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The adoption and termination of suppliers over the business cycle $\stackrel{\star}{\sim}$



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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.

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

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

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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 (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. 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 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 3609 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

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.

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.

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 ($\Delta v_{i,I}/v_{i,I-1}$), the adoption rate ($s_{i,N,I}$), and the termination rate ($s_{i,T,I}$) of each producer by their intermediate input expenditures to construct the aggregate indexes $\Delta v_i/v_{i-1}$, $s_{N,I}$, and $s_{T,I}$. 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 $\Delta v_i/v_{i-1} = s_{N,I} - s_{T,I}$.

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. Fig. 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, Fig. 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:

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

The derivation of Eq. (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 Eq. (1)) equals 83%, and the contribution of the aggregate termination rate equals 17%. Together with the results shown in Fig. 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.

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.

Fig. 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

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.





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 $(s_{N,i})$ and Aggregate rate of termination $(s_{T,i})$ are the weighted averages of $s_{i,N,i}$ 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



Fig. 2. Cyclicality of adoption and termination of suppliers for producers with different numbers of suppliers *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

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.

gross output of private industries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Panel (a) in Fig. 2 shows that the adoption rate is procyclical across all producers, consistent with the procyclical aggregate rate of adoption shown in Fig. 1. Moreover, the adoption rate is more procyclical for producers with fewer suppliers compared to



Fig. 3. Cyclicality of job creation and destruction for establishments with different numbers of employees

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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 retain them 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 Fig. 1 of Fact 1.

For comparison, Fig. 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 Fig. 3 shows that the cyclicality of job creation closely mirrors the cyclicality of supplier adoption in panel (a) of Fig. 2: establishments uniformly entail procyclical job creation (with small establishments displaying more pronounced procyclicality than big ones).

In contrast, panel (b) in Fig. 3 shows that the cyclicality of job destruction differs significantly from the cyclicality of supplier termination in panel (b) of Fig. 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 Fig. 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:

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

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.

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", "100 to 2499", "2500 to 4999", "5000 to 9999", and "10000+".

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:

$$\hat{s}_{i,N,t} = \sum_{j} \omega_{i,t_0(i)}(j) \cdot s_{N,t}(j) \quad \text{and} \quad \hat{s}_{i,T,t} = \sum_{j} \omega_{i,t_0(i)}(j) \cdot s_{T,t}(j), \tag{3}$$

where $\omega_{i,l_0(i)}(j)$ 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 $\omega_{i,l_0(i)}(j)$ is endogenously determined by changes in producer *i*'s productivity and other business conditions between t_0 and *t*. Intuitively, $\omega_{i,l_0(i)}(j)s_{N,t}(j)$ and $\omega_{i,l_0(i)}(j)s_{T,t}(j)$ serve as natural predictions of producer *i*'s rates of adoption and termination of suppliers from sector *j*. Thus, $\hat{s}_{i,N,t}$ and $\hat{s}_{i,T,t}$ predict producer *i*'s adoption and termination rates, and consequently predict churning and growth rates of the number of suppliers. Table B.4 271 in Appendix B shows the first-stage results, verifying that $\hat{s}_{i,N,t}$ and $\hat{s}_{i,T,t}$ 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 Eq. (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

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

⁶ Specifically, $\omega_{l,l_0(i)}(j) \equiv v_{l,l_0(i)}(j)/v_{l_0(j)}$, where $v_{l,l_0(j)}(j)$ is the number of producer *i*'s suppliers in sector *j*, while $v_{l,l_0(i)}$ is the total number of producer *i*'s suppliers. We classify sectors according to one-digit NAICS industries such that no firm is sufficiently large in order to shift the aggregate sectoral dynamics of linkages. $s_{N,l}(j) \equiv v_{N,l}(j)/v_{l-1}(j)$ and $s_{T,l}(j) \equiv v_{T,l}(j)/v_{l-1}(j)$. $v_{l-1}(j)$. $v_{N,l}(j)$, and $v_{T,l}(j)$ 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 $s_{CH,l}(j) \equiv \min\{s_{N,l}(j), s_{T,l}(j)\}$ and construct $\hat{s}_{l,CH,l} = \sum_{i} \omega_{l,a_{i}(l)}(j) \cdot s_{CH,l}(j)$ 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 $s_{i,N,J}$ and $s_{i,T,J}$ in columns (3)–(4) because including two of them is colinear with $d \ln(v_{i,J}) \approx d \ln(v_{i,J}) = s_{i,N,J} - s_{i,T,J}$. Also note that the coefficient of the growth rate of the total number of suppliers is negative and 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).

Tuble 1

Responses of	sales t	to the	total	number	and	churning	of	suppliers.	
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	(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	1831	1831	1831	1831	1831
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 $\hat{s}_{i,N,I}$ to instrument the growth rate of the number of suppliers. Column (2) uses $\hat{s}_{i,N,I}$, $\hat{s}_{i,T,I}$, and $\hat{s}_{i,CH,I}$ to instrument the growth rate of the number of suppliers and the rate of churning. Column (3)-(5) use $\hat{s}_{i,N,I}$ and $\hat{s}_{i,T,I}$ 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.

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 one unit of a distinct input to the producer.¹² 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.¹³

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:

 $y_{i,k}\left(z_{k}\right)=Aa_{i}z_{k}, \quad \forall \ k\in\left\{E,N\right\}, \ \forall \ z_{k},$

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 producersupplier relationship is the output produced by the corresponding production line, $y_{i,k}(z_k)$, which is split between the producer and

¹¹ For each producer *i*, its measure of active suppliers in the production stage is a function $V_i^*(\tilde{V}_i^*, A)$ of the measure of existing suppliers with which the producer starts (\tilde{V}_i^*) and the aggregate TFP (*A*). The steady-state measure of suppliers, \tilde{V}_i^* , is the unique fixed point for the above mapping from \tilde{V}_i^* to V_i^* when the aggregate TFP is at the steady-state level $A = \bar{A}$, i.e., $V_i^*(\tilde{V}_i^*, \bar{A}) = \tilde{V}_i^*$.

¹² Each supplier providing exactly one unit of input generates imperfect substitution between inputs from different suppliers.

¹³ 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)

the supplier by Nash bargaining over the price charged by the supplier $(p_{i,k}(z_k))$, according to the surplus-sharing condition:

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

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 $s_{i,N} = (1 - z_{i,N}) / \bar{V}_i^*$ and $s_{i,T} = (z_{i,E} - 1 + \bar{V}_i^*) / \bar{V}_i^*$.

4.5. Costs of management, adoption, and termination of suppliers

Costs of managing suppliers. Producers incur costs in managing suppliers, consistent with the *span of control* problem (Lucas, 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: $G(z_{i,N}, z_{i,E}) = \xi \cdot V_i^2/2$, where $V_i = 2 - z_{i,N} - z_{i,E}$ is the total measure of active suppliers for each producer *i*, or the total measure of suppliers whose idiosyncratic productivity levels are above the threshold for selection in each vintage.¹⁴

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).¹⁵

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:¹⁶

$$Y_{i} = \int_{z_{i,E}}^{1} y_{i,E}(z_{E}) dz_{E} + \int_{z_{i,N}}^{1} y_{i,N}(z_{N}) dz_{N},$$
(5)

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

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

¹⁴ 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.

¹⁵ 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.

 $^{^{16}}$ 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.

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$$-\underbrace{\left[c^{-}\left(z_{i,E}-1+\bar{V}_{i}^{*}\right)+c^{+}\left(1-z_{i,N}\right)\right]}_{\text{Adjustment costs}}-\underbrace{\xi\cdot\left(2-z_{i,N}-z_{i,E}\right)^{2}/2}_{\text{Management cost}},$$
(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 ($c^-(z_{i,F}-1+\bar{V}_i^*)$) and adoption costs ($c^+(1-z_{i,N})$). The quadratic management cost encapsulates administrative costs for the management of suppliers.

Combining the bargained input price in Eq. (4) with Eq. (6) yields:

$$\begin{split} \Pi_{i} &= \max_{\{z_{i,E}, z_{i,N}\}} \alpha \left\{ \int_{z_{i,E}}^{1} Aa_{i} z_{E} dz_{E} + \int_{z_{i,N}}^{1} Aa_{i} z_{N} dz_{N} \right\} - \left[c^{-} \left(z_{i,E} - 1 + \bar{V}_{i}^{*} \right) + c^{+} \left(1 - z_{i,N} \right) \right] \\ &- \xi \cdot \left(2 - z_{i,N} - z_{i,E} \right)^{2} / 2. \end{split}$$

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

$$z_{i,E}^{*} + \frac{c^{-}}{\alpha A a_{i}} = \frac{\xi V_{i}^{*}}{\alpha A a_{i}},$$

$$z_{i,N}^{*} - \frac{c^{+}}{\alpha A a_{i}} = \frac{\xi V_{i}^{*}}{\alpha A a_{i}},$$
(8)

where $V_i^* = 2 - z_{i,N}^* - z_{i,E}^*$ is the total measure of suppliers for producer *i* in equilibrium. Eqs. (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 Eqs. (7) and (8) yields:

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

Eq. (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 Eqs. (7) and (8), the next lemma holds.

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

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

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:

$$\frac{\partial lnY_i^*}{\partial s_{i,N}^*} = \frac{c^+ + c^-}{\alpha Y_i^* / \bar{V}_i^*} > 0.$$

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., $ds_{i,N}^*/dlnA = ds_{i,T}^*/dlnA > 0$) (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:

$$\frac{ds_{i,N}^*}{d\ln A} = \underbrace{\frac{1}{2} \frac{d\ln V_i^*}{d\ln A}}_{\text{Scaling effect on adoption>0}} + \underbrace{\frac{\partial s_{i,N}^*}{\partial \ln A}}_{\text{Switching effect > 0}}.$$
(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.¹⁷

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 switching effects:

$$\frac{dS_{i,T}^*}{d\ln A} = -\frac{1}{2} \frac{d\ln V_i^*}{d\ln A} + \frac{\partial S_{i,T}^*}{\partial \ln A}$$
(11)

Scaling effect on termination < 0 Switching effect > 0

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. Eq. (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 Fig. 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 Eq. (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.

¹⁷ To derive Eqs. (10) and (11), we combine Eqs. (7) and (8), and the definitions of $s_{l,N}^*$ and $s_{l,T}^*$, which yields the producer's rates of adoption and termination: $s_{l,N}^* = \frac{V_l^*}{2P_l^*} - \frac{c^* + c^-}{2aAa_l P_l^*}$ and $s_{l,T}^* = 1 - \frac{V_l^*}{2P_l^*} - \frac{c^* + c^-}{2aAa_l P_l^*}$.

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.¹⁸ 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., $ds_{i,T}^*/dlnA < 0$).

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 (Fig. 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 Fig. 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 501 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 Fig. 3).

As Eq. (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 Eq. (11) — decreases with producer size, as evinced in Fig. 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 Eq. (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.

¹⁸ 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.

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.

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 Eq. (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 (Fig. 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 3000 producers ($i \in \{1, 2, ..., 3000\}$) with i.i.d. idiosyncratic productivities drawn from the calibrated distribution. Then, we simulate 1000 economies ($j \in \{1, 2, ..., 1000\}$) for the same 3000 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 3000 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:

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



Fig. 4. Coefficient of regressing the rate of termination on sales: Data vs. 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 2988 (3000) 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 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 heterogeneous 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 regression¹⁹:

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

Panels (a) and (c) in Fig. 4 show the regression results for Eq. (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 Eq. (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

¹⁹ 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 $dlog(Y_i)$ is the growth rate of the real gross output.



Fig. 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

adoption and termination rates across the producers with different measures of suppliers. This result is also consistent with the theoretical findings in Proposition 1.20

Another important similarity between the observed data and the simulated model that emerges from Fig. 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:

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

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

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 Fig. 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

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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.²¹ Several policies and legislative measures were targeted at small and medium-sized enterprises (SMEs), largely

²⁰ 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.

²¹ Bai et al. (2024) and references therein provide an overview of the severity of global supply disruptions for the U.S. economy.

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.²² 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.²³

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*, 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.,

$$wc_{i} \equiv \left(\int_{z_{i,E}}^{1} p_{i,E}(z_{E})dz_{E} + (1-\tau_{N})\int_{z_{i,N}}^{1} p_{i,N}(z_{N})dz_{N}\right) + \left[c^{-}\left(z_{i,E} - 1 + \bar{V}_{i}^{*}\right) + c^{+}\left(1 - z_{i,N}\right)\right] + \xi \cdot \left(2 - z_{i,N} - z_{i,E}\right)^{2}/2,$$
(16)

which is subject to the following constraint:

$$wc_i \le \theta_i A^{\eta_{A,i}} \Pi_i^{ss} + \tau_I(A) \max\{wc_i^s - \theta_i A^{\eta_{A,i}} \Pi_i^{ss}, 0\}.$$
(17)

The first term on the RHS of Eq. $(17) - \theta_i A^{\eta_{A,i}} \prod_i^{ss}$ 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*, \prod_i^{ss} .²⁴ The parameter θ_i captures the tightness of 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.²⁵

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 Eq. (17)— $\tau_L(A) \max\{wc_i^* - \theta_i A^{\eta_{A_j}} \Pi_i^{ss}, 0\}$ —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

²² 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".

²³ 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.

 $^{^{24}}$ 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 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.

²⁵ See Appendix F.2 for the estimates of the panel regressions and the calibration of the parameters.

loans—i.e., the working capital in the baseline model without credit constraints, denoted by wc_i^* —and the amount of external financing $\theta_i A^{\eta_{A,i}} \prod_i^{ss}$. 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 Eq. (17):

$$\Pi_{i} = \max_{\{z_{i,E}, z_{i,N}\}} \underbrace{\left(\int_{z_{i,E}}^{1} y_{i,E}(z_{E}) dz_{E} + \int_{z_{i,N}}^{1} y_{i,N}(z_{N}) dz_{N} \right)}_{\text{Final output}} - \underbrace{\left(\int_{z_{i,E}}^{1} p_{i,E}(z_{E}) dz_{E} + (1 - \tau_{N}) \int_{z_{i,N}}^{1} p_{i,N}(z_{N}) dz_{N} \right)}_{\text{Input costs}} - \underbrace{\left[c^{-} \left(z_{i,E} - 1 + \bar{V}_{i}^{*} \right) + c^{+} \left(1 - z_{i,N} \right) \right]}_{\text{Adjustment costs}} - \underbrace{\xi \cdot \left(2 - z_{i,N} - z_{i,E} \right)^{2} / 2}_{\text{Management costs}}.$$
(18)

In addition to the credit constraint, the optimization problem in Eq. (18) differs from the analogous problem in the benchmark model (Eq. (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 Eq. (4). The extended model nests the baseline version without credit constraints and policies, by setting $\theta_i = +\infty$ and $\tau_I(A) = \tau_N = 0$.

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 2020.²⁶ We set the rate of input subsidies $\tau_N = 2.6\%$, such that 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 lumpsum 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.²⁷

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 underadjustment 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 Fig. 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.

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

²⁶ Appendix F.2 describes how we calibrate the rates of credit injection and input subsidies to match the observed data.

 $^{^{27}}$ 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.



Fig. 6. Welfare loss under different levels of TFP.

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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 upwardsloping 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 towards 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 Fig. 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. To study the role of convex management costs and linear adjustment costs—which is a central theme of our analysis—panel (b) in Fig. 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 Fig. 3(b)), but it is inconsistent with the pattern in the producer-supplier market (as shown in Fig. 2(b)).

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



Fig. 7. Output improvement by policies under low TFP.

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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 comparison between panel (a) to panel (b) in Fig. 6 illustrates the critical role of our documented Facts 1 and 2 in disciplining the sizes and convexity of management versus adjustment costs and, in turn, in determining the relative effectiveness of the policies of credit injection and input subsidies.

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 Fig. 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 Fig. 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 (panel by, 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.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmoneco.2025.103730.

Data availability

Data will be made available on request.

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