

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

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Abstract

We assemble a firm-level dataset to study the adoption and termination of suppliers over business cycles. We document that the aggregate number and rate of adoption of suppliers are procyclical. The rate of termination is acyclical at the aggregate level, and the cyclicalities of adoption and termination encompass 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 cyclicalities in the adoption and termination rates at the producer and aggregate levels. We study the welfare implications of credit injections and subsidies on new inputs—the two main classes of supply-chain policies adopted in the U.S. since the COVID-19 pandemic. Credit injections generally outperform subsidies on new inputs, except when aggregate TFP is exceptionally high.

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

JEL: E32, L14, L24.

[†]We are grateful to Jesús Fernández-Villaverde, Yuriy Gorodnichenko, Dirk Krueger, Morten Ravn, Johannes Wieland, Yongseok Shin, Charles Zhang, Zhesheng Qiu, Linyi Cao, Xican Xi, an anonymous referee, and participants at the 2023 SED annual meeting, 2023 Shanghai Macroeconomics Workshop, 2022 European Meetings of the Econometric Society, 2022 Asian Meetings of the Econometric Society (Shenzhen and Tokyo), Shanghai Jiao Tong University, and East China Normal University for valuable comments and suggestions. Le Xu acknowledges the financial support from the Shanghai Pujiang Program (Grant number 22PJJC070), and Francesco Zanetti from the British Academy (Grant number SRG22/221227).

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1. Introduction

Production of final output in modern economies requires inputs from multiple suppliers, so the adoption, termination, and management of suppliers are important decisions in the production of final goods. Despite abundant work dedicated to the adoption and termination of suppliers in models of international trade and in operation management textbooks, little is known about the cyclical regularities of these margins of adjustment at the producer level or their effects on the broader aggregate economy.¹ Consequently, several fundamental questions remain unanswered: What are the patterns of adoption and termination of suppliers at the producer level, and how are those linked with the business cycle? Are the adoption and termination of suppliers similar across different producers? What forces explain the empirical regularities? What are the different welfare effects of the main classes of supply-chain policies adopted in the U.S.?

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

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

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

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

35 (unlike acyclical supplier termination).

36 Fact 2 shows that the acyclical aggregate rate of termination conceals large heterogeneity in the cycli-
37 cality of the termination rate across producers having different numbers of suppliers. The termination rate
38 is countercyclical for producers with a large number of suppliers but procyclical for producers with a small
39 number of suppliers; this is in stark contrast to the more countercyclical job destruction for larger than
40 smaller establishments in the labor market. The aggregate acyclicity in the rate of termination results
41 from the countervailing adjustments in the termination of suppliers across producers with different numbers
42 of suppliers.

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

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

53 Management and adjustment costs have different implications for changes in the adoption and termi-
54 nation of suppliers. *Management costs* constrain the scale of operations through decreasing the adoption
55 of new suppliers and increasing the termination of existing suppliers. *Adjustment costs* discourage both
56 the adoption of new and the termination of existing suppliers and influence the composition of suppliers.
57 Accordingly, the two separate costs lead to two distinct effects of the aggregate TFP on the adoption and
58 termination of suppliers. One is the *scaling effect*: the higher TFP decreases the relevance of management
59 costs for the profits of the producer, leading to an optimal increase in the measure of suppliers for the pro-
60 duction of the final goods. This effect fosters a rise in the adoption and a decline in the termination of
61 suppliers. The second is the *switching effect*: the higher TFP reduces the relevance of adjustment costs for
62 the producer's profits, engendering greater churning of suppliers. This effect induces a rise in both the rates
63 of adoption and termination of suppliers. Scaling and switching effects jointly generate a positive correla-
64 tion between the adoption of new suppliers and aggregate TFP, consistent with Facts 1 and 2. In contrast,
65 the two forces exert countervailing effects on the correlation between the rate of termination and TFP.

66 The model reveals that producers' different measures of suppliers—determined by their idiosyncratic
67 productivities in the model—are critical to the heterogeneous responses of the termination rates across
68 producers to aggregate TFP shocks, as well as to the overall acyclical response in the aggregate rate of ter-
69 mination. For an individual producer, its idiosyncratic productivity and the associated measure of suppliers
70 are central to the relevance of adjustment costs for the adjustment in suppliers. The producer with high

71 idiosyncratic productivity and a large measure of suppliers experiences low adjustment costs relative to its
72 profit. This generates limited benefits from replacing existing with new suppliers when TFP increases (i.e.,
73 the scaling effect dominates). The producer with low idiosyncratic productivity and a small measure of
74 suppliers, however, faces high adjustment costs relative to its profit, generating large benefits from replac-
75 ing existing with new suppliers when TFP increases (i.e., the switching effect dominates). Thus, consistent
76 with our Fact 2, producers with a large (vs. a small) measure of suppliers display a negative (vs. a positive)
77 response of the termination rate to changes in aggregate TFP—which is driven by the dominating scaling
78 (vs. switching) effect.

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

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

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

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

²Section 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.

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

114 Our analysis is related to several areas of research. It is linked to the literature on endogenous changes in
115 producer-supplier relations over the business cycle. Related work primarily focuses on the network structure
116 of producer-supplier relations ([Atalay, 2017](#); [Acemoglu and Tahbaz-Salehi, 2023](#); [Grassi, 2017](#); [Huneus, 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
119 and the acyclical rate of relationship separation (i.e., termination of suppliers), focusing on the critical role
120 of management and adjustment costs in replicating these facts and the welfare implications of the major
121 classes of U.S. government policies since the COVID-19 pandemic.

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

135 The remainder of the paper is structured as follows. Section 2 outlines the construction of the data and
136 defines the empirical variables. Section 3 describes the empirical results. Section 4 develops a simple model

³A notable exception is [Baqae 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.

137 to study the empirical evidence. Section 5 presents the analytical results of the model. Section 6 discusses
138 the quantitative results and compares them to the data. Section 7 provides policy analyses as applications to
139 the model. Section 8 concludes.

140 2. Data and variables

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

151 Using the above data, we first define our main variables of interest. We denote by variable $v_{i,t}$ the
152 number of suppliers that are in partnerships with the producer i in year t . Our central interest is measuring
153 the rates of adoption and termination of suppliers. We define the *rate of adoption* of each producer i in
154 period t as $s_{i,N,t} \equiv v_{i,N,t}/v_{i,t-1}$, where $v_{i,N,t}$ is the number of new suppliers that producer i adopted in year
155 t (the subscript N refers to new suppliers). Similarly, we define the *rate of termination* for each producer i
156 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
157 in year t (the subscript T refers to the termination of suppliers). In the data, the rate of termination is on
158 average smaller, and less volatile than the rate of adoption, with means of 0.144 vs. 0.287 and standard
159 deviations of 0.203 vs. 0.449. Shown in Table A.3 in Appendix A are the summary statistics of the rates of
160 adoption and termination at the producer level.

161 To study the economy-wide changes in the total number and churning of suppliers, we weight the growth
162 rate of the number of suppliers ($\Delta v_{i,t}/v_{i,t-1}$), the adoption rate ($s_{i,N,t}$), and the termination rate ($s_{i,T,t}$) of
163 each producer by their intermediate input expenditures to construct the aggregate indexes $\Delta v_t/v_{t-1}$, $s_{N,t}$,
164 and $s_{T,t}$. These indexes track the growth rate of the aggregate number of suppliers, the aggregate rate of
165 adoption and the aggregate rate of termination in the economy, respectively. By construction, we have
166 $\Delta v_t/v_{t-1} = s_{N,t} - s_{T,t}$.

167 3. Empirical results on adoption and termination of suppliers

168 In this section, we establish three novel facts on producer-supplier relations. Fact 1 shows that the
169 aggregate adoption of new suppliers is procyclical, while the aggregate termination of existing suppliers is

170 acyclical. Fact 2 studies the cross-sectional patterns of adoption and termination and reveals the dispersion
 171 in their cyclicalities across producers with different sizes. Fact 3 shows that the output of producers increases
 172 with the total number, the adoption, and the termination of producer-supplier relationships.

173 *Fact 1: Procyclical adoption and acyclical termination of suppliers*

174 We focus on aggregate adoption and termination rates that jointly determine the aggregate number of
 175 suppliers. Figure 1 decomposes the growth rate of the aggregate index of the number of suppliers (i.e.,
 176 $\Delta v_t/v_{t-1}$, solid green line with circles) into the following metrics: (i) the aggregate rate of adoption (i.e.,
 177 $s_{N,t}$, solid red line with circles), and (ii) the aggregate rate of termination (i.e., $s_{T,t}$, dash-dotted blue line)
 178 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
 179 aggregate number of suppliers (Δv_t) and the aggregate rate of adoption ($s_{N,t}$) shows that fluctuations in
 180 the aggregate number of suppliers are primarily driven by the large fluctuations in the aggregate adoption
 181 rate while the aggregate termination rate ($s_{T,t}$) remains substantially unchanged over the sample period. In
 182 general, the level of the aggregate adoption rate is higher than the aggregate termination rate, generating an
 183 upward trend in the aggregate number of suppliers. This is consistent with the increasingly denser input-
 184 output networks (Acemoglu and Azar, 2020; Ghassibe, 2023).

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

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

$$194 \quad \frac{Cov(\Delta v_t/v_{t-1}, s_{N,t})}{Var(\Delta v_t/v_{t-1})} + \frac{Cov(\Delta v_t/v_{t-1}, -s_{T,t})}{Var(\Delta v_t/v_{t-1})} = 1. \quad (1)$$

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

⁴Figure 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.

201 In sum, our results show that the processes of adoption and termination of suppliers are notably different
202 from the creation and destruction of jobs in the labor market, as discussed in the seminal study of [Caballero](#)
203 [and Hammour \(1994\)](#). Although the labor market features the cleansing effect of recessions that leads to a
204 countercyclical job destruction that cleanses the labor market from low-productivity jobs in recessions, the
205 destruction margin remains inactive in producer-supplier relationships.

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

207 In Fact 2, we link procyclicality of aggregate adoption and acyclicity of aggregate termination (estab-
208 lished in Fact 1) to differences in the cyclicalities in the adoption and termination rates across producers
209 with different numbers of suppliers. Additionally, we compare these patterns to the labor market cyclicity
210 of job creation and destruction across establishments with different numbers of employees.

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

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

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

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

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

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

240 *Fact 3: Returns from more and from new relationships*

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

$$246 \quad d \ln(\text{sale}_{i,t}) = \beta_0 + \beta_1 d \ln(v_{i,t}) + \beta_2 x_{i,t} + \beta_3 \ln(v_{i,t-1}) + \beta_4 \ln(\text{sale}_{i,t-1}) + \alpha_i + \gamma_t + \epsilon_{i,t}, \quad (2)$$

247 where $x_{i,t} \in \{s_{i,N,t}, s_{i,T,t}, s_{i,CH,t}\}$,

248 where the dependent variable is the growth rate of the producer's real sales ($d \ln(\text{sale}_{i,t})$). On the right-hand
 249 side of regression (2), $d \ln(v_{i,t})$ is the growth rate of the total number of suppliers. $x_{i,t}$ includes producer
 250 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
 251 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
 252 and year fixed-effects, respectively. We control for the total number of suppliers and sales of producer i in
 253 the previous year, as they may influence the sales in the current year. A positive β_1 indicates the returns
 254 from more relationships, while a positive β_2 reflects the returns from new relationships. This is because the
 255 adoption of new suppliers, the termination of existing suppliers, and the churning of suppliers all contribute
 256 to a newer portfolio of suppliers for the producer.

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

$$263 \quad \widehat{s}_{i,N,t} = \sum_j \omega_{i,t_0(i)}(j) \cdot s_{N,t}(j) \quad \text{and} \quad \widehat{s}_{i,T,t} = \sum_j \omega_{i,t_0(i)}(j) \cdot s_{T,t}(j), \quad (3)$$

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

265 i 's appearance in the sample. $s_{N,t}(j)$ and $s_{T,t}(j)$ are the sectoral rates of adoption and termination for
 266 sector j .⁶ The key idea of the instrumental variable is that neither $s_{N,t}(j)$ (vs. $s_{T,t}(j)$) nor $\omega_{i,t_0(i)}(j)$ is
 267 endogenously determined by changes in producer i 's productivity and other business conditions between t_0
 268 and t . Intuitively, $\omega_{i,t_0(i)}(j)s_{N,t}(j)$ and $\omega_{i,t_0(i)}(j)s_{T,t}(j)$ serve as natural predictions of producer i 's rates of
 269 adoption and termination of suppliers from sector j . Thus, $\widehat{s}_{i,N,t}$ and $\widehat{s}_{i,T,t}$ predict producer i 's adoption and
 270 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 $\widehat{s}_{i,N,t}$ and $\widehat{s}_{i,T,t}$ predict the foregoing variables.

272 Table 1 presents the estimation results of regression (2), where the growth rate of the number of sup-
 273 pliers, as well as the rates of churning, adoption, and termination, are instrumented using Bartik-type IVs,
 274 as specified in equation (3).⁷ Column (1) shows that an increase in the number of suppliers raises the sales
 275 of producers, as evidenced by the positive coefficients for the growth rate of the number of suppliers. This
 276 finding indicates a positive *return from more relationships*, corroborating the central tenet of the “returns
 277 from more varieties” in models of varieties (Hamano and Zanetti, 2017). Using the constructed instrumental
 278 variables, our results establish *causal effects* of the number of suppliers on sales, contributing to the existing
 279 literature focused on the correlation between the number of suppliers on sales (e.g., Lim 2018 for the U.S.,
 280 Bernard et al. 2019 for Japan, and Arkolakis et al. 2023 for Chile). A notable exception is Baqaee et al.
 281 (2023); they study the causal effect of the number of suppliers on producers' marginal costs in Belgium,
 282 using an alternative instrumental variable.⁸

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

⁶Specifically, $\omega_{i,t_0(i)}(j) \equiv v_{i,t_0(i)}(j)/v_{i,t_0(i)}$, where $v_{i,t_0(i)}(j)$ is the number of producer i 's suppliers in sector j , while $v_{i,t_0(i)}$ is the total number of producer i 's suppliers. We classify sectors according to one-digit NAICS industries such that no firm is sufficiently large in order to shift the aggregate sectoral dynamics of linkages. $s_{N,t}(j) \equiv v_{N,t}(j)/v_{t-1}(j)$ and $s_{T,t}(j) \equiv v_{T,t}(j)/v_{t-1}(j)$. $v_{t-1}(j)$, $v_{N,t}(j)$, and $v_{T,t}(j)$ are the total number, the adoption, and the termination of sector j suppliers, respectively. The sectoral rates of adoption and termination of suppliers are regressed on the year and sector fixed effects, and we use the residuals as the shocks in the sectoral rates of adoption and termination for the construction of the Bartik-type instrumental variables. We also define $s_{CH,t}(j) \equiv \min\{s_{N,t}(j), s_{T,t}(j)\}$ and construct $\widehat{s}_{i,CH,t} = \sum_j \omega_{i,t_0(i)}(j) \cdot s_{CH,t}(j)$ as the Bartik-type instrumental variable for the rate of churning.

⁷Tables 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.

⁸Baqaee 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.

⁹Notably, we include only one of $s_{i,N,t}$ and $s_{i,T,t}$ in columns (3)-(4) because including two of them is colinear with $d \ln(v_{i,t})$

291 4. A model of adoption and termination of suppliers

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

294 4.1. Baseline environment and timing

295 The economy is static, and it is populated by a continuum of final-goods producers $i \in [0, 1]$. Each
296 producer i has an idiosyncratic productivity a_i drawn from a log-normal distribution with zero mean and
297 standard deviation σ_a ; this is the only source of heterogeneity in the model.¹⁰ We assume that there is no
298 shock to idiosyncratic productivity (i.e., a_i is fixed for each producer). The final good market is perfectly
299 competitive, with the price normalized to one. Each producer manufactures goods by assembling interme-
300 diate inputs that existing (E) and new (N) suppliers provide. Each vintage $k \in \{E, N\}$ is populated by a
301 continuum of suppliers. Each supplier offers intermediate inputs to different producers.

302 At the beginning of the period, each producer i starts with the steady-state measure of total suppliers
303 \bar{V}_i^* .¹¹ Each producer optimally sets the mix of existing and new suppliers to maximize profits. The adjust-
304 ment in the measure of suppliers involves costs for termination (c^-) and adoption (c^+) of suppliers. Prices
305 of intermediate inputs are determined by Nash bargaining between the producer and suppliers. Producer i
306 manufactures the final good (Y_i) using the supplied inputs from new and existing suppliers at the established
307 price. Summarized in Figure H.11 in Appendix H is the model's timeline.

308 4.2. Suppliers

309 Each supplier provides one unit of a distinct input to the producer.¹² Suppliers of each vintage k are
310 indexed by their match-specific efficiency z_k . Within the new vintage, match-specific efficiency is uniformly
311 distributed over the interval $[0, 1]$ with unitary density. Within the existing vintage, match-specific efficiency
312 is uniformly distributed over the interval $[1 - \bar{V}_i^*, 1]$ with unitary density.¹³

as $d \ln(v_{i,t}) = s_{i,N,t} - s_{i,T,t}$. Also note that the coefficient of the growth rate of the total number of suppliers is negative and 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.

¹⁰In 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).

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

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

¹³We 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.

313 *4.3. Producers and the bargained input price*

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

$$316 \quad y_{i,k}(z_k) = Aa_i z_k, \quad \forall k \in \{E, N\}, \forall z_k,$$

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

319 We assume that each supplier manufactures intermediate goods without cost. The total surplus $TS_{i,k}(z_k)$
 320 from the producer-supplier relationship is the output produced by the corresponding production line, $y_{i,k}(z_k)$,
 321 which is split between the producer and the supplier by Nash bargaining over the price charged by the sup-
 322 plier ($p_{i,k}(z_k)$), according to the surplus-sharing condition:

$$323 \quad p_{i,k}(z_k) = (1 - \alpha)TS_{i,k}(z_k), \quad \forall i \in [0, 1], \forall k \in \{E, N\}, \forall z_k, \quad (4)$$

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

325 *4.4. Measures of adoption and termination*

326 We denote by $z_{i,k}$ the marginal supplier of vintage k used by producer i . Specifically, producer i adopts
 327 the new suppliers whose idiosyncratic productivity levels are sufficiently high to generate profits and there-
 328 fore adopts new suppliers with $z_N \in [z_{i,N}, 1]$. Similarly, producer i terminates existing suppliers whose
 329 idiosyncratic productivity levels are insufficient to generate profits and therefore terminates existing sup-
 330 pliers with $z_E \in [1 - \bar{V}_i^*, z_{i,E}]$. Measures of adopted new and terminated existing suppliers are equal to
 331 $1 - z_{i,N}$ and $z_{i,E} - 1 + \bar{V}_i^*$, respectively. To retain consistent notation with Section 2, we denote by $s_{i,N}$ and
 332 $s_{i,T}$ the rate of adoption (of new suppliers) and the rate of termination (of existing suppliers), respectively,
 333 with $s_{i,N} = (1 - z_{i,N}) / \bar{V}_i^*$ and $s_{i,T} = (z_{i,E} - 1 + \bar{V}_i^*) / \bar{V}_i^*$.

334 *4.5. Costs of management, adoption, and termination of suppliers*

335 *Costs of managing suppliers.* Producers incur costs in managing suppliers, consistent with the *span of*
 336 *control* problem (Lucas Jr, 1978) and the “diminishing returns to management” (Coase, 1991). Following
 337 Gopinath and Neiman (2014), we assume a quadratic management cost that is a function of the total measure
 338 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
 339 suppliers for each producer i , or the total measure of suppliers whose idiosyncratic productivity levels are
 340 above the threshold for selection in each vintage.¹⁴

¹⁴In 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.

341 *Costs of adjusting suppliers.* In addition to the costs of managing suppliers, the adoption and termination
 342 of suppliers are also costly, and they involve unitary costs of adoption c^+ and of termination c^- . We defer
 343 the discussion on the functional form of management and adjustment costs to Section 5.2.1.

344 Consistent with the seminal idea in Coase (1991) and subsequent studies, we assume that both manage-
 345 ment and adjustment costs are not contractable and, therefore, are paid entirely by producers—in conse-
 346 quence to asset specificity and appropriability problems, as studied in Caballero and Hammour (1996).¹⁵

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

359 4.6. Optimal choices of adoption and termination

360 We now describe the optimization of each producer i that chooses the adoption and termination of sup-
 361 pliers to maximize profits. For a given set of marginal suppliers $z_{i,E}$ and $z_{i,N}$, each producer i manufactures
 362 final output with the linear production function:¹⁶

$$363 \quad Y_i = \int_{z_{i,E}}^1 y_{i,E}(z_E) dz_E + \int_{z_{i,N}}^1 y_{i,N}(z_N) dz_N, \quad (5)$$

¹⁵Specifically, 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.

¹⁶We 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 cyclicity of termination.

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

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

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

371 Combining the bargained input price in equation (4) with equation (6) yields:

$$\begin{aligned}
372 \quad \Pi_i = & \max_{\{z_{i,E}, z_{i,N}\}} \alpha \left\{ \int_{z_{i,E}}^1 Aa_i z_E dz_E + \int_{z_{i,N}}^1 Aa_i z_N dz_N \right\} - [c^- (z_{i,E} - 1 + \bar{V}_i^*) + c^+ (1 - z_{i,N})] \\
373 \quad & - \xi \cdot (2 - z_{i,N} - z_{i,E})^2 / 2.
\end{aligned}$$

374 The solution to the above maximization problem yields the optimal conditions for the marginal suppliers
375 $z_{i,E}^*$ and $z_{i,N}^*$:

$$376 \quad z_{i,E}^* + \frac{c^-}{\alpha Aa_i} = \frac{\xi V_i^*}{\alpha Aa_i}, \quad (7)$$

$$377 \quad z_{i,N}^* - \frac{c^+}{\alpha Aa_i} = \frac{\xi V_i^*}{\alpha Aa_i}, \quad (8)$$

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

379 Equations (7) and (8) outline the distinct roles of the management and adjustment costs for the adoption
380 and termination of suppliers. The management cost increases the marginal costs of using both new and
381 existing suppliers and, therefore, deters expansion in the total measure of suppliers. The cost of adoption
382 (c^+) decreases the marginal benefit of using new suppliers, and the cost of termination (c^-) increases the
383 marginal benefit of retaining existing suppliers. Combining equations (7) and (8) yields:

$$384 \quad z_{i,N}^* - z_{i,E}^* = \frac{c^+ + c^-}{\alpha Aa_i} > 0. \quad (9)$$

385 Equation (9) shows that the adjustment costs generate the differential in marginal productivity between
386 new and existing suppliers, such that new suppliers have higher marginal productivity than existing ones
387 in equilibrium. As we discuss in the next section, the productivity differential is critical to the incentive
388 for producers to adopt new suppliers (Lemma 2), and for the different cyclicity in the rate of termination

389 across producers with different idiosyncratic productivity (Proposition 1).

390 5. Analytical results

391 In this section, we show that our model based on optimizing producers, distinct management and ad-
392 justment costs, and idiosyncratic productivity of producers generates the empirical results in Facts 1-3. We
393 begin by presenting the returns from more and new relationships that directly result from the model and
394 generate Fact 3 (Section 5.1). We then analyze the cross-sectional cyclicity of termination across produc-
395 ers with different productivity to study Fact 2 (Section 5.2.1). We conclude by extending the analysis to the
396 aggregate economy to study Fact 1 (Section 5.2.2).

397 5.1. Returns from more relationships and new relationships (Fact 3)

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

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

$$406 \quad \frac{\partial \ln Y_i^*}{\partial \ln V_i^*} = \frac{Aa_i V_i^*}{Y_i^*} z_{i,E}^* > 0.$$

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

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

411 **Lemma 2.** Returns from new relationships (Fact 3). *When $c^+ > 0$ or $c^- > 0$, the semi-elasticity of final*
412 *output (Y_i^*) to the adoption rate ($s_{i,N}^*$) is positive and equal to:*

$$413 \quad \frac{\partial \ln Y_i^*}{\partial s_{i,N}^*} = \frac{c^+ + c^-}{\alpha Y_i^* / V_i^*} > 0.$$

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

419 5.2. Responses of adoption, termination, and output to changes in aggregate TFP (Facts 1-2)

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

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

428 5.2.1. Effect of aggregate TFP on the producer's decisions

429 The changes in aggregate TFP exert two distinct *scaling* and *switching* effects on the producers' rates
 430 of adoption and termination of suppliers. The *scaling* effect embeds a positive (vs. negative) response of
 431 producers' adoption of new suppliers (vs. termination of existing suppliers) to a higher aggregate TFP (i.e.,
 432 $d \ln V_i^* / d \ln A > 0$) (Lemma 3 in Appendix D), since producers increase the total measure of suppliers to
 433 benefit from the increased aggregate productivity (and profits) relative to the unchanged management costs.
 434 The *switching* effect embeds positive responses of both producers' adoption and termination to a higher
 435 aggregate TFP (i.e., $\partial s_{i,N}^* / \partial \ln A = \partial s_{i,T}^* / \partial \ln A > 0$) (Lemma 4 in Appendix D), since producers replace
 436 more existing suppliers with new ones to benefit from the increased aggregate productivity (and profits)
 437 relative to the unchanged adjustment costs.

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

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

$$443 \quad \frac{ds_{i,N}^*}{d \ln A} = \underbrace{\frac{1}{2} \frac{d \ln V_i^*}{d \ln A}}_{\text{Scaling effect on adoption} > 0} + \underbrace{\frac{\partial s_{i,N}^*}{\partial \ln A}}_{\text{Switching effect} > 0}. \quad (10)$$

444 Because the switching and scaling effects are both positive on the adoption rate, the response of the adoption
 445 rate to a positive aggregate TFP shock is always positive for the producer.¹⁷

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

¹⁷To derive equations (10) and (11), we combine equations (7) and (8), and the definitions of $s_{i,N}^*$ and $s_{i,T}^*$, which yields the
 producer's rates of adoption and termination: $s_{i,N}^* = \frac{V_i^*}{2V_i^*} - \frac{c^+ + c^-}{2\alpha A a_i V_i^*}$ and $s_{i,T}^* = 1 - \frac{V_i^*}{2V_i^*} - \frac{c^+ + c^-}{2\alpha A a_i V_i^*}$.

448 switching effects:

$$449 \quad \frac{ds_{i,T}^*}{d \ln A} = \underbrace{\frac{1}{2} \frac{d \ln V_i^*}{d \ln A}}_{\text{Scaling effect on termination} < 0} + \underbrace{\frac{\partial s_{i,T}^*}{\partial \ln A}}_{\text{Switching effect} > 0}. \quad (11)$$

450 The scaling effect implies a negative response of the termination rate to a positive aggregate TFP shock.
 451 This is because the producer achieves an increase in the scale of production by reducing the rate of ter-
 452 mination of existing suppliers. In contrast, the switching effect implies a positive response of the rate of
 453 termination—consistent with the positive impact of the switching effect on the rate of termination to enact
 454 the replacement of existing suppliers with new ones. Equation (11) shows that the sign of the response of
 455 the termination rate to changes in aggregate TFP is determined by the relative strength of the switching and
 456 scaling effects.

457 *Cross-sectional responses of the termination rate across different producers (Fact 2).* To examine the coun-
 458 terbalancing forces of the scaling and switching effects in determining the response of the termination rate of
 459 the producer to changes in aggregate TFP, as well as how the forces vary across different producers, we
 460 show in Figure 5 the impacts of the scaling (i.e., solid red curve) and switching (i.e., dashed blue curve)
 461 effects on the responses of termination against the producer’s idiosyncratic productivity, together with the
 462 combined total impact (i.e., solid black curve with circles) implied by the calibrated model.

463 Consistent with equation (11), the scaling (vs. switching) effect exerts a negative (vs. positive) impact on
 464 the response of termination to changes in aggregate TFP. Both curves converge towards zero, showing that
 465 the magnitudes of both effects decline with the producer’s idiosyncratic productivity, as shown in Lemmas
 466 3 and 4 of Appendix D. Intuitively, facing a negative aggregate TFP shock, smaller producers—those
 467 that have smaller idiosyncratic productivity a_i —experience larger increases in the relevance of the fixed
 468 management and adjustment costs in relation to their decreased profits. Therefore, they are more inclined
 469 to refrain from expanding and adjusting suppliers, and hence display larger scaling and switching effects.

470 Moreover, the scaling effect is less sensitive to changes in idiosyncratic productivity than the switch-
 471 ing effect, as evinced by the steeper curve associated with the switching effect.¹⁸ As a result, the total
 472 impact, shown by the solid-black curve with circle markers, follows the switching effect to decline with
 473 idiosyncratic productivity. Termination becomes acyclical when the total impact reaches zero at the (log)
 474 idiosyncratic productivity of -0.01. When log idiosyncratic productivity is lower than -0.01, the switching
 475 effect dominates, implying that the rate of termination increases with aggregate TFP (i.e., $ds_{i,T}^*/d \ln A > 0$).
 476 In contrast, when log idiosyncratic productivity is higher than -0.01, the scaling effect dominates, implying
 477 that the rate of termination decreases with aggregate TFP (i.e., $ds_{i,T}^*/d \ln A < 0$).

¹⁸The 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.

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

481 **Proposition 1.** Heterogeneous cyclicality in termination (Fact 2). *When both ξ and $c^+ + c^-$ are sufficiently*
482 *large, the rate of termination is countercyclical for producers with high idiosyncratic productivity while*
483 *procyclical for producers with low idiosyncratic productivity.*

484 The proof of Proposition 1 can be found in [Appendix H](#). Note that the steady-state measure of suppliers
485 (\bar{V}_i^*) increases with the idiosyncratic productivity. This is because the management cost is less relevant
486 for the producers with higher idiosyncratic productivity, and these producers maintain a large scale of pro-
487 duction with a large measure of suppliers. Therefore, Proposition 1 suggests that the rate of termination
488 is countercyclical for producers with many suppliers, but procyclical for producers with a smaller measure
489 of suppliers. This result is consistent with Fact 2 ([Figure 2](#)), which shows that producers with a large (vs.
490 small) measure of suppliers display a countercyclical (vs. procyclical) rate of termination.

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

497 Our benchmark model assumes quadratic management costs and linear adjustment costs. This differs
498 from the conventional formulation in the literature, which typically assumes linear management costs for
499 suppliers (e.g., [Lim, 2018](#); [Huneus, 2018](#)) and strictly convex adjustment costs for labor inputs (e.g., [Ca-](#)
500 [ballero 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
502 the labor literature—generate a positive correlation between the procyclicality of termination and producer
503 size, which is inconsistent with our Fact 2 but consistent with that of job destruction in the labor market
504 (Panel b in [Figure 3](#)).

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

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

516 5.2.2. Effect of aggregate TFP on the aggregate rates of adoption and termination

517 We now investigate the effect of aggregate TFP on the aggregate rates of adoption and termination.
 518 Consistent with the empirical analysis, we define the aggregate measure of suppliers (V^*) and rates of
 519 adoption (s_N^*) and termination (s_T^*) as the weighted average of their counterparts at the producer level:

$$520 \quad V^* = \sum_i V_i^* \frac{\bar{Y}_i^*}{\bar{Y}^*}, \quad s_N^* = \sum_i s_{i,N}^* \frac{\bar{Y}_i^*}{\bar{Y}^*}, \quad \text{and} \quad s_T^* = \sum_i s_{i,T}^* \frac{\bar{Y}_i^*}{\bar{Y}^*},$$

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

523 *Effect of aggregate TFP on the aggregate rate of adoption.* Because equation (10) implies a positive rela-
 524 tionship between the rate of adoption of each producer and the aggregate TFP, the aggregate rate of adoption
 525 and the aggregate TFP are positively correlated, as summarized in the proposition below.

526 **Proposition 2.** Pro-cyclical aggregate rate of adoption (Fact 1). *The aggregate rate of adoption of suppliers,*
 527 *s_N^* , increases in A .*

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

530 *Effect of aggregate TFP on the aggregate rate of termination.* The effect of aggregate TFP on the aggre-
 531 gate rate of termination is less definite and depends on several parameters. First, as shown in Proposition
 532 1, the effect of aggregate TFP on the producer's rate of termination is heterogeneous across producers
 533 and decreases with the producer's idiosyncratic productivity. Thus, the cyclicity of the aggregate rate of
 534 termination depends on the distribution of producers' idiosyncratic productivity.

535 Second, as shown in equation (11), the effect of aggregate TFP on the rate of termination of each
 536 individual producer is determined by the sizes of the scaling and the switching effects, which depend on
 537 the magnitudes of the management and adjustment costs. Hence, the management and adjustment costs are
 538 both crucial determinants of the cyclicity of the aggregate rate of termination.

539 We will show in our quantitative analysis that the aggregate rate of termination is acyclical—consistent
 540 with Fact 1 (Figure 1)—for a realistic calibration of the distribution of idiosyncratic productivity of different
 541 producers and with the management and adjustment costs calibrated to the U.S. data. Overall, our analysis
 542 reveals that our parsimonious model with optimizing producers and distinct costs for the management and
 543 adjustment of suppliers replicates the novel empirical findings on the adoption and termination of suppliers.

544 6. Quantitative analysis

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

548 6.1. Calibration

549 We calibrate the standard deviation of the log idiosyncratic productivity of each producer, σ_a , equal
550 to 0.2, which is the middle value between the estimates of 0.15 and 0.24 in [Syverson \(2004\)](#) and [Fostera
551 et al. \(2015\)](#), respectively. The standard deviation of the log aggregate TFP, σ_A , is set to 0.024 to match the
552 standard deviation of the cyclical (HP-filtered) annual log real gross output in the U.S. data for the period
553 2003-2019 (2.7%). We set the bargaining share of the producer (α) equal to 0.36 to match the ratio of the
554 producers' operating surplus to intermediate input costs for the U.S. economy.

555 We assume symmetric costs of adoption and termination of suppliers, i.e., $c^+ = c^-$. Given the calibrated
556 bargaining share and the average idiosyncratic productivity normalized to one, we jointly calibrate the
557 parameters for the adjustment and management costs, c^+ (and equivalently, c^-) and ξ , to match two target
558 moments. First, we match the ratio of the adjustment costs to the operating costs, set equal to 0.5 in
559 [Caballero and Hammour \(1994\)](#) on the basis that the yearly adjustment costs in production amount to one-
560 half of the operating costs (i.e., intermediate input costs in our model). The average observed duration
561 of relationships is about 3.5 years, implying that the expected adoption and termination occur every 3.5
562 years. We calibrate c^+ and c^- to 0.077, so that the ratio of the total adjustment cost ($c^+ + c^-$) to the total
563 operating cost over the expected duration of the relationship (i.e., $3.5 \times$ yearly operating cost) is equal to
564 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
565 sum of operating surplus and intermediate input costs for the producer, which is equal to approximately 9%
566 ([Gopinath and Neiman, 2014](#)). Summarized in Table 2 is the calibration of the model.

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

572 6.2. Heterogeneity in the cyclicity of the rates of adoption and termination across producers

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

576 We divide the 3,000 simulated producers into 10 equal-interval groups according to the (log) measure of
577 suppliers, with each group indexed by k . To investigate the heterogeneous responses of the termination rate

578 to changes in the business condition across different groups of producers, we conduct the following panel
 579 regression for each k -group of producers separately using our simulated data:

$$580 \quad s_{k,p,j} = a_{p,k} + b_{p,k} \cdot d\log(Y_j) + \epsilon_{k,j}, \quad p \in \{N, T\}, \quad (12)$$

581 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 ,
 582 which equals the ratio of the group-wise number of adopted new (vs. terminated existing) suppliers to the
 583 steady-state number of suppliers in group k . $d\log(Y_j)$ is the percentage deviation of the aggregate output
 584 from the steady state in economy j . The coefficients $b_{N,k}$ and $b_{T,k}$ measure the responses of the rates of
 585 adoption and termination to aggregate output for the group k , respectively. They are the central focus of
 586 our analysis, as they capture the heterogenous cyclicity of the adoption and termination rates for different
 587 groups of producers, respectively. We perform a similar analysis using the observed data by estimating the
 588 following regression:¹⁹

$$589 \quad s_{k,p,t} = a_{p,k} + b_{p,k} \cdot d\log(Y_t) + \epsilon_{k,t}, \quad p \in \{N, T\}. \quad (13)$$

590 Panels (a) and (c) in Figure 4 show the regression results for equation (13) estimated with the observed
 591 data. Blue dots show the point estimates of the different $b_{N,k}$ (vs. $b_{T,k}$) coefficients (y-axis) against the
 592 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
 593 of observations in group k . The red line is the fitted line, estimated using OLS. Panels (b) and (d) show
 594 the results for equation (12) estimated with the simulated data from our baseline model. In all panels, the
 595 correlations between the cyclicity of the adoption and termination rates (measured by $b_{N,k}$ and $b_{T,k}$, re-
 596 spectively) and the size of producers (measured by V_k) are negative. This shows that the model generates
 597 empirically congruous heterogeneity in the cyclicity of the adoption and termination rates across the pro-
 598 ducers with different measures of suppliers. This result is also consistent with the theoretical findings in
 599 Proposition 1.²⁰

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

$$604 \quad s_{T,j} = a + b \cdot \log(Y_j) + \epsilon_j, \quad (14)$$

$$605 \quad s_{T,t} = a + b \cdot \log(Y_t) + \epsilon_t, \quad (15)$$

¹⁹Different 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 $d\log(Y_t)$ is the growth rate of the real gross output.

²⁰The 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.

606 where $s_{T,j}$ and $s_{T,t}$ are the average termination rates in economy j (for the simulated data) and period t
607 (for the observed data), and Y_j and Y_t are the aggregate output. The estimated values for the coefficient b
608 are 0.004 and 0.06 for the simulated and the observed data, respectively. Both estimates are close to zero,
609 evincing that the model is consistent with the observed acyclical aggregate rate of termination in Figure 1.
610 Appendix E illustrates the crucial role of the existence of *both* management *and* adjustment costs for the
611 observed patterns of adoption and termination rates at both the aggregate and the cross-sectional levels.

612 7. Policy analysis

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

617 7.1. Supply-chain-related policies in the aftermath of the COVID-19 pandemic

618 The resilience of the supply chain has become central to U.S. government policies and legislation in the
619 aftermath of the COVID-19 pandemic.²¹ Several policies and legislative measures were targeted at small
620 and medium-sized enterprises (SMEs), largely implemented through the federal agency the Small Business
621 Administration (SBA) during the pandemic. These initiatives primarily consisted of *loan policies* aimed at
622 alleviating the financial constraints that SMEs faced.²² For example, In December 2020, the U.S. Congress
623 approved the “Economic Aid to Hard-Hit Small Businesses, Nonprofits, and Venues Act” as an amendment
624 to the “Small Business Act,” in which *supplier costs* were—for the first time—included as eligible expenses
625 for the Paycheck Protection Program (PPP) loan. The Trump administration then reopened the PPP in
626 January 2021 as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act.²³

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

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

²²Major 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*.”

²³Other 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.

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

635 7.2. An extended model with credit constraints and supply chain policies

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

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

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

$$651 \quad wc_i \equiv \left(\int_{z_{i,E}}^1 p_{i,E}(z_E) dz_E + (1 - \tau_N) \int_{z_{i,N}}^1 p_{i,N}(z_N) dz_N \right) + [c^- (z_{i,E} - 1 + \bar{V}_i^*) + c^+ (1 - z_{i,N})] \quad (16)$$

$$652 \quad + \xi \cdot (2 - z_{i,N} - z_{i,E})^2 / 2,$$

653 which is subject to the following constraint:

$$654 \quad wc_i \leq \theta_i A^{\eta_{A,i}} \Pi_i^{ss} + \tau_L(A) \max\{wc_i^* - \theta_i A^{\eta_{A,i}} \Pi_i^{ss}, 0\}. \quad (17)$$

655 The first term on the RHS of equation (17) — $\theta_i A^{\eta_{A,i}} \Pi_i^{ss}$ — represents the external financing obtained from
 656 the financial intermediary linked to the net worth of the producer, which is a function of the aggregate
 657 TFP, A , and the steady-state profits of the producer i , Π_i^{ss} .²⁴ The parameter θ_i captures the tightness of

²⁴In 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

658 the credit constraints, and $\eta_{A,i}$ is the elasticity of the net worth of the producer i to the aggregate TFP.
659 A positive $\eta_{A,i}$ indicates that producers face tighter credit constraints during economic downturns. We set
660 $\theta_i = 4.1 + 1.5 \ln(V_i^{ss})$ and $\eta_{A,i} = 1.6 - 6.1 \ln(V_i^{ss} / \text{median}(V_i^{ss}))$ based on the estimates from producer-level
661 panel regressions of the debt-to-profit ratio on the number of suppliers and real aggregate output.²⁵

662 To replicate the central aspect of government programs that supply loans to SMEs proportionally to the
663 severity of individual financial constraints, the second term on the RHS of equation (17)— $\tau_L(A) \max\{wC_i^* -$
664 $\theta_i A^{\eta_{A,i}} \Pi_i^{ss}, 0\}$ —captures the amount of government’s credit injection to producers at the state-contingent
665 rate $\tau_L(A)$, which increases with the gap between the producer’s demand for loans—i.e., the working capital
666 in the baseline model without credit constraints, denoted by wC_i^* —and the amount of external financing
667 $\theta_i A^{\eta_{A,i}} \Pi_i^{ss}$. The injected credit is financed by lump-sum taxes and repaid to the government within the
668 period after producers receive revenues. These funds are then rebated to the representative household as
669 lump-sum subsidies. The credit injection rate is positive and uniform for financially constrained producers
670 that voluntarily solicit for the credit injection, and it is zero for unconstrained producers.

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

$$\begin{aligned}
672 \quad \Pi_i = & \max_{\{z_{i,E}, z_{i,N}\}} \left(\underbrace{\int_{z_{i,E}}^1 y_{i,E}(z_E) dz_E + \int_{z_{i,N}}^1 y_{i,N}(z_N) dz_N}_{\text{Final output}} \right) - \underbrace{\left(\int_{z_{i,E}}^1 p_{i,E}(z_E) dz_E + (1 - \tau_N) \int_{z_{i,N}}^1 p_{i,N}(z_N) dz_N \right)}_{\text{Input costs}} \\
673 \quad & - \underbrace{\left[c^- (z_{i,E} - 1 + \bar{V}_i^*) + c^+ (1 - z_{i,N}) \right]}_{\text{Adjustment costs}} - \underbrace{\xi \cdot (2 - z_{i,N} - z_{i,E})^2 / 2}_{\text{Management costs}}. \tag{18}
\end{aligned}$$

674 In addition to the credit constraint, the optimization problem in equation (18) differs from the analogous
675 problem in the benchmark model (equation 6) for the presence of government subsidies (τ_N) given to pro-
676 ducers for the purchases of input from new suppliers. The new formulation captures the essence of U.S.
677 policies that encourage the adoption of new technologies. The subsidies on new inputs increase the total
678 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
679 surplus is split between producer and supplier according to the Nash-bargaining rule in equation (4). The
680 extended model nests the baseline version without credit constraints and policies, by setting $\theta_i = +\infty$ and
681 $\tau_L(A) = \tau_N = 0$.

682 We set the credit injection rate $\tau_L(A)$ to have the ratio of the amount of credit injection on producers
683 to the aggregate output in the model equal to 0.72% for any level of aggregate TFP, A , which matches the
684 observed ratio during the COVID-19 year of 2020.²⁶ We set the rate of input subsidies $\tau_N = 2.6\%$, such that

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

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

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

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

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

$$693 \quad C(A) = Y(A) - \delta \left(\int_0^1 \tau_N \int_{z_{i,N}}^1 p_{i,N}(z_N) dz_N di + \int_0^1 \tau_L(A) \max\{wc_i^* - \theta_i A^{\eta_{A,i}} \Pi_i^{ss}, 0\} di \right),$$

694 where the aggregate consumption equals the total output minus the efficiency costs associated with provid-
 695 ing input subsidies and credit injections.²⁷

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

702 7.3. Simulation of the extended model

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

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

²⁷As 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.

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

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

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

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

744 *The role of convex management costs and linear adjustment costs.* To study the role of convex management
745 costs and linear adjustment costs—which is a central theme of our analysis—panel (b) in Figure 6 presents
746 the results for the welfare analysis in an economy with counterfactual linear management costs and convex

747 adjustment costs. This setup implies a cross-sectional cyclicity of terminations that is consistent with the
748 pattern in the labor market (as shown in Figure 3b), but it is inconsistent with the pattern in the producer-
749 supplier market (as shown in Figure 2b).

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

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

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

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

783 credit injections. In contrast, in the counterfactual economy with linear management costs (panel b), output
784 improvement (weakly) decreases in the productivity and size of producers, as evinced by the downward-
785 slopping solid red line.

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

792 **8. Conclusion**

793 Our analysis establishes several novel facts concerning the adoption and termination of suppliers. At
794 the aggregate level, the rate of adoption of new suppliers and the total number of suppliers are procyclical,
795 while the termination of existing suppliers is acyclical. The acyclical rate of termination at the aggregate
796 level arises from the different cyclicity in the rate of termination across producers with different numbers
797 of suppliers. At the producer level, producer sales positively co-move with the churning of suppliers and
798 the expansion in the total number of suppliers.

799 To account for this new evidence, we develop a simple model of producers that optimally adjust the total
800 measure and the composition of new and existing suppliers subject to distinct management and adjustment
801 costs. The model shows the central and separate roles of the costs of managing, adopting, and terminating
802 suppliers in altering the incentives to scale up the measure of suppliers (i.e., scaling effect) and to replace
803 existing with new suppliers (i.e., switching effect) in response to aggregate TFP shocks. The scaling and
804 switching effects are critical to replicate the observed procyclicality in the adoption of new suppliers and
805 the total measure of suppliers. They generate the observed differences in the cyclicity of the rate of
806 termination across producers that result in the acyclical rate of termination at the aggregate level.

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

811 Our study suggests several interesting avenues for future research. First, there is limited empirical
812 evidence that distinguishes between management and adjustment costs, whose differences we find critical
813 to the optimizing decision of producers and the resulting movements in the aggregate rates of adoption and
814 termination of suppliers. Second, the analysis could be extended to consider the intertemporal dimension in
815 the adoption and termination of suppliers, which will link the optimal choices of producers to the discount
816 rate, asset prices, and the expected benefits of the producer-supplier relationship. Third, we find that the
817 heterogeneity in the productivity of producers is important for the adoption and termination of suppliers.

818 Future work could focus on the optimal sorting between producers and suppliers with different productivity
819 levels, which may enhance the cooperation between firms and improve productivity (Fernández-Villaverde
820 et al., 2023). Finally, though we focus on the relationship between a single producer and several suppliers,
821 the analysis could be extended to explore the linkages between producers and suppliers in the context of
822 a network economy (Baqae et al., 2023), and the endogenous changes in the structure of the network
823 (Ghassibe, 2023). We plan to investigate some of these issues in future work.

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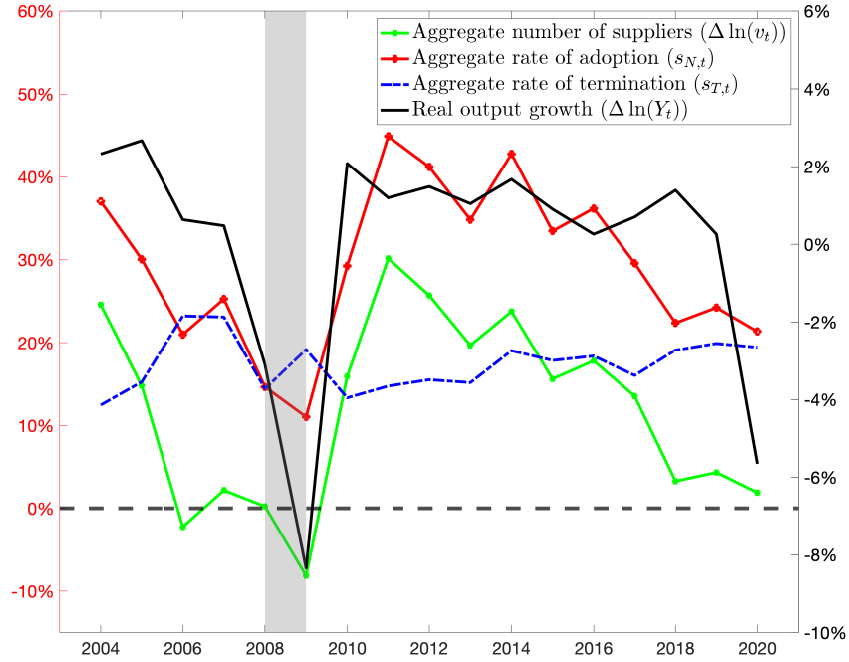
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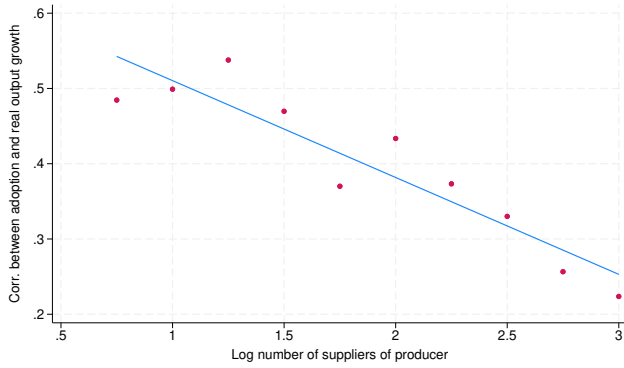
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Figure 1: Procyclical adoption and acyclical termination of suppliers

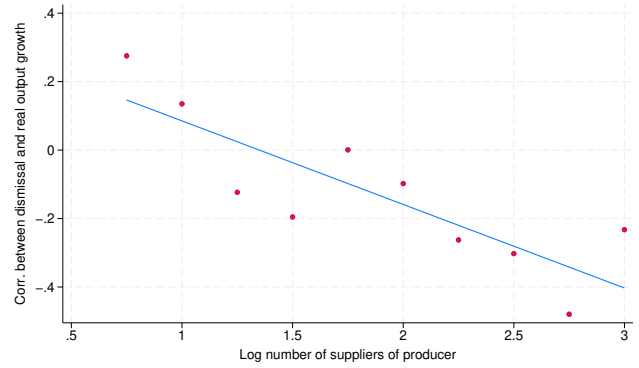


Notes: The figure shows the growth rate of the aggregate number of suppliers (i.e., solid green line with circles), the aggregate rates of adoption (i.e., solid red line with circles) and termination (i.e., dash-dotted blue line), and the growth rate of real output (i.e., solid black line). The aggregate index of the number of suppliers is the weighted average of the number of suppliers across all producers, with the costs of goods sold by each producer as the weight. The real output is the BEA chain-type quantity index of gross output of private industries. Aggregate number of suppliers is the aggregate index of the number of suppliers. Aggregate rate of adoption ($s_{N,t}$) and Aggregate rate of termination ($s_{T,t}$) are the weighted averages of $s_{i,N,t}$ and $s_{i,T,t}$ across all producers, respectively, with the costs of goods sold of each producer as the weight. Real output growth is demeaned. Shaded areas indicate NBER-defined recession years. The samples whose adoption and termination rates are among the top and bottom 2.5% of the sample or larger than one are winsorized.

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



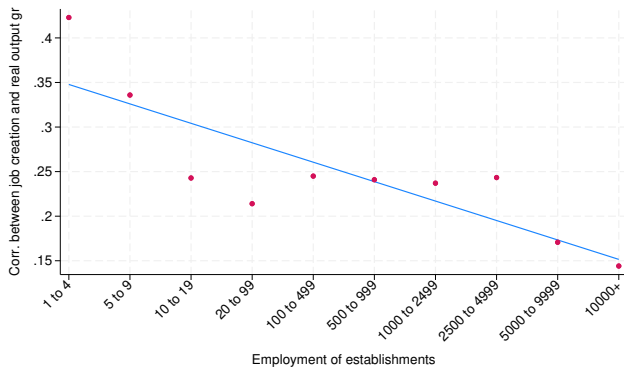
(a) Cyclicity of adoption



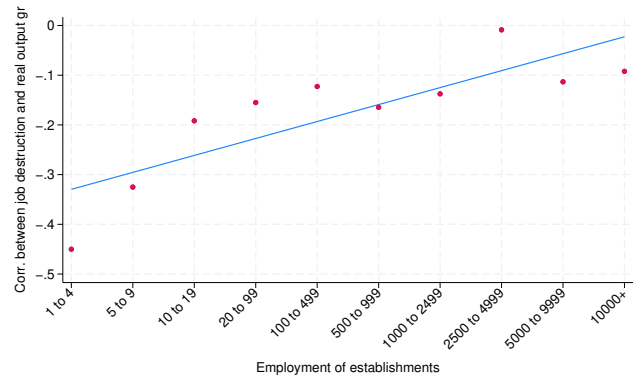
(b) Cyclicity of termination

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

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



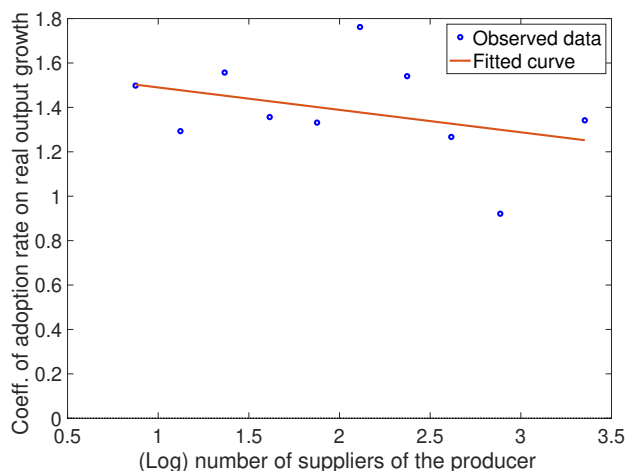
(a) Cyclicity of job creation



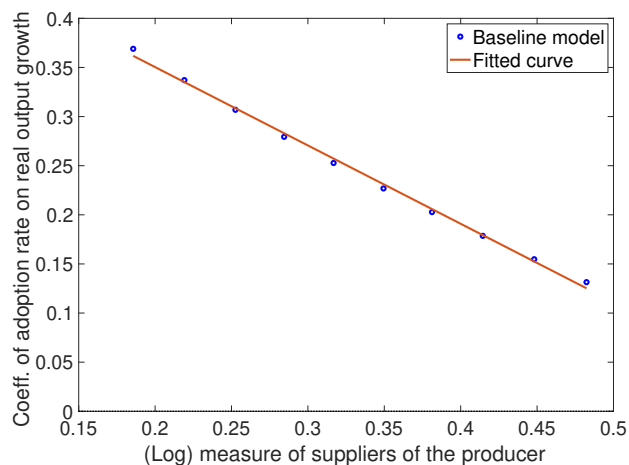
(b) Cyclicity of job destruction

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

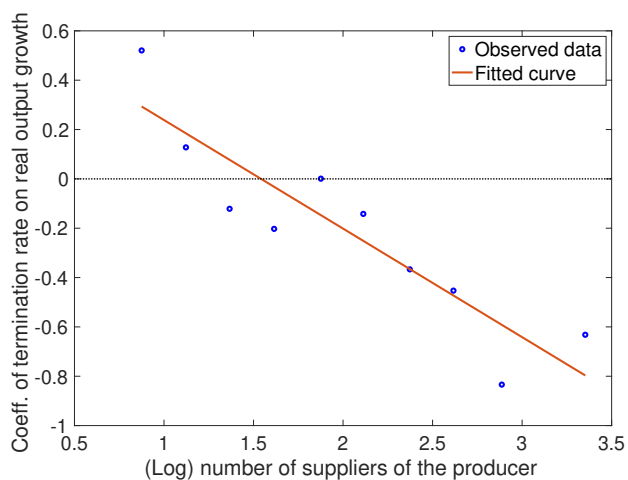
Figure 4: Coefficient of regressing the rate of termination on sales: Data vs. baseline model



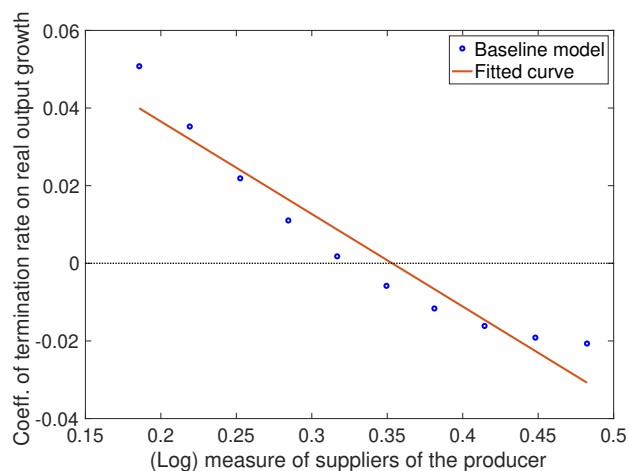
(a) Adoption in data



(b) Adoption in baseline model



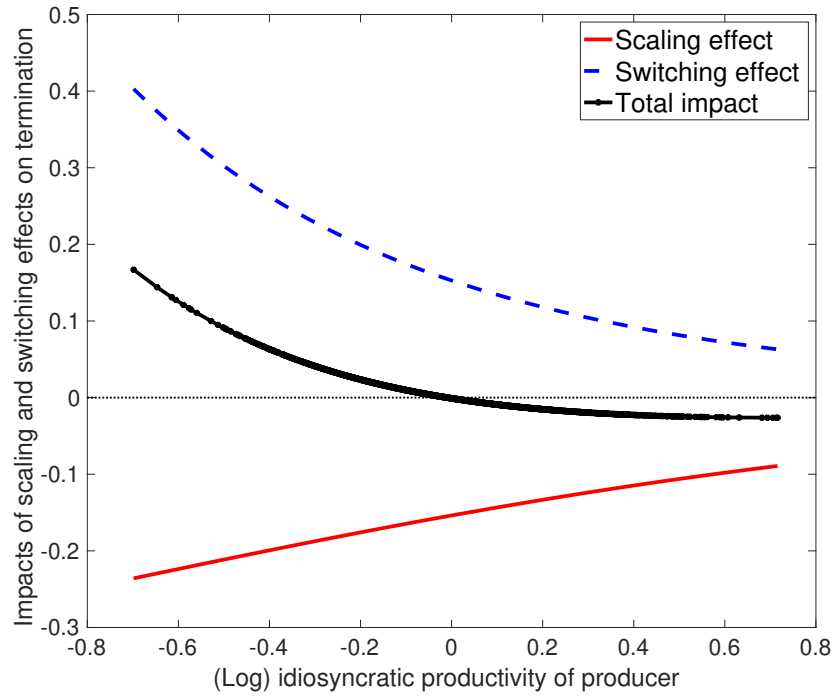
(c) Termination in data



(d) Termination in baseline model

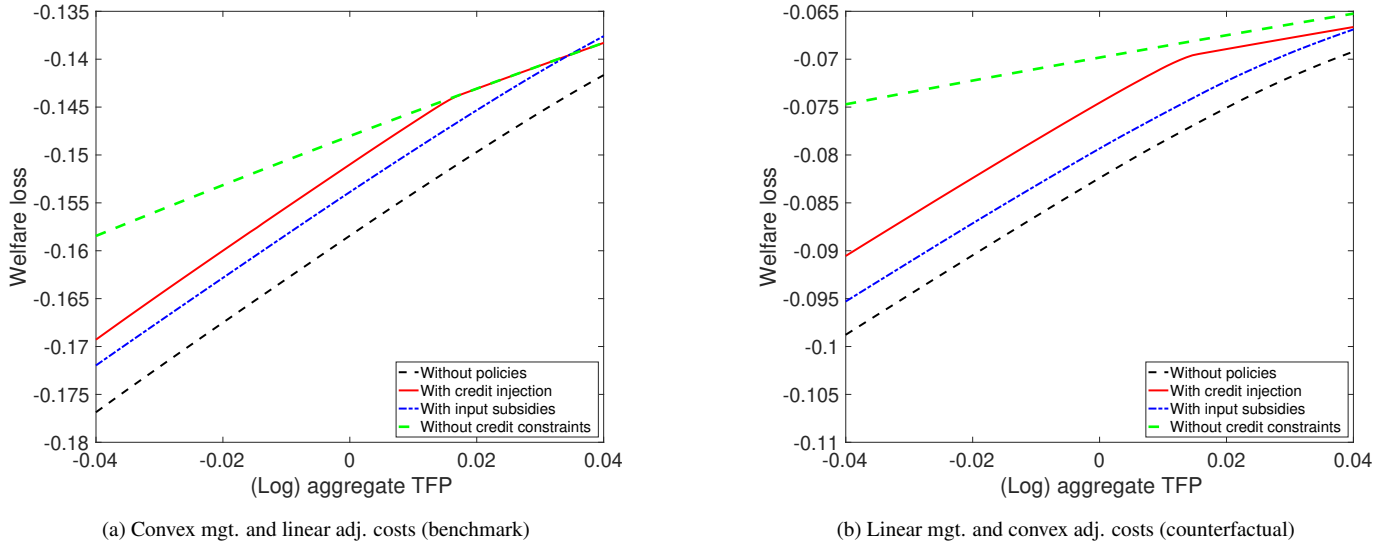
Note: Panels (a) and (b) (vs. c and d) plot the coefficients of regressing the adoption (vs. termination) rate on real output growth for different producer groups using the observed data (Panels a and c) and the simulated data from the baseline model (Panels b and d), respectively. In Panel (a) and (c)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

Figure 5: Impacts of scaling and switching effects on termination as functions of a_i



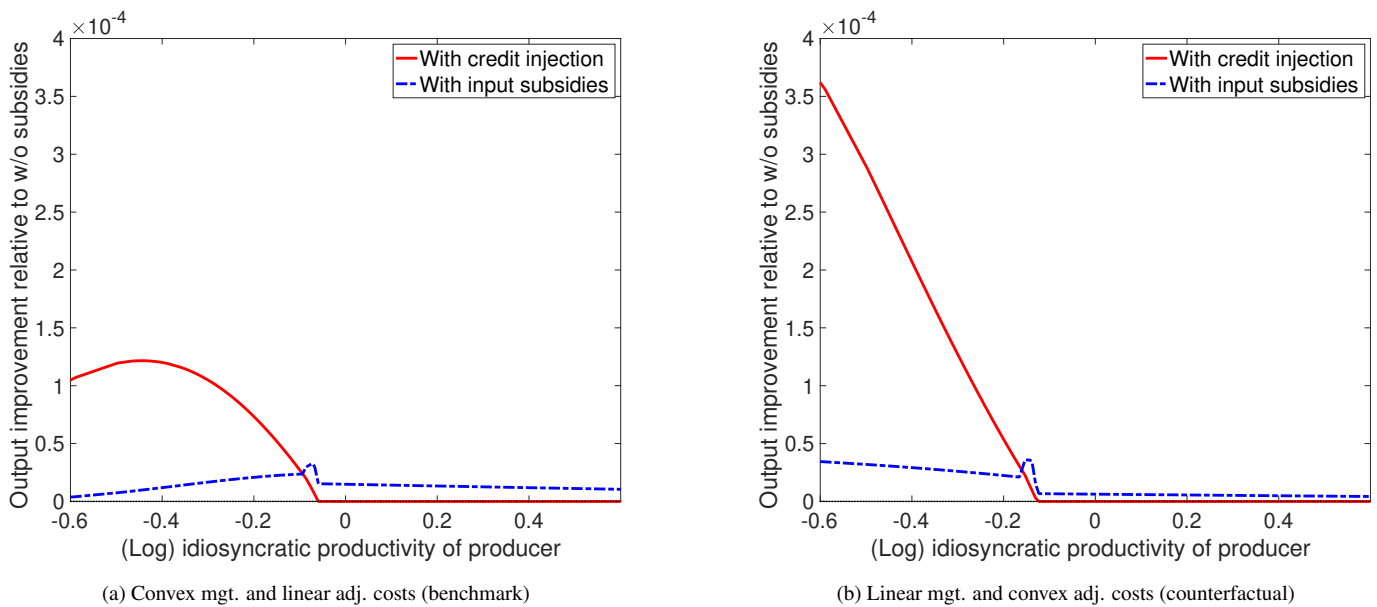
Notes: The figure plots the impacts of scaling (solid red curve) and the switching (dashed blue curve) effects on the response of termination rate to changes in aggregate TFP as functions of the (log) idiosyncratic productivity of the producer, respectively. The solid black curve with circles is the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

Figure 6: Welfare loss under different levels of TFP



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

Figure 7: Output improvement by policies under low TFP



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

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

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

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

Table 2: Calibration of the model

Parameter	Value	Target moment
α	0.36	The ratio of producers' surplus to intermediate input costs.
ξ	0.081	Steady-state share of management costs (Gopinath and Neiman, 2014).
$c^+(c^-)$	0.077	Steady-state share of adjustment costs in operating costs (Caballero and Hammour, 1994).
σ_a	0.2	Middle estimate between Syverson (2004) and Foster et al. (2015) .
σ_A	0.024	The standard deviation of the HP-filtered log real gross output.

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

Online Appendix

The Adoption and Termination of Suppliers over the Business Cycle

(Le Xu, Yang Yu, and Francesco Zanetti)

1 Appendix A. Data

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

5 The FactSet Revere Supply Chain Relationships data consists of 784,325 producer-supplier relationship
6 records between 152,119 producers and 95,932 suppliers from 2003 to 2021. Each record includes the start
7 and end dates of the relationship. The database systematically collects producer-supplier relationship in-
8 formation from public sources such as SEC 10-K annual filings, investor presentations, and press releases
9 reported by either the producer or the supplier. Compared to the commonly used Compustat Customer Seg-
10 ment database (e.g., the dataset used by [Lim, 2018](#))—which only includes major customers who contribute
11 to more than 10% of a supplier’s revenue—FactSet Revere provides a much less truncated set of suppliers.¹
12 The broader coverage results in more accurate measures of producer-supplier relationships, the number
13 of suppliers, and their adoption and termination. As a result, FactSet Revere captures many supply-chain
14 linkages that would be otherwise missing if the Compustat data were used instead.

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

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

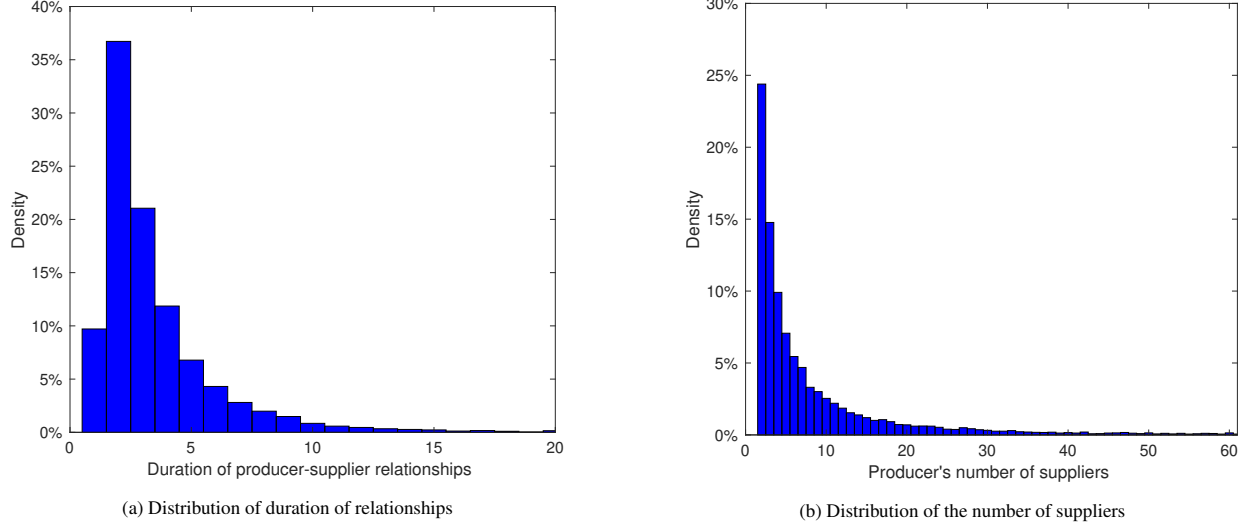
24 *Summary statistics of the supply-chain relationship data.*

Table A.3: Summary statistics of the rates of adoption and termination

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

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

Figure A.8: Distributions of producer-supplier relationship durations and the number of suppliers



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

25 *Derivation of number of suppliers and rates of adoption and termination.* We describe how we derive the
 26 number of suppliers and the rates of adoption and termination at both the producer and the aggregate levels.

27 To compute the aggregate series, we need the share of each producer's intermediate input expenditure in
 28 the total intermediate input expenditure of all producers. We denote the share of producer i 's intermediate
 29 input expenditure in the total intermediate input expenditure as $COGS_share_{i,t}$, which is computed as

$$30 \quad COGS_share_{i,t} = \frac{cogs_{i,t}}{\sum_{i'} cogs_{i',t}},$$

31 where $cogs_{i,t}$ is the *cost of goods sold* (COGS) of producer i documented in Compustat.²

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

$$34 \quad \frac{\Delta v_t}{v_{t-1}} \equiv \sum_i \left(COGS_share_{i,t} \cdot \frac{\Delta v_{i,t}}{v_{i,t-1}} \right). \quad (A.1)$$

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

$$36 \quad \frac{\Delta v_{i,t}}{v_{i,t-1}} = s_{i,N,t} - s_{i,T,t},$$

¹Publicly-traded companies are required to report their major customers in accordance with Financial Accounting Standards No. 131, which is the source of Compustat Customer Segments.

²COGS in Compustat is a commonly used measure of the variable cost. According to the Compustat data manual, it "represents all expenses that are directly related to the cost of merchandise purchased or the cost of goods manufactured that are withdrawn from finished goods inventory and sold to customers."

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

$$42 \quad \text{aggregate rate of adoption : } s_{N,t} \equiv \sum_i \left(COGS_share_{i,t} \cdot s_{i,N,t} \right),$$

$$43 \quad \text{aggregate rate of termination : } s_{T,t} \equiv \sum_i \left(COGS_share_{i,t} \cdot s_{i,T,t} \right).$$

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

$$46 \quad \frac{\Delta v_t}{v_{t-1}} = s_{N,t} - s_{T,t}. \quad (A.2)$$

47 Based on equation (A.2), we compute the variation of the growth rate of the aggregate number of sup-
 48 pliers as

$$49 \quad Var\left(\frac{\Delta v_t}{v_{t-1}}\right) = Cov\left(\frac{\Delta v_t}{v_{t-1}}, s_{N,t} - s_{T,t}\right) = Cov\left(\frac{\Delta v_t}{v_{t-1}}, s_{N,t}\right) + Cov\left(\frac{\Delta v_t}{v_{t-1}}, -s_{T,t}\right),$$

50 which indicates the following equation showing the percentage contributions of the aggregate rates of adop-
 51 tion and termination to the growth rate of the aggregate number of suppliers

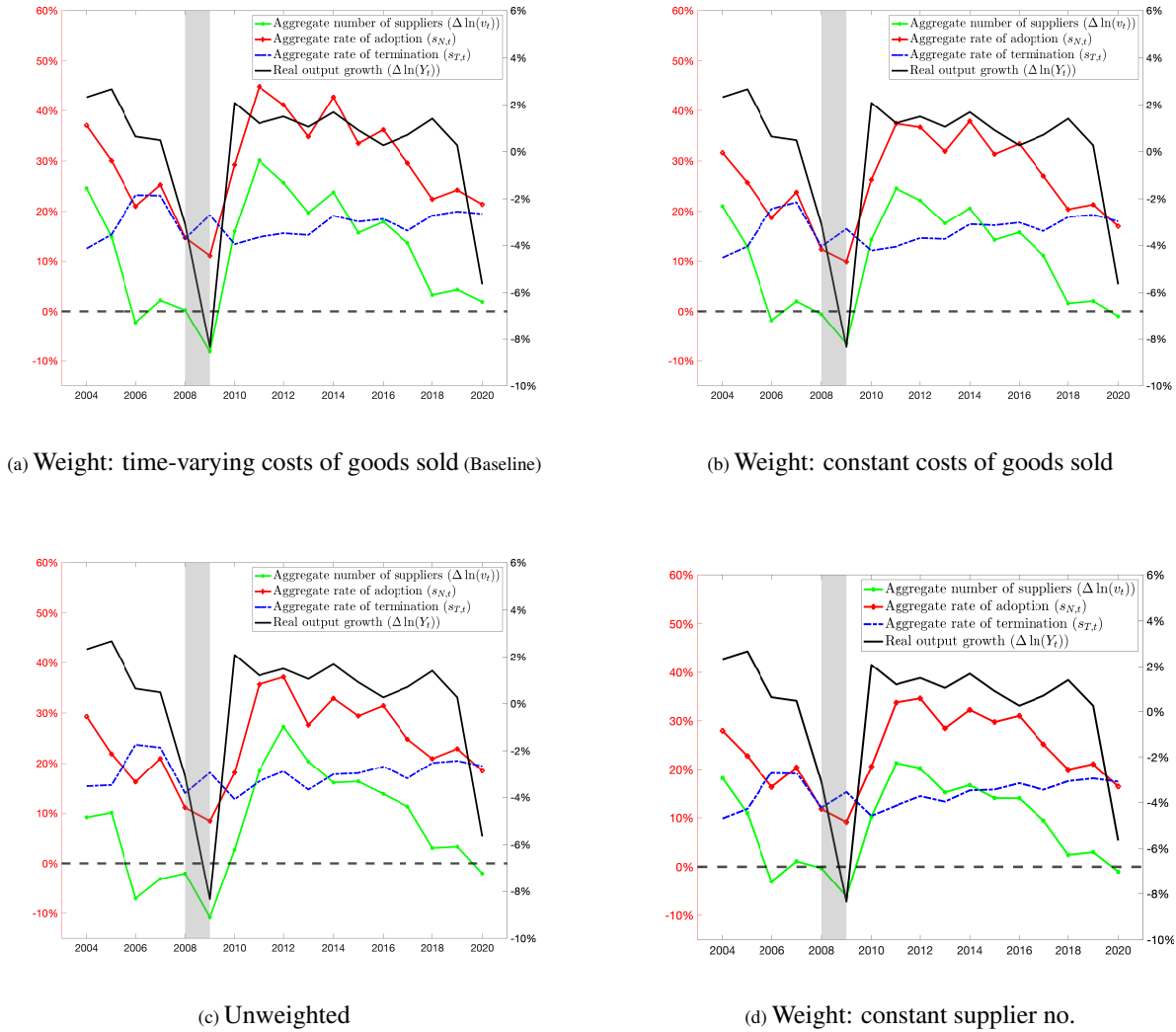
$$52 \quad \frac{Cov\left(\frac{\Delta v_t}{v_{t-1}}, s_{N,t}\right)}{Var\left(\frac{\Delta v_t}{v_{t-1}}\right)} + \frac{Cov\left(\frac{\Delta v_t}{v_{t-1}}, -s_{T,t}\right)}{Var\left(\frac{\Delta v_t}{v_{t-1}}\right)} = 1,$$

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

55 *Alternative ways of aggregating adoption and termination rates.* To check the robustness of Figure 1 in
 56 Fact 1, particularly to control for the changes in the weights, we reproduce Figure 1 with the follow-
 57 ing three alternative ways of aggregating producer-level adoption and termination rates: (i) we weigh
 58 producer-level rates of growth in the number of suppliers, the adoption, and the termination using the
 59 time-average share of costs of goods sold of the producer that is constant over time, i.e., we replace
 60 $COGS_share_{i,t} = (\sum_{t'} cogs_{i,t'}) / (\sum_{t'} \sum_{i'} cogs_{i',t'})$ in equation (A.1) (Panel b in Figure A.9); (ii) we
 61 compute the unweighted aggregate number of suppliers, aggregate number of adopted new suppliers, and
 62 aggregate number of terminated existing suppliers in each year, and use them to compute the growth rate
 63 of aggregate number of suppliers, aggregate rate of adoption, and aggregate rate of termination (Panel c in

64 Figure A.9),³ (iii) we weigh producer-level rates of growth in the total number of suppliers, the adoption,
 65 and the termination using the time-average share of supplier numbers of the producer that is constant over
 66 time, i.e., we replace $COGS_share_{i,t} = (\sum_{t'} v_{i,t'}) / (\sum_{i'} \sum_{t'} v_{i',t'})$ in equation (A.1) (Panel d in Figure
 67 A.9).

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



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

³We normalize aggregate number of suppliers, aggregate number of adopted new suppliers, and aggregate number of terminated existing suppliers in each year by the total number of producers in that year to avoid higher adoption and termination rates that are due to more producers. This is not a concern for other ways of aggregation, in which the aggregate rates are the weighted averages of producer-level rates in each year.

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

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

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

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

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

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

69 **Appendix C. Estimation of the curvature of management costs**

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

82 First, we generalize the management cost function in our baseline model to allow flexible curvature η ,
 83 i.e., $G(z_{i,N}, z_{i,E}) = \xi \cdot V_i^\eta / \eta$. Then, we use the indirect inference method following [Gourieroux et al.](#)
 84 [\(1993\)](#) to estimate η . Specifically, we conduct panel regressions of the log number of suppliers on the log
 85 real sales of the producer, controlling for producer fixed effects, using both data and model-simulated data
 86 under different values of η :⁴

$$87 \quad \ln(V_{i,t}) = \beta_0 + \beta_1^{data} \ln(Y_{i,t}) + \alpha_i + \epsilon_{i,t}, \quad (C.1)$$

$$88 \quad \ln(V_{i,j}) = \beta_0 + \beta_1^{model} \ln(Y_{i,j}) + \alpha_i + \epsilon_{i,j}, \quad (C.2)$$

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

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

98 **Appendix D. Scaling and switching effects**

99 We show that changes in aggregate TFP exert two distinct scaling and switching effects on the total
 100 measure and the composition of suppliers. These forces are critical for the responses of the adoption and

⁴We simulate 100 economies, each composed of 300 producers as in Section 7.3.

101 termination rates of the single producer to aggregate TFP shocks.

102 The response of the single producer to aggregate TFP shocks critically depends on the economic rele-
 103 vance of the costs of management, adoption, and termination of suppliers, which are measured by the costs
 104 of management, adoption, and termination of suppliers in units of the idiosyncratic productivity of the pro-
 105 ducer a_i , and are defined as $\tilde{\xi}_i \equiv \xi/a_i$, $\tilde{c}_i^+ \equiv c^+/a_i$, $\tilde{c}_i^- \equiv c^-/a_i$, respectively. A higher $\tilde{\xi}_i$ indicates that the
 106 producer faces a larger management cost relative to its idiosyncratic productivity; similarly, a higher \tilde{c}_i^+ (vs.
 107 \tilde{c}_i^-) indicates that the producer faces a greater adoption (vs. termination) cost relative to its idiosyncratic
 108 productivity. For notational convenience, we define the total adjustment costs in units of the idiosyncratic
 109 productivity as: $\tilde{c}_i = \tilde{c}_i^+ + \tilde{c}_i^-$, which measures the economic relevance of total adjustment costs.

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

115 **Lemma 3.** *The producer increases the total measure of new and existing suppliers to expand the scale of*
 116 *production in response to an increase in aggregate TFP. The size of the scaling effect is equal to:*

$$117 \quad \text{Scaling effect} \equiv \frac{d \ln V_i^*}{d \ln A} = \frac{2\tilde{\xi}_i \bar{V}_i^* + (\tilde{c}_i^+ - \tilde{c}_i^-)}{(2\tilde{\xi}_i + \alpha \bar{A}) \bar{V}_i^*} > 0, \quad (\text{D.1})$$

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

119 *Proof:* In [Appendix H](#).

120 Lemma 3 shows that the magnitude of the scaling effect increases with the economic relevance of the
 121 management cost ($\tilde{\xi}_i$), which governs the constraints on the producer's scale of production, when $\tilde{c}_i^+ - \tilde{c}_i^-$
 122 is close to zero and \bar{V}_i^* is positive. In particular, producers with higher $\tilde{\xi}_i$ are more constrained by the
 123 burden of management costs and hence reduce the scale of production more strongly in response to a
 124 negative aggregate TFP shock. Because $\tilde{\xi}_i$ is inversely related to idiosyncratic productivity, the scaling
 125 effect decreases with idiosyncratic productivity.

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

129 *The switching effect.* Adjustment costs generate a positive co-movement between rates of adoption and
 130 termination and aggregate TFP. For instance, the increase in aggregate TFP reduces the productivity dif-
 131 ferential between new and existing suppliers (see equation 9) and, therefore, incentivizes the producer to
 132 adjust the composition of suppliers by replacing existing with new suppliers. This incentive of switching

133 suppliers enhances both rates of termination and adoption of suppliers. We refer to this phenomenon as the
 134 *switching effect*, as formalized in the next lemma.

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

$$137 \quad \text{Switching effect} \equiv \frac{\partial s_{i,N}^*}{\partial \ln A} = \frac{\partial s_{i,T}^*}{\partial \ln A} = \frac{\tilde{c}_i}{2\alpha \bar{A} \bar{V}_i^*} > 0, \quad (\text{D.2})$$

138 *which increases in \tilde{c}_i and decreases in a_i .*

139 *Proof: In [Appendix H](#).*

140 Because replacing existing with new suppliers involves simultaneous adoption and termination of sup-
 141 pliers, the switching effect entails equal changes in the rates of adoption ($s_{i,N}^*$) and termination ($s_{i,T}^*$) of
 142 suppliers. Lemma 4 shows that the size of the switching effect increases with \tilde{c}_i , which declines in idiosyn-
 143 cratic productivity a_i . In particular, smaller producers with lower a_i are more prone to a negative aggregate
 144 TFP shock than larger producers with higher a_i in their replacement of existing suppliers with new ones.
 145 This is because smaller producers endure larger increases in the relevance of the fixed adjustment costs in
 146 relation to their decreased profits. Therefore, they are more inclined to refrain from adjusting suppliers and
 147 hence display larger declines in adoption and termination rates (i.e., a larger switching effect).

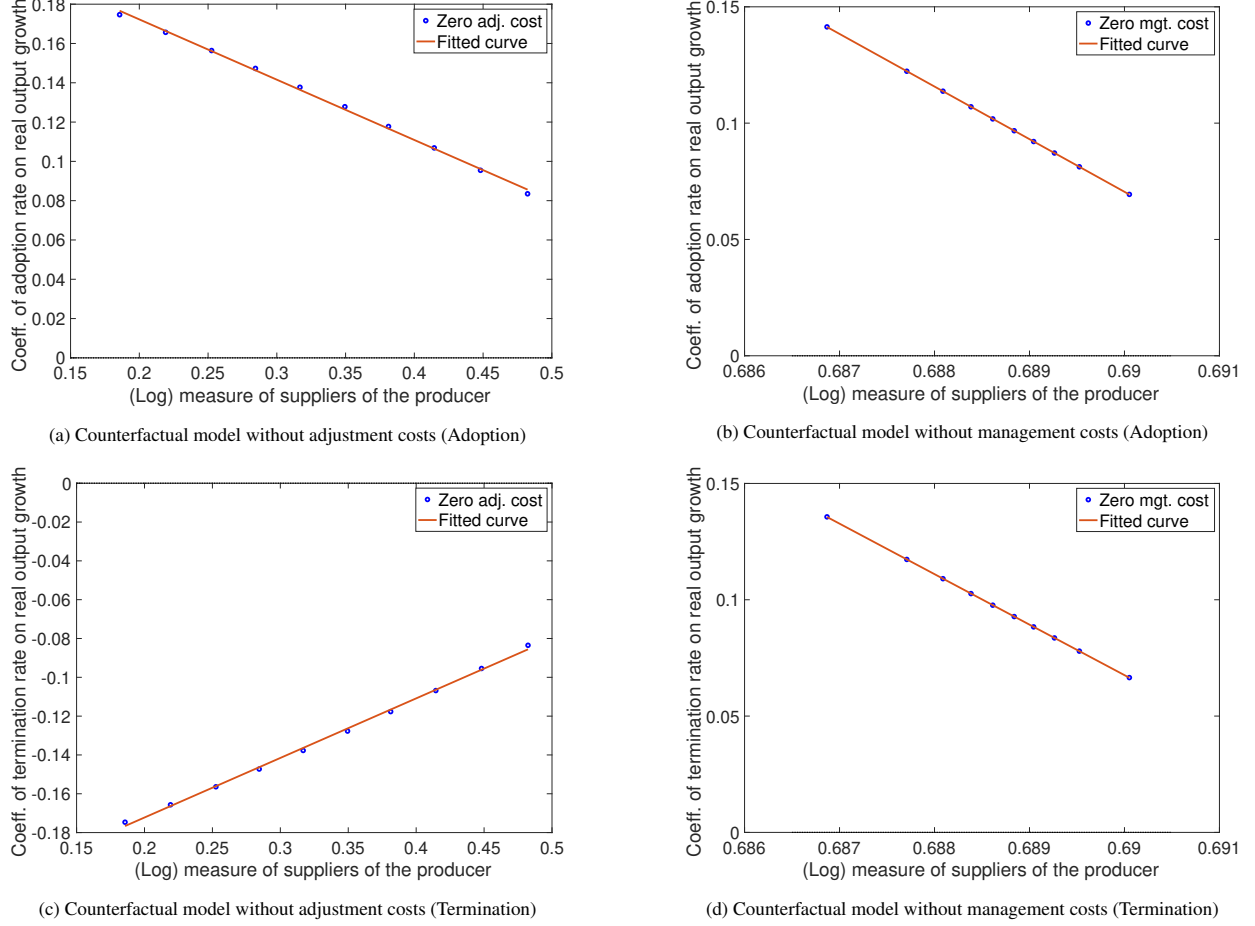
148 **Appendix E. The role of the existence of both management and adjustment costs**

149 To clarify the role of management and adjustment costs in the heterogeneous cyclicity of the termina-
 150 tion rate across producers, we estimate the cyclicity of the adoption and termination rates for each group,
 151 $b_{N,k}$ and $b_{T,k}$, using data simulated with two counterfactual models. One is a model without adjustment
 152 costs (Panels a and c in Figure E.10), and the other is a model without management costs (Panels b and d in
 153 Figure E.10).

154 When there are no adjustment costs (Panels a and c), the switching effect is absent (Lemma 4), and the
 155 cyclicity of termination is uniquely determined by the scaling effect. These results imply that producers
 156 reduce the size of production by terminating existing suppliers in response to a lower aggregate TFP. As
 157 a result, the rate of termination is countercyclical for all producers and highly countercyclical for smaller
 158 and lower-productivity suppliers, as the scaling effect is stronger for them. This is in stark contrast to
 159 the data where the rate of termination is procyclical for smaller producers and countercyclical for larger
 160 producers. Without adjustment costs, the aggregate rate of termination is countercyclical: the coefficient of
 161 log aggregate output in equation (14) is estimated as -0.14, which is also inconsistent with the data.

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

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



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

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

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

169 Appendix F.1. Optimality conditions of the extended model

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

$$172 \quad z_{i,E}^* + \frac{(1 + \lambda_i) c^-}{[\alpha - \lambda_i (1 - \alpha)] A a_i} = \frac{(1 + \lambda_i) \xi V_i^*}{[\alpha - \lambda_i (1 - \alpha)] A a_i}, \quad (\text{F.1})$$

$$173 \quad z_{i,N}^* - \frac{(1 + \lambda_i) c^+}{[\alpha - (\lambda_i - (1 + \lambda_i) \tilde{\tau}_N) (1 - \alpha)] A a_i} = \frac{(1 + \lambda_i) \xi V_i^*}{[\alpha - (\lambda_i - (1 + \lambda_i) \tilde{\tau}_N) (1 - \alpha)] A a_i}, \quad (\text{F.2})$$

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

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

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

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

193 Specifically, we follow Lian and Ma (2021) to measure the profits and debts of the producer using
 194 CompuStat earnings before interest, taxes, depreciation, and amortization (EBITDA) and the sum of Long-
 195 term Debts (DLTT) and Debt in current Liabilities (DLC), deflate them using the GDP deflator, and denote
 196 them by $b_{i,t}$ and $\pi_{i,t}$, respectively, for each producer i in each year t . We further denote the average profit of
 197 producer i over time by $\bar{\pi}_i \equiv (\sum_{t=1}^T \pi_{i,t})/T$, and use the ratio of debt to average profit $b_{i,t}/\bar{\pi}_i$ to measure the
 198 corresponding debt-to-profit ratio in the model—viz., the ratio of the LHS of equation (17) to the steady-
 199 state profit Π_i^{ss} on the RHS.⁵

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

$$203 \quad b_{i,t}/\bar{\pi}_i = \beta_0 + \beta_1 \ln(\bar{v}_i) + \gamma_t + \epsilon_{i,t}, \quad (\text{F.3})$$

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

⁵Because our model is static and has no capital, we can only model the credit constraint based on the profits rather than the asset value of the producer. However, all our empirical results are robust to using the debt-to-asset ratio (i.e., the ratio of the debt to the average asset over the years of the firm, with the asset measured by the total asset (AT) in CompuStat) instead of the debt-to-profit ratio. As a result, the RHS of our credit constraint in equation (17) can be alternatively specified as a multiplier of the long-term value of asset of the producer in a dynamic model.

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

$$208 \quad d \ln(b_{i,t}/\bar{\pi}_i) = \beta_0 + \beta_1 d \ln(Y_t) + \beta_2 \ln(\bar{v}_i / \text{med}(\bar{v}_i)) \cdot d \ln(Y_t) + \alpha_i + \epsilon_{i,t}, \quad (\text{F.4})$$

209 where Y_t is the growth rate of real gross output in year t . We are interested in the coefficients β_1 and
 210 β_2 , which capture the cyclicity of the tightness of the credit constraint and the relationship between this
 211 cyclicity and the number of suppliers, respectively.⁶ A positive coefficient of β_1 indicates that the credit
 212 constraints are tighter in recessions than in booms, and a negative β_2 indicates that the increase in the
 213 tightness of credit constraints is more severe for small producers with fewer suppliers.

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

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

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

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

⁶ \bar{v}_i is divided by the sample-median $\text{med}(\bar{v}_i)$ so that β_1 captures the cyclicity of the tightness of the credit constraint for the producer with the median number of suppliers.

223 large producers with more suppliers.

224 *Calibration of the parameters.* We use the estimation of coefficient β_1 in equation (F.3) to calibrate θ_i .
225 Specifically, we assume that $\theta_i = \theta_{i0} + \beta_\theta \ln(V_i^{ss})$ is a linear function of the number of suppliers. Because
226 the range of the log number of suppliers in the data is larger than that in the model-simulated data (3.5
227 vs. 0.4), we calibrate β_θ to be $0.174 * 3.5/0.4 \approx 1.5$, which is 8.75 times the coefficient of the number
228 of suppliers in Column (1) of Table F.6. Given the calibrated β_θ , we then calibrate θ_{i0} so that one-third of
229 all producers have binding credit constraints in the steady state.⁷ We further use the estimation results of
230 equation (F.4) to calibrate $\eta_{A,i}$. Specifically, we assume that $\eta_{A,i} = \eta_{A,i0} + \beta_\eta \ln(V_i^{ss}/med(V_i^{ss}))$ is a linear
231 function of the number of suppliers, where $med(V_i^{ss})$ is the number of suppliers of the median producer.
232 We calibrate $\eta_{A,i0}$ to be 1.6, consistent with the coefficient of the real output growth in Column (2) of Table
233 F.6. Because the range of the log number of suppliers in the data is larger than that in the model-simulated
234 data (3.5 vs. 0.4), we calibrate β_η to be $-0.7 * 3.5/0.4 \approx -6.1$, which is 8.75 times the coefficient of the
235 interaction term in Column (2) of Table F.6.

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

247 **Appendix G. A brief literature review of switching costs**

248 This section of the Appendix reviews literature on the switching cost and categorizes its various dimen-
249 sions into adoption and termination costs. Switching costs are mainly incurred in two types of situations—
250 when consumers/households switch suppliers or retailers and when producers switch suppliers/vendors.
251 Our adoption and termination costs correspond to the switching costs in the second situation.⁸

252 Most theoretical work on switching costs builds on the switching costs for consumer/household purchas-
253 ing. However, most of their analyses on the switching costs apply to our situation of producers switching
254 suppliers as well. Among these works, [Klemperer \(1987, 1995\)](#) first provided a taxonomy of switching

⁷In the FEDS Notes by [Perez-Orive and Timmer \(2023\)](#), the authors use data from S&P Global, Compustat, and Wharton Research Data Services to calculate the shares of financially-distressed firms in the U.S. since the 1970s, which range from 10% to 50% and average around 30%.

⁸[Whitten and Wakefield \(2006\)](#) and [Van Deventer \(2016\)](#) provide comprehensive reviews on the research of switching costs.

255 costs. He classified switching costs into the compatibility of equipment, transaction costs of switching sup-
256 pliers, learning costs in the use of new brands, uncertainty about the quality of untested brands, loyalty costs
257 for the issuance of discount coupons and similar marketing strategies to adopt producers, contractual costs,
258 and psychological costs. Among these types of switching costs, compatibility of equipment, learning costs
259 in the use of new brands, and uncertainty about the quality of untested brands are purely adoption costs;
260 transaction, contractual, and psychological costs of switching suppliers involve both adoption and termina-
261 tion costs; and loyalty costs are purely termination costs. With the taxonomy of switching costs, [Klemperer](#)
262 (1995) used a model to show that switching costs reduce competition and increase prices.

263 Compared to the theoretical work, empirical studies on switching costs are more recent. Scholars have
264 examined the costs for producers to switch suppliers in an array of vendor industries, such as hardware,
265 computer purchasing, chemical, insurance, and IT outsourcing, with IT outsourcing as the most studied
266 industry. ([Ping, 1993](#); [Heide and Weiss, 1995](#); [Nielson, 1996](#); [Whitten and Wakefield, 2006](#); [Whitten,](#)
267 [2010](#); [Whitten et al., 2010](#); [Barroso and Picón, 2012](#)) The focus of their efforts was to identify various
268 dimensions of switching costs. Most of the dimensions uncovered were similar to those in [Klemperer \(1987,](#)
269 [1995\)](#); however, some additional dimensions specific to the producer-supplier relationship environment
270 were revealed. For example, [Nielson \(1996\)](#), [Whitten and Wakefield \(2006\)](#), [Whitten \(2010\)](#), and [Whitten](#)
271 [et al. \(2010\)](#) explored the costs of hiring and retaining skilled workers during switching, which belong to
272 the adoption costs. [Whitten and Wakefield \(2006\)](#), [Whitten \(2010\)](#), and [Whitten et al. \(2010\)](#) investigated
273 the costs of upgrading the management system along vendor switching, which entail both adoption and
274 termination costs. [Whitten and Wakefield \(2006\)](#) and [Whitten \(2010\)](#) explored the sunk costs attendant
275 with vendor switching (i.e., the non-recoverable time/money/effort associated with the existing vendor).
276 The sunk costs are psychological but greatly influence the switching decision. The sunk costs belong to
277 termination costs.

278 Empiricism on switching costs has also documented the important role of the costs in vendor switch-
279 ing. [Whitten and Wakefield \(2006\)](#) found that switching costs prevented producers from switching from
280 unsatisfactory vendors. [Whitten \(2010\)](#) discerned that high switching costs promoted the continuation of
281 producer-supplier relationships.

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

286 **Appendix H. Model timeline and proofs for propositions**

287 *Timeline of the model.*

Figure H.11: Timeline



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

288 *Proofs for propositions.*

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

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

292 and

$$293 \quad (1 - \bar{V}_i^* s_{i,N}^*) = \frac{\xi V_i^* + c^+}{\alpha A a_i}. \tag{H.2}$$

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

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

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

$$\begin{aligned}
 298 \quad \iff \bar{V}_i^* &= \frac{2\alpha \bar{A} a_i - c^+ + c^-}{\alpha \bar{A} a_i + 2\xi} \\
 299 \quad &= \frac{2\alpha \bar{A} - \tilde{c}^+ + \tilde{c}^-}{\alpha \bar{A} + 2\tilde{\xi}}. \tag{H.3}
 \end{aligned}$$

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

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

303 and

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

306 and

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

309 In equilibrium, the output of producer i satisfies:

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

311 *Lemma 1*

312 *Proof.* Taking the partial derivative of equation (H.7) wrt. $\ln V_i^*$, we have

$$313 \quad \frac{\partial \ln Y_i^*}{\partial \ln V_i^*} = \frac{A a_i V_i^*}{Y_i^*} z_{i,E}^* > 0.$$

314

□

315 *Lemma 2*

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

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

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

319

□

320 *Lemma 3*

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

$$322 \quad 2 = V_i^* + \frac{\xi V_i^* - c^-}{\alpha A a_i} + \frac{\xi V_i^* + c^+}{\alpha A a_i}. \quad (\text{H.8})$$

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

$$324 \quad \begin{aligned} \frac{dV_i^*}{d \ln A} &= \frac{2\xi \bar{V}_i^* + (c^+ - c^-)}{2\xi + \alpha \bar{A} a_i} \\ &= \frac{\alpha \bar{A} a_i (z_{i,E}^* + z_{i,N}^*)}{2\xi + \alpha \bar{A} a_i} > 0. \end{aligned}$$

325 Therefore,

$$326 \quad \begin{aligned} \frac{d \ln V_i^*}{d \ln A} &= \frac{2\tilde{\xi}_i \bar{V}_i^* + (\tilde{c}_i^+ - \tilde{c}_i^-)}{(2\tilde{\xi}_i + \alpha \bar{A}) \bar{V}_i^*} \\ 327 \quad &= \frac{2\alpha \bar{A} / \bar{V}_i^* - \alpha \bar{A}}{2\tilde{\xi}_i + \alpha \bar{A}}. \end{aligned} \quad (\text{H.9})$$

328 When $c^+ = c^-$,

$$329 \quad \frac{d \ln V_i^*}{d \ln A} = \frac{2\tilde{\xi}_i}{2\tilde{\xi}_i + \alpha \bar{A}}. \quad (\text{H.10})$$

330 □

331 *Lemma 4*

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

$$333 \quad \frac{\partial s_{i,N}^*}{\partial \ln A} = \frac{\partial s_{i,T}^*}{\partial \ln A} = \frac{\tilde{c}_i}{2\alpha \bar{A} \bar{V}_i^*} > 0. \quad (\text{H.11})$$

334 □

335 *Proposition 1*

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

$$337 \quad \begin{aligned} \frac{ds_{i,T}^*}{d \ln A} &= \underbrace{-\frac{1}{2} \frac{d \ln V_i^*}{d \ln A}}_{\text{Scaling effect} < 0} + \underbrace{\frac{\tilde{c}_i}{2\alpha \bar{A} \bar{V}_i^*}}_{\text{Switching effect} > 0} \\ 338 \quad &= -\frac{1}{2} \frac{2\alpha \bar{A} / \bar{V}_i^* - \alpha \bar{A}}{(2\tilde{\xi}_i + \alpha \bar{A})} + \frac{\tilde{c}_i / \bar{V}_i^*}{2\alpha \bar{A}}. \end{aligned} \quad (\text{H.12})$$

339 Therefore,

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

344 where the first term is always negative while the second term is negative for small a_i and positive for
345 large a_i . Note that applying the implicit function theorem to equation (H.8) in the steady state, we have

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

347 Thus, when a_i increases from zero, $ds_{i,T}^*/d \ln A$ first declines and then increases.

348 Note that

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

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

$$354 \quad \frac{ds_{i,T}^*}{d \ln A} = -\frac{2}{2\bar{V}_i^*} + \frac{1}{2} = -\frac{2 - \bar{V}_i^*}{2\bar{V}_i^*} < 0.$$

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

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

$$359 \quad \frac{ds_{i,N}^*}{d \ln A} = \frac{1}{2} \frac{d \ln V_i^*}{d \ln A} > 0,$$

$$360 \quad \frac{ds_{i,T}^*}{d \ln A} = -\frac{1}{2} \frac{d \ln V_i^*}{d \ln A} < 0,$$

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

362

□

363 *Proposition 2*

Proof.

$$364 \quad \frac{ds_{i,N}^*}{d \ln A} = \frac{1}{2} \frac{d \ln V_i^*}{d \ln A} + \frac{1}{2} \frac{\tilde{c}_i}{\alpha A \bar{V}_i^*} > 0.$$

365 Therefore,

$$366 \quad \frac{ds_N^*}{d \ln A} = \sum_i \frac{ds_{i,N}^*}{d \ln A} \frac{\bar{Y}_i^*}{\bar{Y}^*} > 0.$$

367

□

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

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

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

372 The management cost becomes

$$373 \quad G(z_{i,N}, z_{i,E}) = \xi_0 V_i + \xi_1 \cdot V_i^2/2, \quad (\text{I.1})$$

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

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

$$379 \quad c^+(V_{i,N}) * V_{i,N} = c_0 V_{i,N} + c_1 V_{i,N}^2/2, \quad (\text{I.2})$$

$$380 \quad c^-(V_{i,T}) * V_{i,T} = c_0 V_{i,T} + c_1 V_{i,T}^2/2, \quad (\text{I.3})$$

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

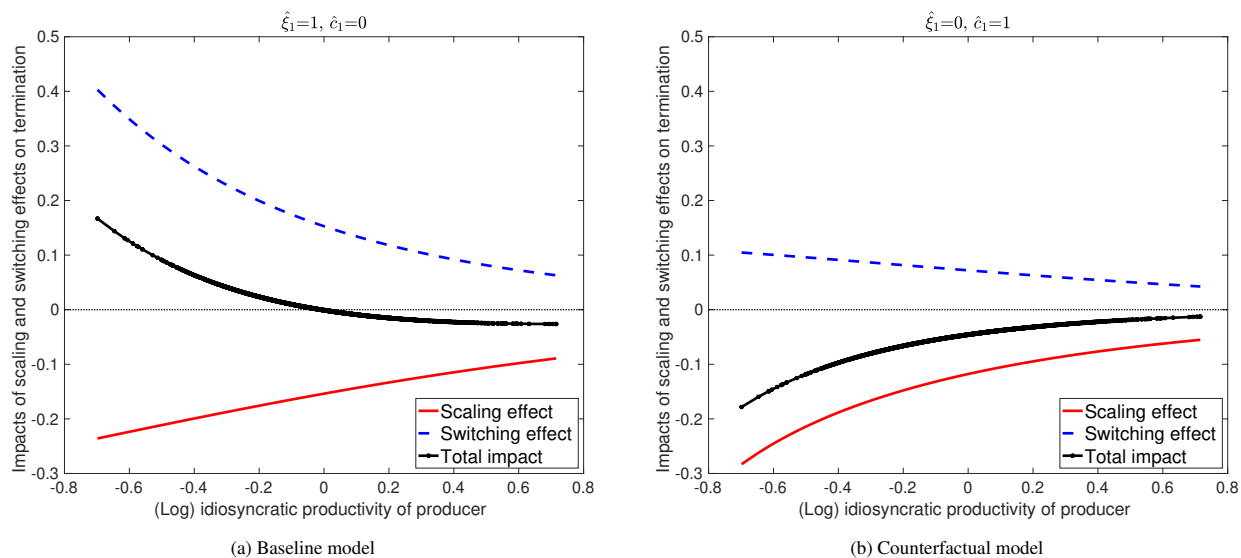
383 c_1 governs the size of the quadratic (i.e., strictly convex) component. The share of the quadratic component
 384 in the entire adoption (vs. termination) cost, denoted by $\hat{c}_1 \equiv c_1/(c_0 + c_1)$, captures the degree of convexity
 385 in the adoption (vs. termination) cost function.

386 In our baseline model of Sections 4 and 5, we have $\hat{\xi}_1 = 1$ and $\hat{c}_1 = 0$ such that the management
 387 cost is quadratic and the adoption and termination costs are linear (i.e., $G(z_{i,N}, z_{i,E}) = \xi_1 \cdot V_i^2/2$ and
 388 $c^+(V_{i,N}) = c^-(V_{i,T}) = c_0$).

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

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

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



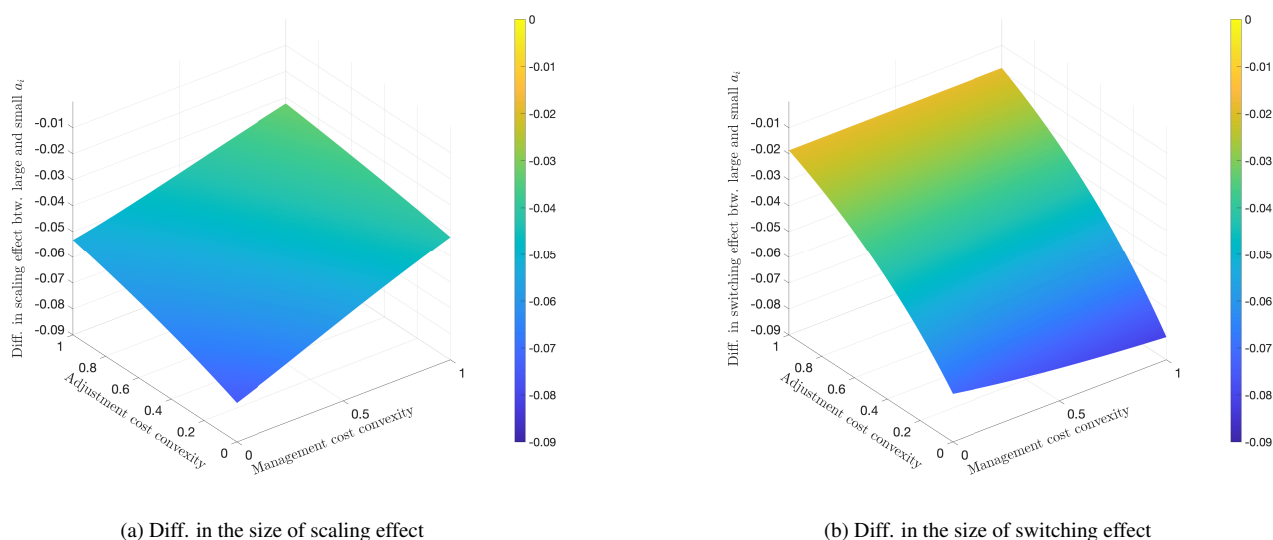
Notes: The figure plots the impacts of scaling (dotted red curve) and the switching (dashed blue curve) effects on the response of termination rate to changes in aggregate TFP as functions of the (log) idiosyncratic productivity of the producer, respectively. The solid black curve with circles is the total impact of the two effects, which indicates the (pro)cyclicality of the rate of termination. Panel (a) is the baseline model with quadratic management cost and linear adjustment costs (i.e., $\hat{\xi}_1 = 1$ and $\hat{c}_1 = 0$), and Panel (b) is the counterfactual model with linear management cost and quadratic adjustment costs (i.e., $\hat{\xi}_1 = 0$ and $\hat{c}_1 = 1$).

396 Panel (a) of Figure I.12 shows our baseline model that has quadratic management costs (i.e., $\hat{\xi}_1 =$
 397 1) and linear adoption and termination costs (i.e., $\hat{c}_1 = 0$). In the baseline model, the switching effect
 398 significantly declines with the idiosyncratic productivity of the producer, while the size (i.e., the absolute
 399 value) of the scaling effect is insensitive to the idiosyncratic productivity. Thus, the total impact (i.e.,
 400 the procyclicality of termination)—which equals the sum of the switching effect and the negative scaling
 401 effect, as shown in equation (11)—decreases with the producer’s idiosyncratic productivity, generating

402 countercyclical termination for large producers and procyclical termination for small producers that are
 403 consistent with Figure 2 of Fact 2.

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

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



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

415 Comparing Panels (a) and (b) in Figure I.12, we can conclude that the *sensitivity* of the scaling (vs.
 416 switching) effect to the producer’s idiosyncratic productivity—defined as the *semi-elasticity* of the size
 417 (i.e., the absolute value) of the scaling (vs. switching) effect to a_i —declines with the degree of convexity
 418 of the management (vs. adjustment) costs. This pattern is verified by Figure I.13, where the difference
 419 in the size of the scaling (vs. switching) effect between the larger and the smaller producers—measuring

420 the *sensitivity* of the scaling (vs. switching) effect to a_i —is plotted against broader combinations of the
 421 degree of convexity in management (vs. adjustment) costs.⁹ Panel a (vs. Panel b) in Figure I.13 shows
 422 that the difference in the size of the scaling (vs. switching) effect between the larger and the smaller
 423 producers is always negative, evincing that the size of the scaling (vs. switching) effect diminishes with the
 424 idiosyncratic productivity of the producer, consistent with Lemmas 3 and 4, and Figure I.12. Moreover, for
 425 the scaling (vs. switching) effect, the difference (between large and small producers) is more negative when
 426 the management (vs. adjustment) cost is closer to linear and less convex, indicating that the sensitivity of
 427 the scaling (vs. switching) effect to a_i declines with the convexity of the management (vs. adjustment) cost,
 428 again consistent with Figure I.12.¹⁰

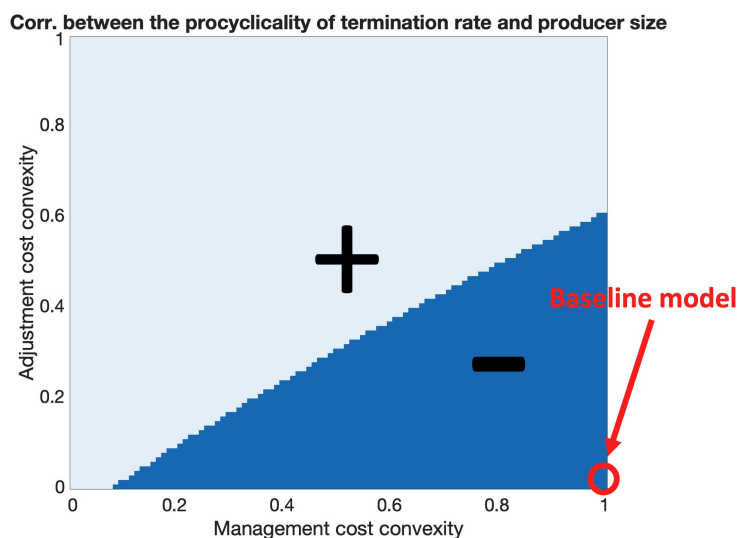


Figure I.14: Difference in (pro)cyclicality of termination btw. small and large producers *vis-à-vis* convexity of costs

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

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

⁹The larger and the smaller producers have log idiosyncratic productivity of 0.2 and -0.2, respectively.

¹⁰In Figure I.13, for the scaling (vs. switching) effect, the difference (between the larger and smaller producers) is also more negative when the adjustment (vs. management) cost is closer to linear and less convex. However, the sensitivity of the scaling (vs. switching) effect to a_i declines more with the convexity of the management (vs. adjustment) cost than with the convexity of the adjustment (vs. management) cost.

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

439 Figure I.14 shows that when the management cost has a sufficiently large degree of convexity and the
 440 adjustment cost has a sufficiently small degree of convexity (i.e., sufficiently close to linear), the procycli-
 441 cality of termination is more negative (i.e., more countercyclical termination) for the large producer than
 442 for the small producer, evinced by the dark-blue area towards the bottom right of the figure that includes the
 443 red circle representing the quadratic management cost and linear adjustment cost in our baseline model. As
 444 Figure I.13 shows, the large convexity in the management cost and the small convexity in the adjustment
 445 cost make the scaling effect insensitive to a_i and the switching effect more sensitive to a_i . Therefore, the
 446 switching effect dominates in the sensitivity of the cyclicity of termination to a_i , making the termination
 447 less procyclical (i.e., more countercyclical) for large producers than for small producers.¹¹

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

454 To understand why the sensitivity of the scaling (vs. switching) effect to the idiosyncratic productivity
 455 declines with the convexity of the management (vs. adjustment) costs, we study equations (I.4) and (I.5).
 456 In these two equations, the sizes of the scaling and switching effects are functions of the convexity of the
 457 management and adjustment costs (i.e., $\hat{\xi}_1$ and \hat{c}_1), the size of the producer (i.e., \bar{V}_i^*), and other parameters.¹³

$$458 \quad \text{Scaling effect} = -\frac{1}{2} \frac{d \ln V_i^*}{d \ln A} = -\frac{1}{2} \left[(\alpha \bar{A} a_i)^2 / 2 + \xi_1 \alpha \bar{A} a_i + (\alpha \bar{A} a_i + \xi_1) c_1 + c_1^2 / 2 \right]^{-1} \quad (\text{I.4})$$

$$459 \quad (\xi_0 + \xi_1) \left[(1 - \hat{\xi}_1) + \hat{\xi}_1 \bar{V}_i^* \right] / \bar{V}_i^* * (\alpha \bar{A} a_i + c_1) .$$

$$460 \quad \text{Switching effect} = \frac{[(1 - \hat{c}_1) + \hat{c}_1 \bar{V}_i^* \bar{s}_{i,N}^*] / \bar{V}_i^*}{(\alpha \bar{A} a_i + c_1)(c_0 + c_1)} . \quad (\text{I.5})$$

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

¹¹Recall that the size of the switching effect diminishes with the size of the producer in Lemma 4, evinced by Figure I.12.

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

¹³Recall that the producer's size in terms of total measure of suppliers (i.e., \bar{V}_i^*) increases with its idiosyncratic productivity, i.e., more (vs. less) productive producers correspond to larger (vs. smaller) producers.

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

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