreover, for the scaling (vs. switching) effect, the difference (between large and small producers) is more negative when the management (vs. adjustment) cost is closer to linear and less convex, indicating that the sensitivity of the scaling (vs. switching) effect to a_i declines with the convexity of the management (vs. adjustment) cost, again consistent with Figure I.12.[36]

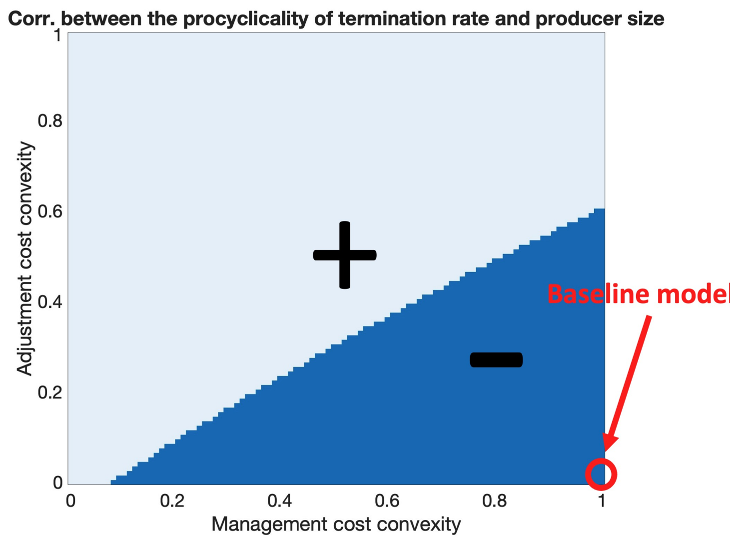


Figure I.14: Difference in (pro)cyclicality of termination btw. small and large producers *vis-à-vis* convexity of costs

Notes: The figure plots the difference in the total impacts of scaling and switching effects (for the termination rate) between a large and a small producer with (log) idiosyncratic productivity equal to 0.2 and -0.2 (measured by the darkness of color) *vis-à-vis* the convexity in the management (x-axis) and the adjustment costs (y-axis). The convexity in the management and adjustment costs are measured by $\hat{\xi}_1$ and $\hat{c}_1$, respectively. Our baseline model with quadratic (i.e., maximum degree of convexity) management and linear (i.e., minimum degree of convexity) adjustment costs is indicated by the red circle in the bottom right of the figure.

Similar to Figure I.13, Figure I.14 plots the difference in the procyclicality of termination between the larger and the smaller producers *against* various combinations of the degree of convexity in management and adjustment costs, where the procyclicality of termination is measured by the total impact of scaling and switching effects. The difference in the total impact between the large and small producers is indicated by the color, where the light (vs. dark) blue area indicates a more positive (vs. negative) total impact and, in turn, more procyclical (vs. countercyclical) rate of termination for the larger producer than the smaller

[35]The larger and the smaller producers have log idiosyncratic productivity of 0.2 and -0.2, respectively.

[36]In Figure I.13, for the scaling (vs. switching) effect, the difference (between the larger and smaller producers) is also more negative when the adjustment (vs. management) cost is closer to linear and less convex. However, the sensitivity of the scaling (vs. switching) effect to a_i declines more with the convexity of the management (vs. adjustment) cost than with the convexity of the adjustment (vs. management) cost.

producer. The convexity in the management (x-axis) and the adjustment costs (y-axis) are measured by $\hat{\xi}_1$ and $\hat{c}_1$, respectively. Our baseline model with quadratic (i.e., maximum degree of convexity) management and linear (i.e., minimum degree of convexity) adjustment costs is represented by the red circle in the bottom right of the figure.

Figure I.14 shows that when the management cost has a sufficiently large degree of convexity and the adjustment cost has a sufficiently small degree of convexity (i.e., sufficiently close to linear), the procyclicality of termination is more negative (i.e., more countercyclical termination) for the large producer than for the small producer, evinced by the dark-blue area towards the bottom right of the figure that includes the red circle representing the quadratic management cost and linear adjustment cost in our baseline model. As Figure I.13 shows, the large convexity in the management cost and the small convexity in the adjustment cost make the scaling effect insensitive to a_i and the switching effect more sensitive to a_i. Therefore, the switching effect dominates in the sensitivity of the cyclicality of termination to a_i, making the termination less procyclical (i.e., more countercyclical) for large producers than for small producers.[37]

In contrast, when the management cost becomes more linear (i.e., towards the left of Figure I.14), and/or adjustment cost becomes more convex (i.e., towards the top of Figure I.14), the switching effect is insensitive to a_i while the scaling effect is more sensitive to a_i. Therefore, the scaling effect dominates in the sensitivity of the cyclicality of termination to a_i, making the termination less countercyclical for large producers than for small producers.[38] This result is consistent with the counterfactual model in Panel (b) of Figure I.12 but contradicts Figure 2 of Fact 2.

To understand why the sensitivity of the scaling (vs. switching) effect to the idiosyncratic productivity declines with the convexity of the management (vs. adjustment) costs, we study equations (I.4) and (I.5). In these two equations, the sizes of the scaling and switching effects are functions of the convexity of the management and adjustment costs (i.e., $\hat{\xi}_1$ and $\hat{c}_1$), the size of the producer (i.e., $\bar{V}_i^*$), and other parameters.[39]

$$\text{Scaling effect} = -\frac{1}{2}\frac{d\ln V_i^*}{d\ln A} = -\frac{1}{2}\left[\left(\alpha\bar{A}a_i\right)^2/2 + \xi_1\alpha\bar{A}a_i + \left(\alpha\bar{A}a_i + \xi_1\right)c_1 + c_1^2/2\right]^{-1} \tag{I.4}$$
$$(\xi_0+\xi_1)\left[(1-\hat{\xi}_1)+\hat{\xi}_1\bar{V}_i^*\right]/\bar{V}_i^* * \left(\alpha\bar{A}a_i + c_1\right).$$
$$\text{Switching effect} = \frac{\left[(1-\hat{c}_1)+\hat{c}_1\bar{V}_i^*\bar{s}_{i,N}^*\right]/\bar{V}_i^*}{(\alpha\bar{A}a_i+c_1)(c_0+c_1)}. \tag{I.5}$$

Equations (I.4) and (I.5) show that sizes of the scaling effect (i.e., $\frac{1}{2}d\ln V_i^*/d\ln A$) and the switching effect are mainly affected by two opposite forces that are functions of the size of the producer: (1) the scaling (vs. switching) effect is positively correlated to the marginal management (vs. adjustment) cost (i.e., $\left[(1-\hat{\xi}_1)+\hat{\xi}_1\bar{V}_i^*\right]$ vs. $\left[(1-\hat{c}_1)+\hat{c}_1\bar{V}_i^*\bar{s}_{i,N}^*\right]$), which increases with the size of the producer $\bar{V}_i^*$ when

[37] Recall that the size of the switching effect diminishes with the size of the producer in Lemma 4, evinced by Figure I.12.

[38] Recall that the size of the scaling effect diminishes with the size of the producer in Lemma 3, evinced by Figure I.12.

[39] Recall that the producer's size in terms of total measure of suppliers (i.e., $\bar{V}_i^*$) increases with its idiosyncratic productivity, i.e., more (vs. less) productive producers correspond to larger (vs. smaller) producers.

the management (vs. adjustment) cost is strictly convex (i.e., $\hat{\xi}_1 > 0$ vs. $\hat{c}_1 > 0$); (2) the scaling (vs. switching) effect is inversely related to the steady-state measure of suppliers of the producer (i.e., $\bar{V}_i^*$) because the ratio of the management (vs. adjustment) cost to the profit—which determines the size of the scaling (vs. switching) effect—is smaller for larger producers with higher profits than for smaller producers. Consequently, the relationship between the scaling (vs. switching) effect and the idiosyncratic productivity (or size) of the producer and, in turn, the sensitivity of the scaling (vs. switching) effect to a_i, depends on the degree of convexity in the management (vs. adjustment) cost. When the management (vs. adjustment) cost is more convex, the marginal cost increases with $\bar{V}_i^*$ by a larger extent, making the ratio of the marginal cost (i.e., the first force) to the size of the producer (i.e., the second force) less variant to changes in the size of the producer and leading to a smaller sensitivity of the scaling (vs. switching) effect to a_i that is consistent with Panel a (vs. Panel b) in Figure I.13.

In our baseline model, the management cost is at the maximum convexity (i.e., quadratic with $\hat{\xi}_1 = 1$) and the adjustment cost is at the minimum convexity (i.e., linear with $\tilde{c}_0 = 0$). Therefore, the scaling effect is insensitive to the producer's idiosyncratic productivity, while the switching effect is significantly sensitive to the idiosyncratic productivity. The switching effect, which is positive and declines with a_i, dominates the changes in the total impacts to a_i and makes the termination rate more procyclical for small producers while more countercyclical for large producers, evinced by Panel (a) in Figure I.12.