Supply Chain Resilience: Evidence from Indian Firms

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Abstract

We characterize what features make supply chains more resilient. Using new data on the universe of firm-to-firm transactions from an Indian state, we identify firms with larger supplier exposure following the Covid-19 lockdowns. Using an event-study design we find firms with suppliers in strict-lockdown districts experienced higher separation rates and larger declines in inputs and sales. We study which characteristics increase supply-chain resilience. Firms that buy more complex products, with fewer available suppliers, are less likely to break links and face lower production disruptions. We explore how firms change post-shock supplier composition. Firms with higher supplier exposure form new links with larger and better-connected suppliers.

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1 Introduction

The rise of complex supply chains is one of the most striking features of recent decades (Johnson, 2017). While the efficiency gains from these supply chains have been well established, a growing literature has found that supply chains transmit shocks across regions with significant economic consequences. For instance, the 2011 Tohoku earthquake disrupted US-based multinational affiliates' supply chains, substantially decreasing US industrial production (Boehm et al., 2019). During the Covid-19 pandemic, significant global supply-chain disruptions ensued, propagating the shock (Bonadio et al., 2021) and amplifying shortages and inflationary pressures worldwide (di Giovanni et al., 2022; LaBelle and Santacreu, 2022). This led to increased interest in policies making supply chains more resilient and robust.[1]

Despite their importance, we lack empirical evidence on which features make supply chains resilient to shocks. In this paper, we study this question using new data on daily firm-to-firm transactions from India, coupled with a large exogenous shock that disrupted supply chains to varying degrees. We measure supply chain resilience following a disruption along three dimensions: whether input usage and output drops, whether supplier links are maintained, and whether it is easy to find new suppliers to replace existing suppliers if links are broken. There is little consensus on the definition of supply-chain resilience in the economics literature. Brunnermeier (2021) emphasizes that resilience rests on the ability of a supply chain to adapt and recover from shocks. The Brookings Institution builds on the literature in supply chain management and logistics to define supply-chain resilience as *"the ability of a given supply chain to prepare for and adapt to unexpected events; to quickly adjust to sudden disruptive changes that negatively affect supply-chain performance; to continue functioning during a disruption (sometimes referred to as "robustness"); and to recover quickly to its pre-disruption state or a more desirable state."* Our measures aim to capture how firms and their supply chains respond to disruptions along these dimensions.

We use event-studies to estimate the causal effect of a supplier-specific disruption on a firm's ability to preserve its supply-chain links, input usage, and output produced. We then assess which characteristics of supply chains made them more resilient.[2] Two particular features of our setting make it ideal to answer this question. First, we obtain

[1] See for instance, the White House's June 2021 100-day review of America's Supply Chains: "Building Resilient Supply Chains, Revitalizing American Manufacturing and Fostering Broad-Based Growth," which recognized key gaps in data and knowledge on global supply chains, that could limit the precision and efficacy of policy interventions.

[2] There is a nascent theoretical literature studying supply chain resilience (Acemoglu and Tahbaz-Salehi, 2024; Elliot et al., 2022; Grossman et al., 2021). We discuss the relationship of our findings to this new literature throughout the paper.

unique daily firm-to-firm data from 2018-2020 on the near universe of transactions, where at least one node of the transaction lies within a large Indian state.[3] Second, we leverage India's mosaic of Covid-19 restriction policies, generating plausibly exogenous variation in the impact on supply-chain links. Between March and May 2020, districts in India were classified into red, orange, or green zones, with red zones facing the most stringent restrictions. In March 2020, the average separation rate from red-zone suppliers was almost double those from green-zone suppliers. Importantly, we show in several balancing tests that the distribution of buyer-supplier links and industries was balanced across districts facing different lockdown stringencies, suggesting that pre-existing differences across districts assigned varied lockdown stringencies were unrelated to firm supply chains or industries.

To estimate the causal impact of the shock on supply-chain disruptions, we use an event-study regression. We begin by constructing a firm-level measure of supplier exposure, based on the existing supplier network before the shock, and the exposure of suppliers to different lockdown policies across India. We then estimate a differences-in-differences specification, comparing the resilience of firms whose suppliers faced strict lockdowns to firms whose suppliers faced mild lockdowns, relative to the period before the lockdowns began. To control for own-demand shocks, we include a rich set of fixed effects such as firm and industry-own-district-time, as well as firm-specific controls for downstream demand exposure. Therefore, we compare firms within a given industry in a district that face similar own-lockdown policies and similar downstream exposure, but differ in their pre-shock upstream supplier compositions.

We find that a one standard deviation increase in supplier exposure was associated with a 5pp higher separation rate three months after the lockdowns started. On average, the effects were persistent, lasting throughout 2020. Firms with high supplier exposure also exhibited lower entry rates, net separations (separations minus entries), lower input values, and output in response to the shock. For instance, firms with one standard deviation higher supplier exposure decreased their input purchases (output) by up to 34% (21%) after the lockdowns. To put these magnitudes into context, a firm with all their suppliers in strict-lockdown zones experienced a separation rate 15.4pp higher than a firm with suppliers in mild-lockdown zones.

Our varied resilience measures present a similar picture: More exposed firms are more likely to break supplier links, struggle to find new suppliers, and decrease their overall input purchases and output. We show that a majority of the observed drop in input purchases can be explained by the extensive margin, where firms break supplier links and

[3] The state is twice Chile's population and three times Belgium's; both popular sources of firm-to-firm data.

are unable to find replacements.

The second part of our analysis uncovers which features of supply chains make them more resilient. As our intensive and extensive margin resilience measures deliver consistent results, we follow Brunnermeier (2021) and largely focus on net-separation rates, emphasizing the recovery of a supply chain from shocks. We extend the specification to include interactions with network characteristics that potentially mitigate or amplify resilience. We find that firms linked to larger or more nodal suppliers had lower net separations. Somewhat surprisingly, firms that buy more complex products or products that tend to exhibit longer buyer-supplier relationships (Martin et al., 2024) were less likely to break links after the shock and faced lower input disruptions. As such firms might assign more value to supplier-specific links, they had likely invested more in resilience prior to the shock, and were better prepared to withstand it.

To inform the emerging theoretical supply-chain resilience literature, we assess whether measures suggested by Elliot et al. (2022) are good proxies for resilience. We find both that firms that sourced products with many available suppliers and that had multiple suppliers for a given product are both more likely to break links. Such findings are consistent with the theory developed in a stylized symmetric network by Elliot et al. (2022), who highlight that fragility should be particularly worrisome for firms that buy products not easily available.

Finally, we study the formation of new links. We find that firms with higher supplier exposure concentrate into larger and better-connected suppliers. At the same time, supply chains get slightly less complex, as firms now source products that require fewer inputs. Overall, our evidence suggests that the most resilient supply chains are when suppliers are larger, inputs are more differentiated, and the number of alternative suppliers is low. We note that throughout, we study the resilience of the relationships between firms and their suppliers, which are a key input into aggregate resilience, but we do not empirically study the general equilibrium response of the aggregate network.

Related literature. We build on a growing research agenda on the role of production networks in shock transmission. International input trade is a key feature of the global economy (Hummels et al., 2001; Yi, 2003), with recent contributions by Johnson and Noguera (2012, 2017) and Caliendo and Parro (2015). More recently, a growing literature has studied the ability of production networks to transmit shocks across countries (Bems et al., 2010; Burstein et al., 2008; Huo et al., 2020; Johnson, 2014). While several of these papers focus on quantitative models, a strand of the literature has used exogenous natural disasters to empirically study the short-run transmission of shocks through trade and supply chain links (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). In contrast, our focus is on the resilience of existing supply chains to large shocks. The heterogeneous incidence of Covid-19 lockdowns across Indian districts, coupled with the size of the shock and detailed firm-to-firm transaction data, offers a unique opportunity to study how large shocks impact firm linkages and supply-chain resilience.

The resilience of supply chains is the focus of an active, emerging theoretical and quantitative literature (Acemoglu and Tahbaz-Salehi, 2024; Castro-Vincenzi et al., 2024; Elliot et al., 2022; Grossman et al., 2021; Kopytov et al., 2024). This literature emphasizes aspects of firm adaptation of supply chains under risk, and the resilience of supply chains, in stylized theories. Our empirical evidence supports some of the findings in this literature in a real-world network setting, and provides guidance on supply chain characteristics that are resilient in the data. While theoretical and quantitative work abstracts from some real-world features of supply chains by necessity, our results can motivate and discipline future theoretical work, guiding key empirical features models of resilience should contain, and features that models can safely abstract from. We expand the discussion of the links between our results and these theories in Section 6.

A few papers leverage firm-to-firm data to calibrate models studying production networks (Arkolakis et al., 2021; Dhyne et al., 2020; Huneeus, 2020; Korovkin et al., 2024). These papers study the formation of links between firms, but do not focus on supply-chain resilience. In contrast, we leverage quasi-exogenous variation in shocks to identify characteristics of supply chains that make them more resilient, which is a useful input for models focusing on economic resilience. We also contribute to the literature studying production network dynamics (Fontaine et al., 2023; Lim, 2018; Martin et al., 2024) showing empirical evidence suggesting that the fixed costs of link formation or the search/matching costs are heterogeneous and correlated with product and firm characteristics. Further, recent work (Baqaee et al., 2024) has shown that supplier churn is an important component of aggregate productivity growth. Our results speak to the reorganization of firm supplier links following a large shock, informing the sources and patterns of such churn.

While our focus is not the Covid-19 pandemic itself, we contribute to work studying Covid-19 impacts. In the closed-economy setting, this includes work on input-output networks (Baqaee and Farhi, 2020; Barrot et al., 2020; del Rio-Chanona et al., 2020). In the open-economy setting, Bonadio et al. (2021) study the international transmission of the shock through global supply chains, but without microdata. Closely related is Cevallos Fujiy et al. (2021), who use the same data to estimate firm-level substitution elasticities, but do not study supply-chain resilience overall.

2 Data and context

Firm-to-firm trade. Our primary data source is daily establishment-level transactions.[4] These data are from the tax authority of a large Indian state with a fairly diversified production structure, roughly 50% urbanization rates, and high population density. Comparing this context to other contexts with firm-to-firm transaction data, we observe that the state has roughly three times Belgium's population, seven times Costa Rica's, and double Chile's.

The data contain daily transactions from April 2018 to October 2020 between all registered establishments within the state, and all transactions where one node of the transaction (either buyer or seller) is in the state. All transactions have unique tax identifiers for both the selling and buying establishments, which include the value of the whole transaction, the value of the items being traded by 8-digit HSN code, the quantity of each item, its unit, and transportation mode. Each transaction also reports the zip-code location of both the selling and buying establishments, which we merge with other geographic data. More information is in Appendix A, with summary statistics in Table A1.

This data is collected by the tax authority's *E-way Bill* system to increase compliance for tax purposes. This is an advantage over standard VAT firm-to-firm trade datasets in developing countries, which suffer from severe under-reporting. By law, anyone dealing with the supply of goods and services whose transaction value exceeds Rs 50,000 (700 USD) must generate E-way bills. Transactions with values lower than 700 USD can also be registered, but it is not mandatory. The E-way bill is generated before transport (usually via truck, rail, air, or ship), and the vehicle driver must carry the bill with them, or the entire shipment of goods can be confiscated. Our data is generated from these bills. This implies that our network is representative of relatively larger firms, but the threshold is sufficiently low that we are likely capturing small firms as well. While, as in any developing context, there is likely to be non-perfect compliance and informality, the shift to the GST regime is estimated to have heavily increased compliance and doubled the taxpayer base, relative to the previous VAT regime (Times of India, 2020).

We observe the tax ID for both the establishment and the parent firm. As such, we have the precise location (zip code) of the establishment, and do not need to rely on the location of the parent company's headquarters. In the lead-up to the Covid-19 crisis, we find that 19% of transactions were between establishments under the same parent firm.

We use the data to construct the buyer-supplier network every period and the total value of inputs purchased and output sold by firms. To obtain a measure of real inputs and output, we use the reported quantity of each transaction to calculate unit values for each

[4] While we use the term 'firm' in the paper, these data are at the granular establishment level.

product, construct a price index, and deflate the total firm-level input purchases and sales.

Our output measure is noisier than inputs, given that we do not observe direct-to-consumer sales. Therefore, whenever using output as an outcome, we restrict the sample to firms with positive sales every period before the lockdowns began. Our estimation of the sales response to shocks should be interpreted as the response of sales to other firms (and not direct-to-consumers). While we do not directly measure firm-level inventories, we do observe detailed industry-level inventories for 2019 (right before the shock), from Prowess (CMIE).

The industrial composition reflects the composition of many large Indian states (Figure A2). In terms of sales, the largest industries are in machinery and mechanical appliances, metals and metal parts, plastics and rubber, and chemical products. Purchases are highest in terms of machinery and mechanical appliances, chemical products, and vehicles/aircrafts/vessels.

Comparison to other sources of firm-to-firm data. We find that in our data, 53% of total purchases are from within the state while 47% are from other states. In terms of sales of producers in our state, 74% of sales are to firms within state, while 26% are to other states. This is comparable to the values reported by Dhyne et al. (2020), for Belgium, where 37% of total sales are exported, and 47% of input purchases are imported. As shown by Castro-Vincenzi et al. (2024), the distribution of customers and suppliers each firm in our data has is very similar to that documented by Alfaro Ureña et al. (2018) for Costa Rica.

Geographic Variation in Lockdowns. On March 25, 2020, India unexpectedly imposed strict Covid-19 lockdown policies nationwide for an indeterminate duration. The lockdown was implemented at the district level, where each district was classified *Red*, *Orange*, and *Green* according to the severity of Covid cases in each district (Table A2 summarizes Covid-19 outcomes). Figure 1a shows a map showing the distribution of lockdowns across India. We use zone information from firms located all over the country as long as one node of the transaction was in the state of our data.

Districts in the red zone saw the strictest lockdowns, with rickshaws, taxis, public transport, barber shops, spas, and salons remaining shut. E-commerce was allowed for essential services. Orange and green zone districts saw fewer restrictions. In addition to the activities allowed in red zones, orange zones allowed the operation of taxis and the inter-district movement of individuals and vehicles for permitted activities. Additionally, in green zones, buses (and depots) were allowed to operate at 50% capacity.[5]

These zones were based on the very initial (relatively low number of) Covid-19 cases, and so are unlikely to be driven by systematic differences across areas. Other work shows balance and falsification tests when studying how these lockdowns affected women's mental health (Bau et al., 2022), domestic violence (Ravindran and Shah, 2023), night-time lights (Beyer et al., 2023), and import substitutability (Fujiy et al., 2022). We further assess whether lockdowns are correlated with relevant outcomes for our data: the types of firms, the distribution of various industries, the size of firms, and the prices charged. In Figures A4, A5, and A6, we show some different sets of balance tests. The top panel of Figure A4 shows that there was balance in the different types of buyers for sellers in each zone color. The bottom panel shows the same for different types of sellers for buyers in each zone. In Figure A5, we test for balance in different industries by lockdown zones. We find that only 2 minor industries seem imbalanced: HS 5 (Minerals) and HS 19 (Ammunitions) had more red zones. These are both minor industries in the state, and the results are robust to dropping them. Finally, in Figure A6, we show that average firm size and unit values are similar across zones as well.

There may be heterogeneity in effects, and so lockdowns will have a different impact in certain districts compared to hypothetical lockdowns in other districts. The implication is that we are estimating the average treatment on the treated (ATT). Finally– while there is little evidence to suggest this– if suppliers of certain industries were protected from lockdowns, this would make it less likely for us to find an effect of the lockdowns on supply chains.

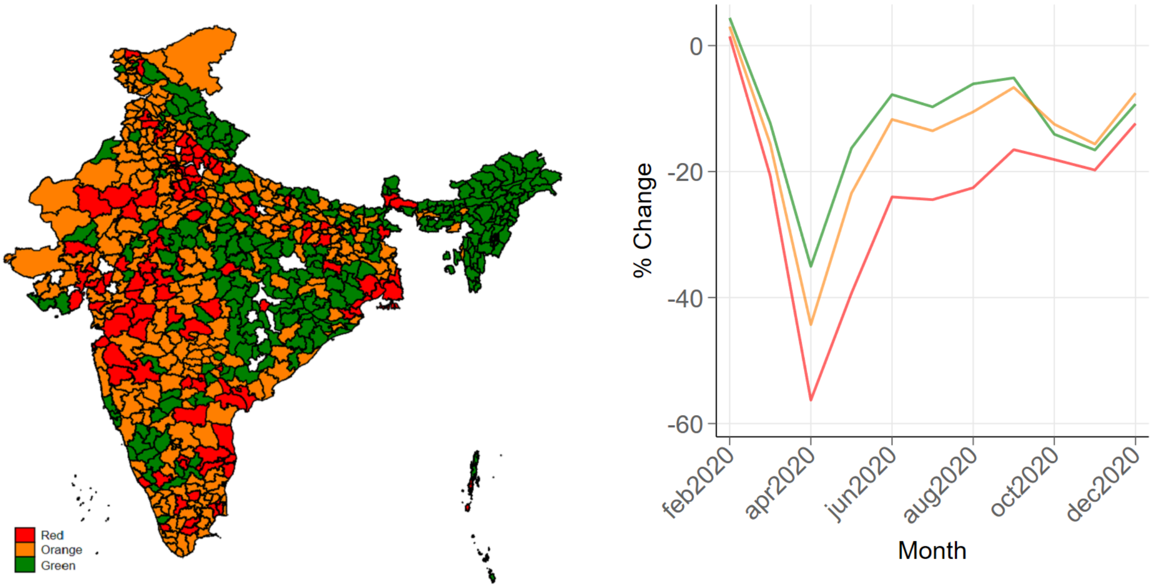
While the balance tests we show provide evidence that the levels in outcomes were similar across zones, our identification strategy does not require this to be the case. That is, we conduct event study exercises that can allow for differences in levels across locations, and we show parallel pre-trends leading up to the shock for all our primary outcomes. Additionally, we will include a rich set of fixed effects, and demand-side controls. These include industry-by-district-by-time fixed effects, that would absorb any industry-by-location-by-time specific shocks or preferential treatment.

As shown in Figure 1b, lockdown stringency was strongly correlated with subsequent measures of economic activity and mobility. We validate our measures of lockdown intensity using Google Mobility data, and satellite nighttime luminosity in Appendix B.

[5]Source: Lockdown: Guidelines for zones

Figure 1: Lockdown Zones and Fall in Visits to Workplaces

(a) India's Covid-19 Lockdown Zones (b) Google Mobility Trends: Workplaces



Note. The left panel shows the lockdown zones across Indian districts, where the lockdown was announced on March 25, 2020. In the right panel, we plot the average Google Mobility Trend for Workplaces by district lockdown stringency. The data shows how the number of visitors to workplaces changed compared to the five-week period from Jan. 3 to Feb. 6, 2020.

3 The Impact of Lockdowns on Resilience

We begin our analysis by measuring how the March 2020 lockdowns affected supply-chain resilience. As mentioned before, there is no unique definition of supply-chain resilience.

We define alternative measures that capture a firm's ability to minimize production disruptions, maintain existing links with their suppliers, and be flexible enough to adapt and recover after a shock. Our measures closely follow the definition of resilience proposed by Brunnermeier (2021), Acemoglu and Tahbaz-Salehi (2024), and the Brookings Institution. Goldberg and Reed (2023) build on our work and consider similar measures in U.S. data when considering supply chain resilience. We view the lockdowns as an idiosyncratic shock to a buyer-supplier relationship. In that sense, our definitions of resilience focus primarily on the destruction and creation of firm links. A firm that concentrated its purchases among suppliers in areas with strict lockdowns should have a higher likelihood of experiencing supply-chain disruptions than firms with suppliers in mild-lockdown areas.

As our first measure of resilience, we compute the supplier-separation rates:

$$\text{Separation Rate}_{j,t+1} = \frac{\text{N of suppliers to } j \text{ in } t\text{, who don't supply in } t+1}{(\text{N of suppliers to } j \text{ in } t)/2 + (\text{N of suppliers to } j \text{ in } t+1)/2}, \quad (1)$$

where the separation rate in period $t+1$ is the number of supplier links of firm j that break when going from t to $t+1$, relative to the average number of suppliers of firm j across periods. Note that we define a link breaking as the absence of any transaction between the buyer and the supplier between t and $t+1$. Our second measure is the net-separation rate, which is the difference between the supplier-separation rate and the supplier-entry rate of firm j:

$$\text{Net-Separation Rate}_{j,t+1} = \text{Separation Rate}_{j,t+1} - \underbrace{\frac{\text{N of suppliers to } j \text{ in } t+1 \text{ and not in } t}{\left[(\text{supp. to } j \text{ in } t) + (\text{supp. to } j \text{ in } t+1)\right]/2}}_{\text{Entry Rate}_{j,t+1}} \tag{2}$$

The entry rate in $t+1$ is the number of new supplier links created between t and $t+1$, relative to the average number of suppliers of firm j. Therefore, the net-separation rate captures how easy it is for a firm to find alternative suppliers following disruptions.

For our third measure of resilience, we quantify the changes in the real value of inputs purchased by firms and real output sold by firms. When looking at real output, we exclude firms that do not reliably sell goods to other firms in our data and focus on firms that are observed selling something at least once every period before February 2020.[6]

3.1 Event-Study Analysis

To evaluate how firms adapt to lockdown-induced supply-chain disruptions, we need to quantify how such firms would have responded if no shock occurred. Even if we observe higher separation rates from suppliers in strict lockdown zones relative to other suppliers (Figure A7), it is possible that those buying from suppliers in red zones were following different trends than those buying from suppliers in green zones. It is also possible that suppliers in red zones have different characteristics than those in orange and green zones, even though our balance checks in Figures A4 - A6 suggest they were similar along many dimensions. Finally, Covid-19 was a national-level shock, such that the observed separation rates or changes in input purchases could be driven by a firm's own demand disruptions instead of its suppliers' behavior.

To address these concerns, we set up an event-study analysis and use the existing supplier network before March 2020 as a measure of the exposure to the shock. Intuitively, we want to compare two firms that faced the same demand and productivity shocks and only differed in the location of their suppliers. By comparing the observed disruptions of a firm whose suppliers were more exposed to lockdowns with a similar firm whose suppliers were less exposed, we can isolate the impact driven by supply-chain disruptions. We can

[6] Goldberg and Reed (2023) build on our work and consider similar measures in U.S. data when considering supply chain resilience.

then assess the characteristics of supply chains that lead to more or less disruption by looking at patterns of responses in affected firms relative to unaffected firms, as a function of observables.

We begin by creating a supplier-exposure index to identify the exposure of the firms in our sample to the lockdowns as shown:

$$(\text{Supplier exposure})_j = \sum_i^N s_{i,j,t_0-1} \times (\text{Supplier } i\text{'s lockdown stringency in } t_0) \ , \tag{3}$$

where s_{ij} stands for the value of purchases that firm j buys from firm i, relative to firm j's total purchases and where N is the total number of firm j's suppliers. Time subscript t_0 represents the period just before the lockdowns begin. The index calculates the weighted average of the lockdown stringency of firm j's suppliers. As we only have three ordinal categories of district lockdowns, we assign green districts a value of 1 (low lockdown), orange districts a value of 2 (medium lockdown), and red districts a value of 3 (high lockdown). We then standardize the supplier exposure index to make it easier to interpret.[7] A higher value of the index implies firm j faces a higher "supplier-exposure," as a larger share of its purchases were coming from areas with stricter lockdowns. The weights are calculated using transactions between December 2019 and February 2020, while lockdown stringency is measured in March 2020.

We set up our baseline regression as shown in equation 4:

$$y_{j,t,r,k} = \sum_{x=t_0-4,\neq t_0}^{t_0+3} \gamma_x \, (\text{Supplier Exposure})_j + \delta_j + \delta_{r,k,t} + \zeta X_{j,t} + \epsilon_{j,t,r,k} \ , \tag{4}$$

where subscript r stands for the district in which firm j is located, and k stands for industry. The outcome $y_{j,t,r,k}$ can be the separation and net separation rates as defined in equations 1 and 2. We also use real inputs and real sales as additional outcomes.

Coefficients γ_x are time dummies that capture the differential separation/net-separation/real input value growth rate for buyers with supplier exposure one standard deviation above the mean. We omit the baseline period December 2019 to February 2020 ($x = t_0$), such that the time dummies should be interpreted as the change in outcomes relative to that omitted period. The firm fixed effect δ_j controls for time-invariant differences across firms. We include own-district-industry-time fixed effects $\delta_{r,k,t}$, which control for a firm's own location lockdown, which can also affect their disruption as well as region-specific industry-wide shocks and changes in demand for specific goods. For instance, if the shock

[7] In Appendix C, we show our results are robust to alternative measures of exposure, such as a binary indicator, including exposure to red and orange zones separately, and using Google mobility as an alternative indicator for the lockdowns.

increased demand for durable goods in a given district, such changes should be captured by these fixed effects. The interpretation of our coefficients of interest γ_x are a reduced form difference-in-difference estimate of the effect of exposure to suppliers' lockdowns.

To make sure our results are driven by shocks to the suppliers, and that such shocks are not correlated with shocks to a firm's consumers, we add a firm-level demand control ($X_{j,t}$), which consists of time dummies interacted with a "consumer exposure measure" calculated as in equation 5.

$$(\text{Consumer Exposure})_j = \sum_i^N c_{j,i,t_0-1} \times (\text{Consumer } i\text{'s lockdown stringency in } t_0) \ , \quad (5)$$

where the consumer exposure is calculdated as a weighted average of firm j consumers in $t_0 - 1$ to lockdown policy in t_0, using the share of sales to i in the pre-period as weights (c_{j,i,t_0-1}).

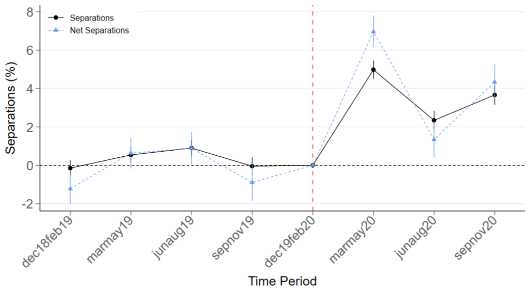
Figure 2 plots γ_x over time for our measures of supply-chain resilience. Reassuringly, the coefficients in the pre-periods are not statistically significant, implying that high- and low-exposed firms had similar trends in terms of their pre-shock supply-chain disruption measures. Consistent with Figure 2a, we see a persistent increase in supplier separations for firms most exposed to the lockdown shock. Between March and May 2020, firms with supplier exposure of one standard deviation above the mean experienced an increase of 5pp in their separation rate from suppliers. The effect is economically significant, as it corresponds to a 16% increase with respect to baseline separation rates. The higher separation rates between high- and low-exposed firms remain through the 2020 period.[8]

In Figure 2a, we also plot effects on the net-separation rate. The patterns follow closely those observed with separations, but the effects are slightly larger, as some firms increase separations and have lower entry of new suppliers. Appendix Figure A8a plots entry rates. Between March and May 2020, firms with supplier exposure of one standard deviation above the mean experienced an increase of 6.5pp in their net-separation rates. Finally, in Figure 2b, we look at changes in real input value, which combine the extensive and intensive margin responses of firms. We see that firms with a one standard deviation

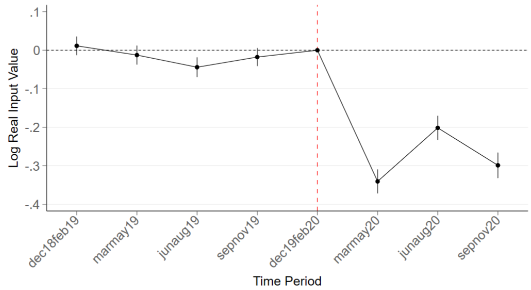
[8]Unweighted supplier entry and exit in non-shock periods are moderately high in India, with the average separation rate being 30.9% and the average net-separation rate -43.2% during the pre-period. Weighted separation rates are lower, averaging 19.4% in the pre-period. This suggests some higher rates are driven by smaller firms having higher "typical" separation rates. Note that these numbers are comparable to those calculated by Goldberg and Reed (2023), who replicate our measures using data from Panjiva on the international suppliers of US firms and find separation and entry rates during the pandemic of between 30-40%. Of course, our difference-in-difference estimates consider differential separation and net separation rates relative to the pre-period baseline.

Figure 2: Baseline Event Studies

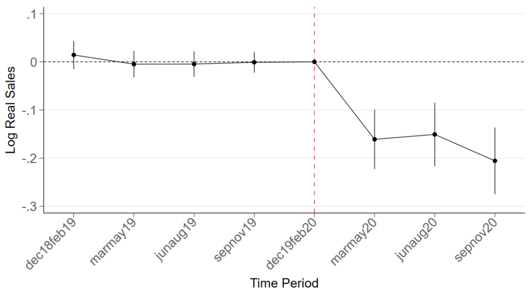
(a) Separations



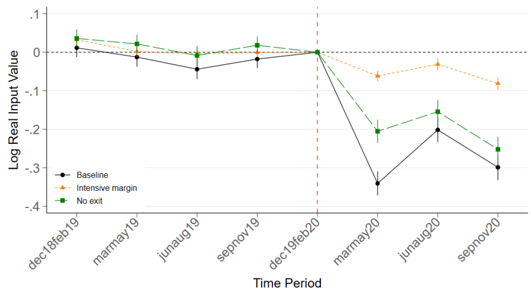
(b) Log Real Input Value



(c) Log Real Sales



(d) Extensive vs. Intensive Margin



Note. We plot the estimated coefficients γ_x from equation 4 and their 95% confidence intervals. The omitted period is December 2019 to February 2020. The average separation rate in the omitted period: 30.9%. Mean net separations in the omitted period: -43.2%. Number of observations: 930,501. In panel (c), the sample is restricted to firms with positive real sales every period before the shock. Number of observations: 163,464. In panel (d), the orange line presents the drop in input purchases using only purchases from suppliers that already supplied to the firm in the previous period (continuing relationships). N obs: 663,872. The green line presents the change in input purchases calculated using only firms that transact at least once in the post-shock periods (do not exit). N obs: 849,291. Standard errors clustered at buyer level.

higher supplier exposure decrease input values by 34% after the shock, and the drop is quite persistent through 2020.

As a final resilience measure, we investigate whether the observed supply-chain disruptions had a negative impact on firm-level output. To look at this outcome, we focus on companies that are observed selling goods to other firms every period between December 2018 to February 2020. Since we don't observe sales made directly to consumers, we need to focus on a sub-sample of firms that we are confident were regular sellers before the shock happened. As shown in Figure 2c, output also drops significantly, where highly-exposed firms experience a drop in real sales of almost 20% for the period of September to November 2020. In sum, our evidence suggests that Covid-19 was a salient shock to firms, and supply-chain disruptions propagated to firm output.

Inputs also drop by a similar magnitude than in the baseline when using the sample for sales, as shown in Appendix Figure A8c. We suspect it is unlikely that firms mitigate their output losses by having inventories to mitigate the production shock, as there does not seem to be a relationship between the output impact from the shock and the average inventory holdings by industry, as shown in Figure A8d. Also, as discussed in Castro-Vincenzi et al. (2024), firms in our sample hold less than one month of inventories, on average. We present the estimates of our main outcomes using a difference-in-difference approach to summarize the estimated effects in Table A3.

Overall, the impact of the shock on our key resilience outcomes is quite persistent throughout 2020. In our setting, while these specific lockdowns were lifted in three months, there were also other Covid measures that were introduced. Importantly, the length of the pandemic, and the likelihood of future outbreaks were very uncertain in 2020, and so there might have been an expectation that further measures may be needed during future outbreaks. The perceived persistence of the underlying shock might have resulted in permanent effects on buyer/seller relationships. In other words, buyers might have perceived increased risk in sourcing from suppliers who had been locked down once already, given the likelihood of a protracted pandemic.

3.2 Intensive and Extensive Margins of Resilience

We investigate the role of the extensive margin on the real input value drop by quantifying the change in input purchases for alternative samples of firms. We begin by excluding from the sample firms that are never observed buying inputs after March 2020. These firms exhibit the largest response to the lockdowns as they break links with their suppliers and presumably exit after the shock. As shown by the green line in Figure 2d, the drop in input purchases goes from 34% to 20% when excluding firms that exit. That is, one-third of the total effect is driven by exiting firms.

We then calculate the real input purchases from suppliers that were already selling to the firm in the previous period and continue selling to the firm in the next period. This measure focuses exclusively on the intensive margin, as we do not consider input purchases from new suppliers or from suppliers that break links with the firm. The orange line in Figure 2d shows that firms with highly exposed continuing suppliers only decrease input purchases by 6%. This suggests that the extensive margin and entry and exit drive approximately 82% of the observed supply-chain disruptions.

3.3 Extensions and Robustness

Before diving into which characteristics are associated with resilience, we perform multiple robustness checks and extensions of our main analysis, to further understand the nature of the shock.

As a first step, we corroborate that our definition of supplier exposure is robust to alternative specifications. In Appendix C, we show that our results are robust to defining the exposure measure as a binary indicator (Table A4) and using Google mobility data as an alternative source to construct lockdown exposure (Table A5). We also show how our results change if we have separate exposures for red-lockdown zones and orange-lockdown zones instead of combining them into a single index. As expected, exposure to red zones has the largest impact on our resilience outcomes, but orange zone exposure also significantly affected resilience (Table A6).

Second, we show our results are robust to excluding specific firms. For instance, intra-firm purchases account for 30.1% of the total transacted value in our sample. However, excluding intra-firm transactions almost doesn't change our results (Table A7). Similarly, our results are robust to excluding likely-retailers and likely-wholesalers, which is suggestive that our results are driven by relationships between manufacturing firms (Tables A8 and A9). Our results are also not driven by firms with highly connected suppliers (Table A10).

In Appendix Figure A10, we corroborate that our results truly capture links that get broken after the shock, and are not just reflecting changes in the frequency of purchases. When defining time periods as groups of four or six months, we still see a persistent increase in separation rates and net-separation rates after the shock. Such findings are also indicative that affected firms do not seem to fully return to their old suppliers shortly after the shock. In Figure A11, we show that while firms experience a rebound in the re-entry rate of old suppliers, they also experience entry of new suppliers by similar magnitudes.

In Figure A9, we corroborate that the separations results are robust to weighting broken links by supplier size. Finally, in Appendix Figure A8b, we run our baseline specification with the log input value as the dependent variable, but add as a control the net separations experienced by the firm. The drop in inputs is still significant but less pronounced when controlling for net-separations.

3.3.1 Prices and alternative levels of aggregation

Next, we look into how our shock affects input prices. Our data has the unique feature that we observe product codes, and quantities for each transaction such that we can back out the price the firm pays for each input purchased. Since our baseline regressions are at the firm-time level and many firms purchase multiple products, we need to re-define our regressions to a different level of aggregation that includes 4-digit products. We look into two alternative levels of aggregation: product-district-time and firm-product-time.

The main specifications we run are similar to our baseline equation 4, but with slightly different fixed effects. For the product-district-time regressions, we calculate the share of total inputs of a given product p purchased by firms in the region r that came from suppliers in green, orange, or red zones and calculate the exposure index in the pre-period for each district-product pair following equation 3. In the regression, we add product-time and district-time fixed effects and cluster standard errors at the product-district level.

For the firm-product-time regressions, we compute for each firm, the exposure in the pre-period using the share of purchases of that product from suppliers in green, orange, and red. We include firm-product, and product-district-time fixed effects to the regressions and cluster standard errors at the firm-product level.

In both cases, our key outcomes are the log of input purchases, and the log of input prices. Since we cannot assign prices to product-district pairs or firm-product pairs that do not purchase anything in a given period, we drop observations with no input purchases. Results are shown in Table 1.

Table 1: Product-district and product-firm regressions

	log(input price)	log(total purchases)	log(input price)	log(total purchases)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Exposure})_j$	0.00683	-0.0183**	0.00186	-0.0414***
	(0.00674)	(0.00924)	(0.00143)	(0.00212)
N	264,543	264,543	2,902,023	2,902,023
Level	product-district	product-district	product-firm	product-firm

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$ The post-period includes March 2020 to August 2020. Columns 1 and 2 come from a regression at the product-district-time where we include product-district, product-time, and district-time fixed effects and cluster standard errors at the firm-product level. We define our exposure measure at the product-district level and standardize it. Columns 3 and 4 come from a regression at the firm-product-time level where we include firm-product and product-district-time fixed effects and cluster our standard errors at the firm-product level. We define our exposure index at the product-firm level and standardize it. In both regressions we drop observations with zero input values in a given period.

For both levels of aggregation, inputs significantly drop for more exposed firms after the lockdowns. The magnitudes are smaller than our baseline analysis because we are not accounting for zeros, such that the firms that are the most affected by the shock are not included in the regressions. The fact that inputs also significantly drop in the product-district-time regressions is suggestive that our results are not only firm-specific shocks that cancel out in the aggregate. Input prices in both regressions are positive, but have a small magnitude and are not significant. However, the positive coefficient is consistent with affected firms paying higher input costs after the shock.

3.3.2 Propagation of the shock through the supply chain

As a final check, we explore whether the lockdown shock propagates through the supply chain. Due to the nature of our data, for most of our analysis we focus on the direct effect of the shock on firms in our state that buy inputs from firms located wherever in India. However, to trace the shock through the supply chain, we lack information on the full set of purchases made by the suppliers to these firms, since some of them might be located out of state and purchase inputs from firms we don't observe. To make progress along this dimension, we look at a narrower sample of firms where we can trace up the full supply chain up to a second degree. We focus on firms that only purchase inputs from firms located within our state during the pre-period. Since these suppliers are also located within our state, we observe their full set of suppliers as well. We compute the second-degree exposure by constructing the lockdown exposure index for each supplier and aggregate this at the buyer level by computing a weighted average of the supplier index using the firm's pre-period purchases from each supplier. We then run a difference-in-difference regression as in equation 4, but add both the direct and second-degree exposure interacted with a post-period dummy. Results with and without the second-degree exposure are shown in Table 2.

Table 2: 2nd degree shock propagation

	Separation Rate %	Net Separation Rate %	Log(Purchases)	Separation Rate %	Net Separation Rate %	Log(Purchases)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Exposure 1st degree})_j$	1.726***	3.447***	-0.0653***	1.613***	3.275***	-0.0592***
	(0.258)	(0.384)	(0.0193)	(0.259)	(0.387)	(0.0194)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Exposure 2nd degree})_j$				0.846***	1.286***	-0.0456***
				(0.218)	(0.320)	(0.0160)
N	422,869	422,869	422,869	422,869	422,869	422,869

Note. $***\, p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$ The post-period includes March 2020 to August 2020. Standard errors clustered at buyer level in parentheses.

The first three columns of Table 2 show the baseline effect of the 1st-degree supplier exposure on separation rates, net separation rates, and log total purchases. Since the sample of firms we focus on is only firms that buy from firms located in our state, the overall estimates are smaller but consistent with those of our baseline sample. Next, we proceed to add both 1st and 2nd degree exposure onto the regression. The fixed effects and controls are identical to our baseline specification. As shown in Table 2, there are significant propagation effects of the lockdowns. While the second-degree effects are smaller than the first-degree ones, the magnitudes are still large. Together, these results speak to the propagation of the shock along the network more broadly.

4 Characterizing Resilience

We now turn to our primary goal: understanding which firms fared better or worse based on the characteristics of their supply chains. We explore this along three measures of supply-chain disruptions for which our data are most comprehensive: separation rates, net-separation rates, and total input purchases.[9] Throughout, we focus on the resilience of firm supply chains, which are the micro-foundation of the resilience of the overall production network.[10]

To understand the characteristics that make the supply chain of buyer j more fragile/resilient, we add interactions between the high-exposure dummies and observable characteristics at the firm level to our baseline specification. The new regression is:

$$\begin{aligned} y_{j,t,r,k} = & \gamma \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times (\text{Supplier Exposure})_j \right] + \alpha \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times Z_j \right] + \\ & \beta \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times (\text{Supplier Exposure})_j \times Z_j \right] + \delta_j + \delta_{r,k,t} + \zeta X_{j,t} + \epsilon_{j,t,r,k} \ , \end{aligned} \tag{6}$$

where γ captures the differential resilience ($y_{j,t,r,k}$) between high-risk and low-risk buyers with the average value of characteristic Z_j. The coefficient β captures the differential resilience for buyers with one standard deviation higher supplier-exposure that are also one standard deviation higher in terms of characteristic of interest Z_j. As before, we include firm, district-industry-time, and control for consumer exposure to lockdowns following equation 5. Under this new specification, we now estimate a triple difference-in-difference regression as opposed to the event studies shown in Section 3.1.[11] All characteristics Z_j are calculated for the period right before the shock, December 2019 to February 2020. In robustness checks, we alternatively add all available firm-level controls $X_{j,t}$, such as firm size interacted with the post-period indicator as well as the triple interaction between firm size, supplier risk, and the post-period.

4.1 Firm Characteristics

We begin by examining attributes of firms that might make their supply chains more resilient. We follow the literature on networks and compute the indegree of the firm (Acemoglu et al., 2012). We calculate the total purchases of buyer j from supplier s as a share of total sales from s, and then add the share across all suppliers of buyer j. This measure captures how nodal buyer j is in the network, as it combines the number of suppliers it has, and the total value of purchases from each supplier.

[9] We also consider output in Figure A12, but the smaller sample implies less precision. For our main goal of understanding characteristics corresponding to supply-chain resilience, we have more statistical power with larger samples, and so we emphasize net-separation rates and input declines. Recall that input and output declines were similar for the restricted output sample.

[10] Direct empirical estimation of aggregate network resilience is not possible in our setting with quasi-exogenous variation. The resilience of the network overall will include general equilibrium effects, which are absorbed by the fixed effects in our estimation. However, our estimates are informative for micro-moments that discipline models assessing aggregate resilience.

[11] We interact our supplier exposure and characteristic measures with a post-February 2020 indicator instead of time dummies for each period. We corroborate that the event-study version of these regressions give the same results, and that the absence of pre-trends holds when incorporating the characteristics interactions.

To complement this standard measure, we construct measures related to the degree of complexity of a buyer j's supply chain. As highlighted by Elliot et al. (2022), the complexity of a firm's supply chain is a key dimension to understand fragility or resilience following disruptions.

We compute the number of distinct products a firm j buys from suppliers, which is both related to the complexity of a supply chain and significantly correlated with firm size, since large firms tend to buy more products. We also calculate the share of total purchases spent on differentiated products following the classification proposed by Rauch (1999). On the one hand, the low substitutability of inputs in production documented by Boehm et al. (2019) might be expected to be a feature of differentiated inputs, leading to a less resilient supply chain. On the other hand, firms that depend more on differentiated products might have invested more in building stronger buyer-supplier links prior to the shock. We also consider alternative measures of supply-chain complexity discussed in Elliot et al. (2022). We construct measures of supply-chain depth (of degrees 1 and 2), which characterizes the average number of inputs necessary to produce each product the firm buys. A higher number suggests a deeper, more complex supply chain. The second-order depth measures whether the products needed to produce the inputs purchased by the firm have a high supply-chain depth themselves.

To construct these measures, we begin by using our full data to establish, for every 4-digit HSN product code sold, how many products, on average, are purchased by firms that sell those goods. We interpret this measure as an index that establishes how many products are needed to produce a given product. As a second step, to construct our measures of supply chain depth, we assign the value of the index to each product purchased by firms in the pre-period, and compute the average across all products purchased by each firm. This is supply chain depth 1, which captures how many products were needed to produce each product the firm purchases. Similarly, for supply chain depth 2, we compute the second degree of this exercise. We use the index to assign to each product purchased, how many products were needed to produce the inputs into the production of the purchased product. As an additional product characteristic, we use the product-level relationship stickiness index developed by Martin et al. (2024), where they measure the average duration of relationships across different products, which they refer to as "stickiness". Firms that buy products associated with longer durations likely invest more in their supplier relationships.

Finally, to capture the stage of the supply chain firms participate in, we consider a measure of downstreamness of the inputs purchased. We use the industry-level index developed by Antras and Chor (2013), to determine the relative downstreamness of each input purchased by firms in the pre-period. We then aggregate to the firm level using pre-period expenditures in each product as weights.

4.2 Supplier Characteristics

As a second set of relevant features, we focus on supplier characteristics that might be associated with higher resilience.

We begin by computing the average outdegree of a firm's suppliers. First, we calculate for each supplier s, the total value of sales from s to buyer i, relative to i's total purchases. We then add these shares across all buyers i of supplier s. Second, for each buyer j, we compute the average of these shares across all of their suppliers. This measure captures how nodal the suppliers of a given buyer j are. Higher numbers mean that suppliers of buyer j have more buyers, and represent a larger share of their buyers' purchases.

Note that to compute indegree and outdegree, for customers or suppliers that are from out of our state, we only see their full set of transactions with firms within the state. Not having the complete indegree and outdegree for firms outside the administrative region collecting the data is a feature of all firm-to-firm network data where firms trade with customers and suppliers outside a country (or administrative region). For instance, when Belgian firms buy inputs from French firms, the degrees of French firms computed with Belgian VAT data would be computed based only on transactions where one end of the transaction is in Belgium, and would not include all the other sales or purchases of the French firms. We should think of our state as similar to countries used in other papers that use firm-to-firm data, with the observation that this state is many times larger than other countries with firm-to-firm data, such as Belgium, Costa Rica, and Chile.

We analyze measures of concentration to quantify a firm's dependency on its current suppliers. We calculate the Hirschman-Herfindahl Index (HHI) of suppliers for each product the firm buys. A higher number would suggest the firm concentrates the purchases in a small number of suppliers. We also compute the HHI of the value of the different products a firm purchases. This index captures the concentration of firm inputs, and is closely related to the number of distinct products purchased by the firm.

As discussed in Elliot et al. (2022), supplier availability could also be associated with supply-chain resilience. Firms with many potential suppliers for each input might find it easier to substitute across suppliers. Relationship-specific investments with suppliers might be less important in these situations. To assess this, we compute the number of total suppliers in our data for each product the firm purchases. To translate this into a firm-level metric, we then calculate a weighted average of the total available suppliers for the firm's inputs, weighted by the value of inputs of that product in total inputs. A high number suggests the firm has several suppliers available in the market for its inputs.

As a second metric, we also compute the number of suppliers per product and firm. A higher number would suggest that firms invested in relationships with multiple suppliers for a given product. After the shock, firms with multiple existing supplier relationships for a product might find it less costly to break links with some of their suppliers.

To construct a firm-specific measure of relationship strength, we calculate for each firm the average number of transactions per supplier. For each buyer-supplier pair, we count the number of transactions with each supplier between March 2018 and February 2020. We then aggregate at the firm level using pre-period purchases as weights. On one hand, we would expect firms with more transactions per supplier to have built stronger relationships with those suppliers. On the other hand, firms that require many transactions might need inputs more often, and so have lower flexibility to withstand a temporary disruption.

Finally, we calculate the HHI of product spatial concentration, which captures whether the available suppliers of the products purchased by the firm are concentrated across lockdown zones. Firms that buy products that are more spatially concentrated might have fewer alternative suppliers and exhibit more disruptions (Grossman et al., 2021).

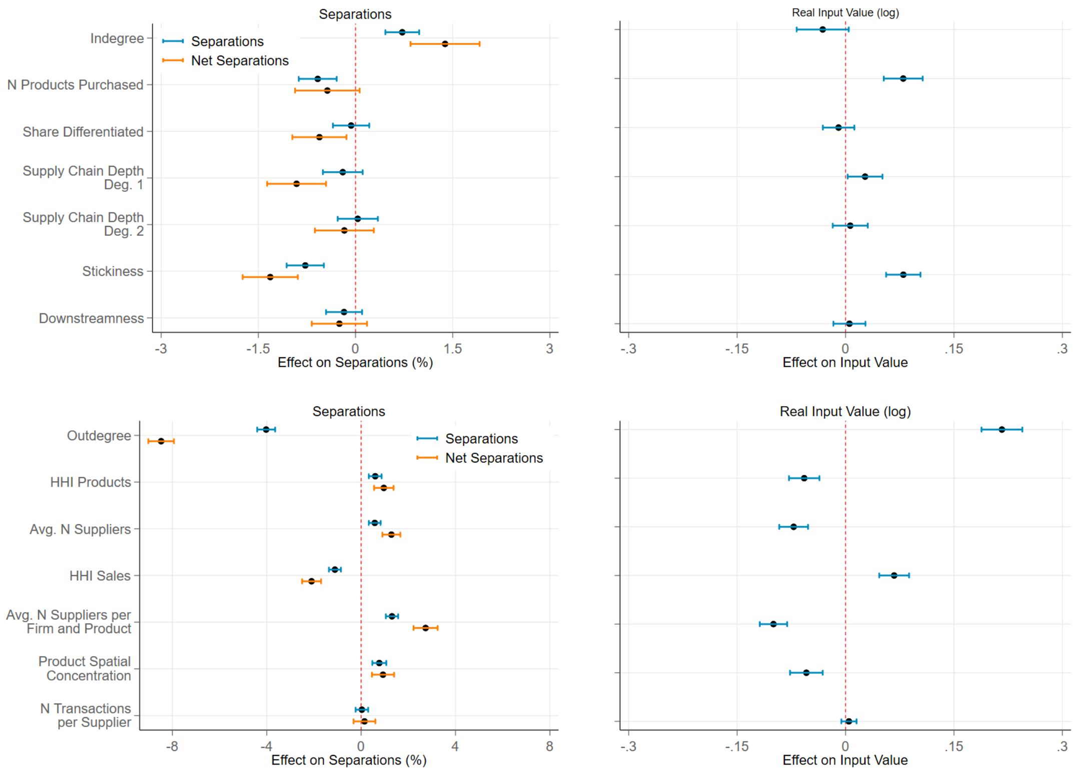
4.3 Results: What Characteristics Determine Resilience?

The left panel of Figure 3 shows the coefficient estimates of β in equation 6 for buyer-separation and net-separation rates, where the firm characteristic used in the interaction is the indegree, number of products purchased, share of differentiated products, supply-chain depth (of degrees 1 or 2), stickiness of products, and average downstreamness of inputs. As in the previous section, the supplier-risk measures are standardized, so the coefficients plot the percentage point change in separation rates as firm characteristic Z_j increases by one standard deviation, for firms with a one standard deviation higher supplier exposure. The right panel of Figure 3 shows the coefficient estimates β when the dependent variable is the log input purchases. As all our resilience measures deliver consistent results, we focus our discussions on net-separation rates, and highlight input purchases or separation rates when relevant.

The top panel of Figure 3 shows that firm characteristics matter for supply-chain resilience. Yet, as the supplier exposure measures and characteristics are standardized, comparing magnitudes requires care. The 1.38pp coefficient on the indegree interaction implies that a firm in the 90th indegree percentile would have a 0.6pp higher net-separation rate than a firm in the 10th indegree percentile. Since the baseline effect of the shock increased net-separation rates by 4.78pp (Table A3), the 0.6pp difference is large.

We also find that the share of differentiated products a firm purchases, and its supply-chain complexity of degree 1 significantly decrease its net-separation rate, suggesting

Figure 3: Effect of Firm Characteristics on Separations/Input Purchases



Note. We plot the triple-interaction coefficients β for each of the characteristics described in Section 4. The left panels present the results for the separation rate and net-separations and the right panels for the input values. 95% confidence intervals reported. Standard errors clustered at the buyer level. In Figures A13 and A14 we show results controlling for firm size (interacted with post dummies), and then the entire range of results controlling for such trends in every other firm characteristic.

that more complex supply chains are more resilient. A firm in the 90th percentile of these characteristics decreases net-separation rates by 3.4pp (share differentiated) and 2pp (supply-chain depth of degree 1). Firms with different second-degree supply-chain depth do not seem to have a differential impact of the shock. An increase in the number of products a firm purchases is not associated with a significant change in net separations for firms with higher supplier exposure. The result on supply-chain complexity suggests that it is possible that firms with complex supply chains invested more in resiliency before the shock, and assign more value in maintaining the buyer-supplier relationship after the shock.

Firms that purchase products that are associated with larger relationship stickiness also exhibit lower separations and net-separation rates. This is consistent with firms being able to maintain links with firms when they purchase products that tend to require longer relationship duration, as suggested by Martin et al. (2024). The stage of the supply chain the firm participates in, as measured by the downstreamness of the products purchased, does not seem to matter for our resilience measures.

The top right panel of Figure 3 considers the effect of firm characteristic heterogeneity on firm input purchases. The effects of firm characteristics on input purchases go in the opposite direction than those on net-separation rates, since higher net-separations are associated with lower input values, as shown in Figure 2b. Firms that purchase a higher number of products are more resilient in terms of input values. Similarly, firms with higher degrees of supply-chain complexity, measured by supply-chain depth of degrees 1, and with higher degrees of relationship duration, as measured by our product-stickiness index, also are more resilient in terms of input drops.

The lower panels of Figure 3 illustrate the effect of supplier characteristics on supply-chain resilience. The figure makes clear that several supplier characteristics have significant effects on net-separations and total input purchases (with the effect on input purchases being in the opposite direction to net-separation rates, as expected). An increase in the average outdegree of the supplier and the HHI of suppliers reduces separation and net-separation rates for firms facing the highest supplier exposure, and increases their input value. This suggests that firms with supply chains that rely on large or well-connected suppliers, which dominate the sales of their product (a high HHI), do not break links in response to the shock even when their suppliers are in high-risk zones.

In fact, as shown in Section 5, these firms respond to the shock by significantly increasing their links with other well-connected important suppliers. This suggests that more concentrated supply chains relying on single supplier nodes might be more resilient in terms of link strength to large shocks, perhaps due to the importance of these supplier relationships, than more diverse supply chains where there are several suppliers for a product. The effects of a larger number of suppliers per product aligns with this intuition: Firms with more suppliers per product experience higher separation rates after the shock. These broken links are not replaced by new links (as evidenced by the larger coefficient on net separations), as these firms presumably have several suppliers for the products, and breaking links with suppliers is less disruptive for them.

Consistent with the predictions of Elliot et al. (2022), firms that buy products that have many suppliers in the market exhibit higher separation rates than firms that buy products with fewer suppliers. For example, a firm in the 90th percentile in terms of available suppliers for the products purchased have a separation rate 1.28pp higher than a firm in the 10th percentile. This suggests that investing in link resiliency is less valuable for firms that can easily find alternative suppliers elsewhere. Once again, supplier characteristics have a similar interpretation when looking at total input value or overall separations as alternative resilience measures. Firms that buy products that are produced by suppliers who are spatially concentrated in one of the lockdown zones exhibit higher net separations and lower input values after the shock, consistent with the implications in Grossman et al. (2021). Finally, the average number of transactions per supplier is not statistically associated with higher or lower resilience.

In Appendix Tables A11-A13, we present the full estimation for the triple difference coefficients in Figure 3. We also run the same analysis for real sales and entry rates (which move in the opposite direction of separation rates), shown in Appendix Figure A12.

Figure 3 illustrates the role of individual supply-chain characteristics on supply-chain resilience in our triple difference specification. However, supply-chain characteristics might be correlated with each other, which might explain the pattern of results. Further, supply chains might typically be characterized by several of these metrics at once in the data. In Figures A13-A14, we show results controlling for firm size (interacted with post dummies), then show the entire range of results controlling for every other firm characteristic (interacted with post dummies). We find the results remain very similar.[12]

Costs of resilience. Our empirical results highlight that supply chains were heterogeneous in their resilience to the Covid shock, suggesting firms with certain characteristics invested relatively more in resilience. What are the costs of such investment? While we do not have data on firm investment to directly measure such costs, in recent work Castro-Vincenzi et al. (2024) find that firms that diversify their suppliers pay systematically higher prices for their inputs. Castro-Vincenzi et al. (2024) and Kopytov et al. (2024) also highlight that supply chain resilience can have general equilibrium consequences that are costly for an economy, with output being lower in aggregate, and production taking place in more resilient but less productive locations.

5 Changes in Supplier Composition

Finally, we look into how firms rebuild their supply chains after the shock. We compute the average characteristics of current suppliers, and use a difference-in-differences approach shown in equation 7.

$$\bar{y}_{j,t,r,k} = \gamma \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times (\text{Supplier Exposure})_j \right] + \delta_j + \delta_{r,k,t} + \zeta X_{j,t} + \epsilon_{j,t,r,k} \; , \quad (7)$$

where $\bar{y}_{j,t,r,k}$ is the average of a certain characteristic across all suppliers of firm j, in time t. The main explanatory variable is the interaction between the supplier-exposure measure with a post-period dummy taking the value one for the period after February 2020. We

[12] Table A14 pairwise correlates all metrics. Barring a few obvious correlations, such as supply chain depth degrees 1 and 2, we do not find much correlation across characteristics, suggesting most of the Z_j considered above are useful metrics of resilience in themselves.

include firm and own-district-industry-time fixed effects as in equation 4 as well as the demand control in equation 5. As we want to track how the supplier composition changes over time, we limit the sample to firms observed buying from at least one other firm every period to keep a consistent sample of firms. We also restrict the sample to firms observed selling their products to other firms, to ensure the firms remain active throughout the period. To understand heterogeneity in responses across firms, we estimate a specification using the top quartile of the outcome ($\bar{y}^{q4}_{j,t,r,k}$).

In Table 3, we present the difference-in-difference results for various characteristics of suppliers. In the top panel, we look at the average size of suppliers, average outdegree, and the share spent on the largest supplier. Firms more exposed to the lockdown, concentrate their purchases in larger suppliers. More specifically, firms with supplier exposure one standard deviation above the mean buy from suppliers that are 7.2% larger than firms with an average supply-chain exposure, likely because larger suppliers have more resilient operations after the shock. They also respond to the shock by buying more from better-connected suppliers (measured by the supplier outdegree) as well as buying more from their top supplier. Firms that were already buying from very large suppliers, as evidenced by the fourth quartile analysis, decrease the average size of their suppliers.

From the second panel of Table 3, we see that firms slightly decrease the number of products they purchase. When looking at product complexity measures, we can see a slight increase in the share spent on differentiated products and a slight decrease in the average supply-chain depth. However, in Appendix Figure A15c, we present the event-study specification of equation 7 for selected outcomes, and show that highly exposed firms reduce their supply-chain depth six months after the initial shock.

Finally, in the third panel, we look at a number of suppliers, the average distance to suppliers, and the share of purchases from the home state. Firms in the fourth quartile of the number of suppliers reduce the number of firms they buy from by 5%. Highly exposed firms also reduce the distance to their suppliers and the share of purchases from other states, likely due to the lower risk of transporting goods across shorter distances.

In Appendix E, we present the event-study specification for a select group of outcomes. Overall, the event studies present a pattern similar to the difference-in-difference results from Table 3, with more exposed firms decreasing the number of suppliers they transact with, and concentrating more in large, well connected, and slightly less differentiated suppliers. We also show that the number of transactions per period is slightly lower for more exposed firms after the shock, and that explains a large part of the input purchase decrease (Figure A16). While the number of products purchased does decrease, we do not find significant changes in the number of products sold, or the number of new products either bought or sold.

Table 3: Changes in Supplier Composition: Difference-in-Differences Estimates.

	Avg Supplier Size		Avg Supplier Outdegree		Share Purch. Largest Supplier	
	Baseline	Quartile 4	Baseline	Quartile 4	Baseline	Quartile 4
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	8.175***	-5.154**	0.743***	0.398	0.384***	0.106
	(0.514)	(2.287)	(0.168)	(0.886)	(0.094)	(0.136)
Pre-period mean	112.38	407.41	42.37	142.48	52.80	90.49
Observations	215,363	45,537	227,073	57,470	227,073	55,125

	Number Products		Share Purch. Diff products		Supply Chain depth	
	Baseline	Quartile 4	Baseline	Quartile 4	Baseline	Quartile 4
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.065**	-0.533***	0.116	0.033	-0.043**	-0.107**
	(0.030)	(0.130)	(0.084)	(0.099)	(0.021)	(0.051)
Pre-period mean	11.88	31.04	59.96	99.66	32.31	42.49
Observations	227,073	56,175	222,824	55,171	227,073	56,476

	Number of Suppliers		Avge Distance to suppliers		Share Purch: non-home state	
	Baseline	Quartile 4	Baseline	Quartile 4	Baseline	Quartile 4
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.330***	-1.629***	-10.798***	-10.355***	-0.434***	-0.155
	(0.051)	(0.341)	(1.653)	(3.621)	(0.107)	(0.163)
Pre-period mean	12.20	32.61	439.23	1266.41	39.06	95.07
Observations	227,073	56,721	227,073	55,776	227,073	55,307

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Estimates from equation 7. Outcomes include the average of a given characteristic across suppliers of firm j in time t. We separately run the analysis for the full sample and the fourth quartile of the outcome. For the outcome of average supplier size, we remove outlier observations of above 1 trillion rupees. Standard errors clustered at buyer level in parentheses.

6 Discussion and Implications

The empirical results throughout this paper clarify that the systematic risk that supply chains and firms face depends on their network characteristics. An emerging theoretical and quantitative literature studying the resilience of supply chains in stylized settings attempts to characterize when firms invest in resilience of their supply chains (Acemoglu and Tahbaz-Salehi, 2024; Castro-Vincenzi et al., 2024; Elliot et al., 2022; Grossman et al., 2021). A natural question is whether our empirical results are supportive of any of the theories. Our evidence shows that firms with supply chains featuring more differentiated products, or connected to higher outdegree suppliers are more resilient. This is consistent with the Elliot et al. (2022) notion of resilience, with firms investing more in relationships with key suppliers, despite the fact that their paper focuses on a symmetric network and our empirical network is asymmetric. Further, we find that firms that are more exposed to the shock tend to diversify the geographic concentration of their suppliers by sourcing more from closer distances and from their home state after the shock. This is consistent with the argument in Grossman et al. (2021) where a key risk that drives investment in resilience and re-shoring is the geographic concentration of key suppliers in external regions. Our analysis, therefore, finds empirical support in a real-world network for some of the theoretical results in these papers that are derived in a more stylized setting (symmetric networks in Elliot et al. (2022) and a single input model in Grossman et al. (2021)).

While our analysis focuses on the resilience of firm supply chains, these findings are an input into understanding the resilience of the production network as a whole. Barrot and Sauvagnat (2016) find that firms that sell more differentiated inputs are more important for the propagation of shocks to downstream consumers. Our results suggest that these firms are also relatively more resilient to the shocks themselves. Hence, it is likely that aggregate shock propagation through production networks is smaller than the counterfactual scenario with no firm heterogeneity in resilience.

Our results are also informative for the larger literature studying supply chain dynamics, albeit without an emphasis on supply chain resilience (e.g. Lim (2018), Martin et al. (2024), Fontaine et al. (2023)). This literature provides theory and empirical evidence on supply chain formation over time. Two common approaches to modeling supply chain dynamics include models with sunk costs of link formation between firms, and models where supply networks are formed in a search and matching framework with search costs. While our empirical results do not help differentiate between whether fixed cost models or search cost models are the true underlying source of supply chain dynamics, our results suggest the fixed costs or the search costs for new suppliers are higher in more differentiated supply chains or with more specialized inputs. Models of supply chain dynamics where such costs are higher will feature more persistent links, with a higher 'SS' inaction band once the link is formed. By implication, these links would be more resilient, as we find in our empirical evidence.

Finally, our results have implications for the emerging literature studying supply chain formation under risk, and the general equilibrium consequences of supplier diversification in anticipation of shocks. In Castro-Vincenzi et al. (2024), supply chains are formed in anticipation of climate risk. This results in sometimes inefficient multi-sourcing and large general equilibrium effects such as wages being higher in less risky regions, even if they are productive. In Kopytov et al. (2024), firms form supply chains considering supplier volatility, resulting in lower aggregate output. In contrast to anticipated risk, in our context, firms are unlikely to have anticipated/planned for the Covid shock. So, our results provide a window into how supply chains restructure after an unexpected shock. Our results suggest that firms did change the structure of their supply chains, as discussed in Section 5. As suggested by this literature, such restructuring by firms themselves to promote the resilience of their own supply chains can have non-trivial aggregate consequences.

7 Conclusion

We study which features of supply chains make them more resilient to shocks. We use a unique dataset on firm-to-firm transactions from a large Indian state and exploit geographical variation in Covid-19 lockdowns across districts. To identify the causal impact of the shock on supply-chain resilience, we use an event-study design and compare firms with suppliers in strict lockdown areas to those with suppliers in mild lockdown areas.

We find that the buyer-supplier links of firms that buy more from large and well-connected suppliers are more resilient. Firms that buy more complex products are less likely to break links, but firms that buy easily available products are more likely to break links after the shock. We validate some of the measures proposed by the theoretical literature on supply chains, in which firms that buy inputs from suppliers that are not easily replaceable should assign more value to preserving supplier links to avoid production disruptions. Our findings suggest that more complex supply chains are not less resilient to shocks.

Our findings carry significant policy implications, particularly for decisions that might disrupt supply chains, such as pandemic-induced lockdowns. Policymakers want to know how resilient supply chains are, to better prepare for such disruptions. For instance, during the Covid-19 pandemic, India's GDP contracted by 7%, one of the steepest declines globally. To effectively allocate aid, it is crucial to identify which supply chains demonstrate greater resilience and to understand the characteristics that make certain chains more vulnerable to severe shocks. Furthermore, during the recovery phase, policymakers must anticipate how supply chains adapt and reorganize in response to these disruptions. Our analysis provides some guidance on all of these fronts, and aims to inspire further research in this area.

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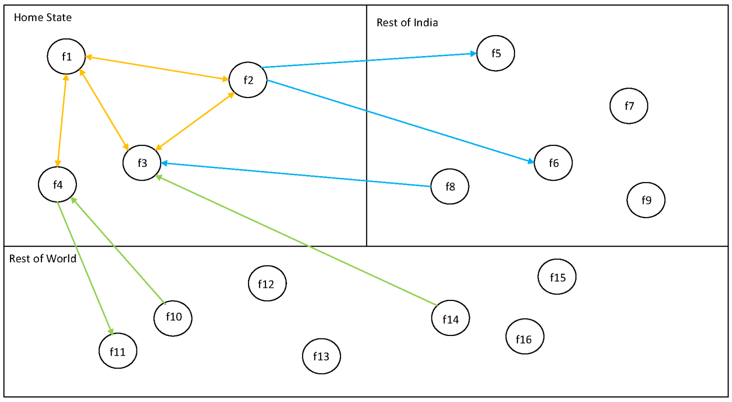
Appendix for online publication only

A Details on the Firm-to-Firm Data

We illustrate a stylized example of our establishment-level networks data in Figure A1. As the diagram shows, we observe all transactions where one node of the transaction is within the state. This includes all transactions between establishments within the state (the yellow lines), any inflows from or outflows to the rest of the country (the blue lines), and all international imports and exports (the green lines).

Figure A1: Stylized Example of Establishment-Level Network



Note. Stylized example of establishment-level data. The upper half represents the country, and the upper left quadrant represents the state in question. The data includes all transactions within the state, and all transactions where one node of the transaction (either buyer or seller) is in the state.

The data report value and quantity of traded items, so we can construct unit values. To do this, we aggregate values and quantities at the four-digit HSN/month/transaction level, and then construct implied unit values. We can then collapse the data at the 4-digit HSN/month level to construct average unit values, the number of transactions between each seller and buyer pair, and total value of the goods transacted. This is the foundation of the firm-to-firm dataset we use in the analysis. Additionally, we can aggregate these data to the buyer level, which we use in our reduced-form section. Table A1 summarizes our primary variables of interest using this dataset.

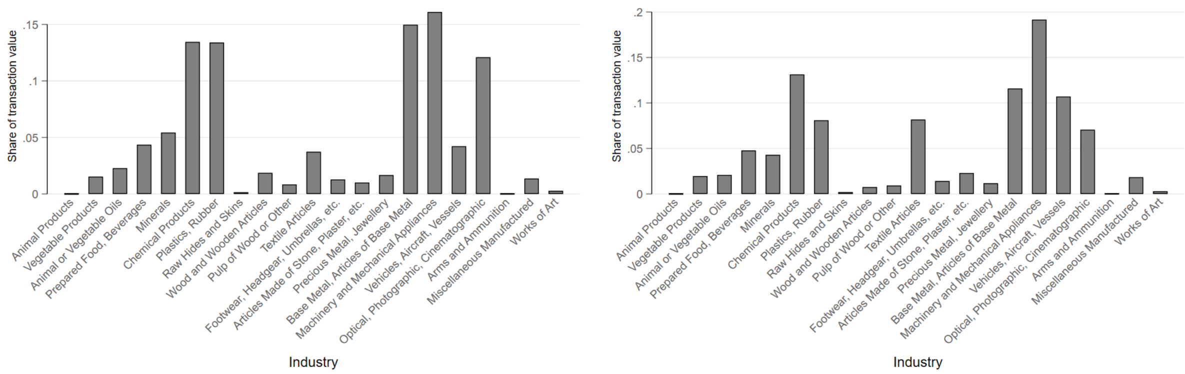
Table A1: Summary Statistics for Main Variables

Outcome	Mean	p25	p50	p75
Separation Rate (%)	30.9	0.00	16.67	52.63
Entry Rate (%)	74.10	5.13	50.00	107.69
Net Separations (%)	-43.21	-71.43	0.00	0.00
Real Input Value (log)	14.91	12.48	14.55	16.95
Real Sales (log)	17.78	15.48	17.66	19.85
Avg. Supplier Size (millions of rupees)	106.55	9.60	34.01	127.89
Avg. Supplier Outdegree	43.00	3.30	10.99	31.96
Share Purch. Lgst. Supplier (%)	52.34	31.04	47.79	71.77
Number Products	12.01	3.00	7.00	14.00
Share Purch. Diff. Prod. (%)	60.08	21.03	72.57	97.78
Supply Chain Depth	32.31	28.14	31.45	36.35
Number Suppliers	12.34	3.00	7.00	14.00
Avg. Distance (km)	436.13	75.99	189.84	541.23
Share Purch. Non-Home State (%)	38.45	0.00	24.19	78.40
Avg. Transactions	29.58	3.50	6.50	15.49
Spatial Concentration	0.38	0.31	0.36	0.44
Downstreamness	0.49	0.39	0.44	0.62
N Suppliers per Firm-Product	3.89	1.00	2.00	4.00
Stickiness	2.83	2.80	3.03	3.17

Note. We calculate summary statistics for key outcomes listed in the first column (as described in Section 3.1), firm characteristics (as described in Section 4), and measures of supplier composition (as described in Section 5). Summary statistics calculated in December 2019-February 2020.

Figure A2: Share of sales/purchases, by product codes

(a) Sales (b) Purchases



Note. For the left panel we plot the share of total sales of firms located in our large Indian state by 1-digit product code. In the right panel we plot the share of total purchases of firms located in our large Indian state by 1-digit product code. The time period for this data is the full 2019 year.

B Validating Lockdown Measures

In Table A2, we summarize the differences in Covid-19-related outcomes across the various lockdown zones. We validate our measures of lockdown intensity using Google Mobility data, and satellite nighttime luminosity data in Figure A3.

Table A2: Summary Statistics by District Lockdown Degree

Zone	Avg. Cases/Million	Avg. Deaths/Million	Avg. Population	Total Cases	Total Deaths	Total Population
Green	26.316	0.1865	1,135,294	7,533	50	287,229,399
Orange	69.841	0.9236	1,990,250	24,713	364	469,698,944
Red	369.80	10.901	3,196,090	143,828	4,796	354,766,033

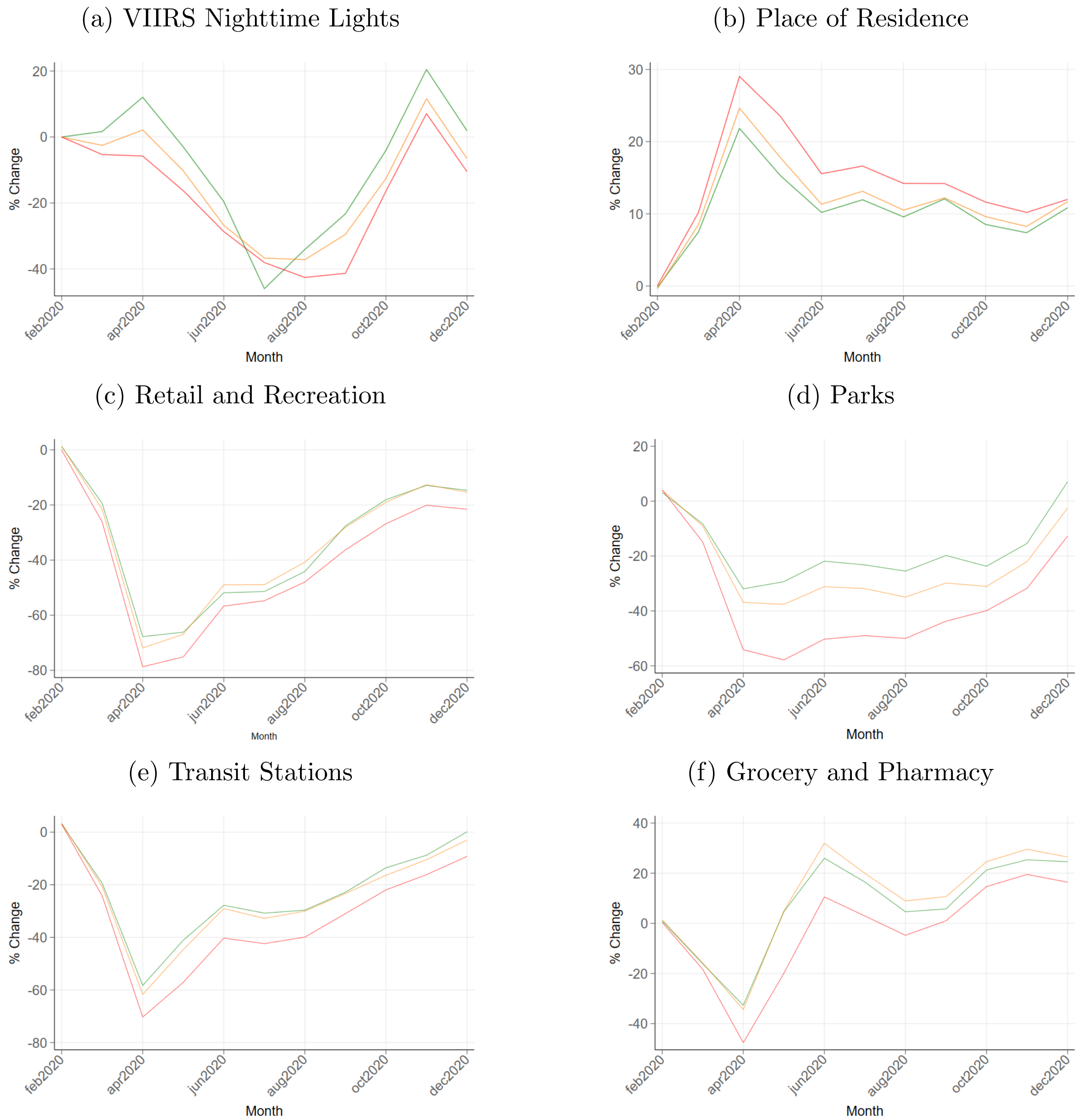
Note. Summary statistics calculated in March-May 2020 by lockdown zone. District-level Covid-19 cases and deaths are collated from official sources by the Development Data Lab https://www.devdatalab.org/covid. Averages/totals taken across districts with the same lockdown risk.

The mobility data show how the number of visitors to (or the time spent in) categorized places change compared to baseline days. The baseline day is the median value from the period Jan 3 to Feb 6, 2020. As is clear from Figure A3b, we see that people in red zones spent more time at home compared to people in either orange or green zones. They also spent less time at retail and recreation establishments, parks, transit stations, grocery stores and pharmacies as shown in Figures A3c to A3e. Such differences also exist between orange and green zones. By December 2020, these differences become smaller.

In Figure A3a, we follow past research in using nighttime lights from the VIIRS system, as a proxy for economic activity (Henderson et al., 2012). More recently, this has been used in India (Chodorow-Reich et al., 2019), where high-frequency, high-spatial resolution economic data is rare. These data have been shown to correlate well with measures of economic activity. The panel shows that the fall in nighttime lights was more pronounced in red zones, than in orange or green zones. Together, these measures validate our use of the geographically varying lockdown zones.

While almost all districts' lockdown zones remained constant in the three months from March 2020, on April 30 2020 one district was reclassified from red to green. We rely on initial lockdown zones as our shock measures throughout.

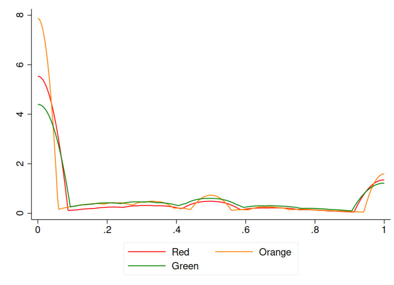
Figure A3: Alternative Lockdown Measures



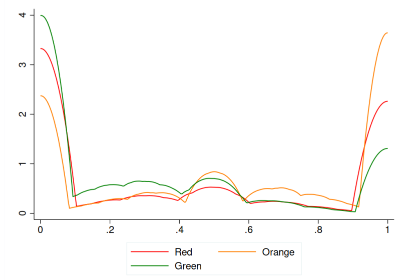
Note. We validate our lockdown measures using he VIIRS Satellite Nighttime lights data in panel (a) and Google Mobility data in panels (b)-(f). Google mobility data shows how the number of visitors to (or the time spent in) categorized places change compared to the period Jan 3 – Feb 6, 2020. Source: https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927

Figure A4: Distribution of links and sales across lockdown zones

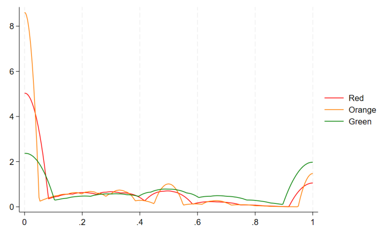
(a) Sellers in Red



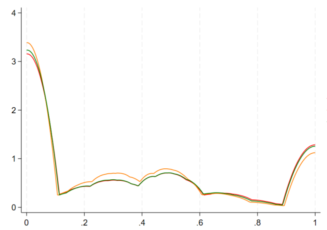
(b) Sellers in Orange



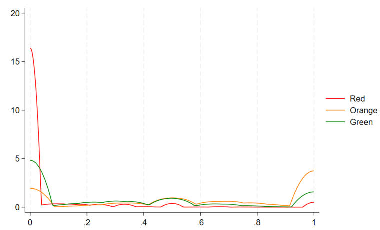
(c) Sellers in Green



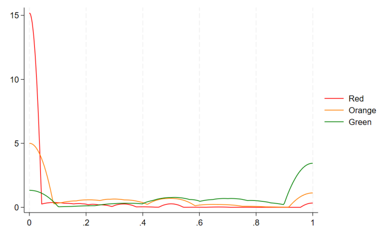
(d) Buyers in Red



(e) Buyers in Orange



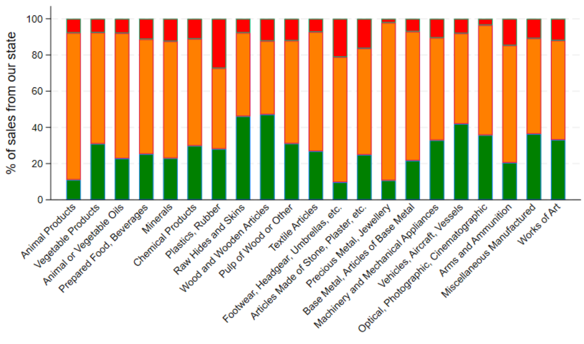
(f) Buyers in Green



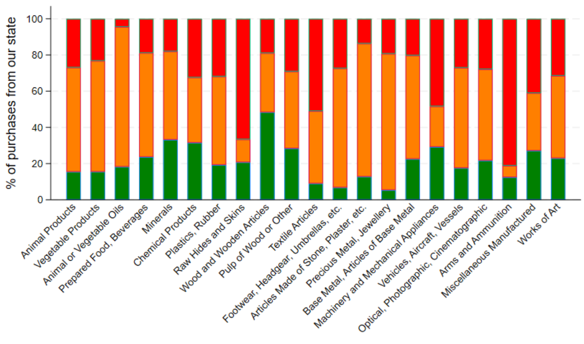
Note. In the three upper figures, each panel plots the distribution of the share of buyers located in *Red*, *Orange*, or *Green* districts. Each figure corresponds to sellers located in their corresponding color district. In the bottom three figures, each figure plots the distribution of the share of sellers located in *Red*, *Orange*, or *Green* districts. Each figure corresponds to buyers located in their corresponding color district. The time period is April 2018 - February 2020.

Figure A5: Share of sales/purchases, by product codes and zone

(a) Sales



(b) Purchases

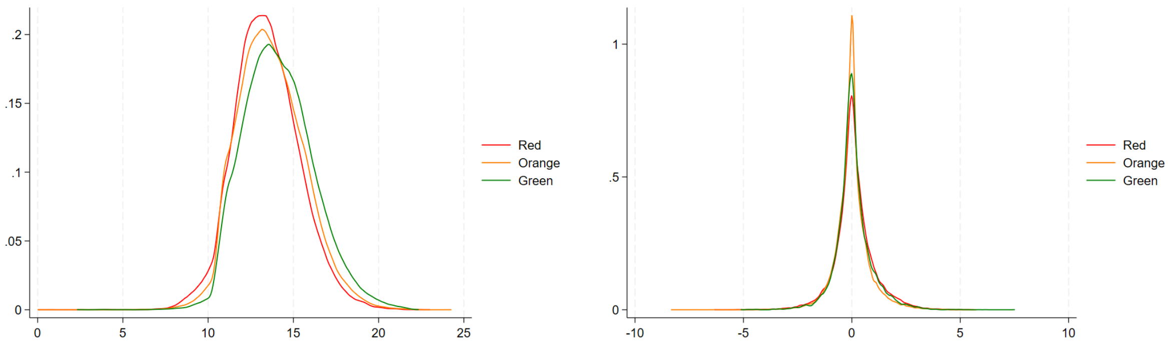


Note. On the left panel, for each 1 digit product code (HS section, horizontal axis), we plot the share of total sales of firms located in our large Indian state by the color of selling districts. In the right panel, for each HS section (horizontal axis), we plot the share of total purchases of firms located in our large Indian state by the color of buying districts. The time period for this data is the full 2019 year.

Figure A6: Log Supplier Size and Average Unit Value distributions by zone

(a) Log Supplier Size

(b) Average Unit Value

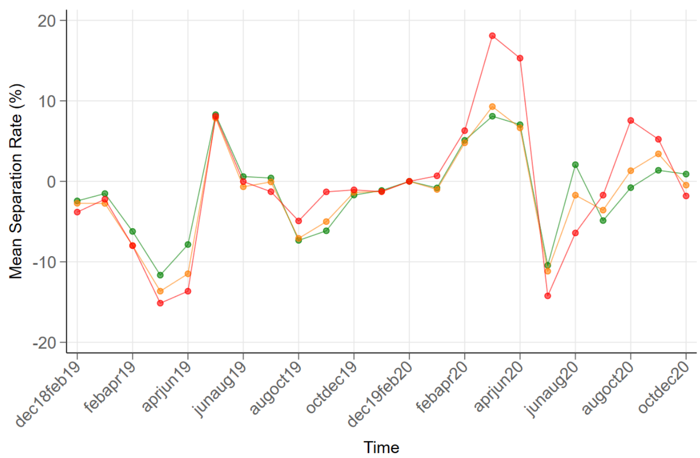


Note. The left panel plots the distributions of supplier size by the color of their district. The right panel plots the average unit value by the color of their district. The time period for this data is the full 2019 year.

To corroborate lockdowns indeed caused supply-chain disruptions, in Figure A7, we plot the mean separation rate over time. For each firm, we compute the separation rates using rolling 3-month periods and calculate a different separation rate for suppliers located in red, orange, and green lockdown zones. We also limit the sample of buyers to firms who are in our state with medium-lockdown districts to avoid differences in firm own-lockdown severity. To control for seasonality in separation rates, we first residualize the separation rates using month-zone fixed effects. We then take the mean of such residuals for each period and normalize to zero the period of December 2019 to February 2020. Hence, the separation rates should be interpreted as relative to this period.

The patterns shown in Figure A7 are striking. The separation rates for suppliers across the three lockdown-severity zones track each other closely until March 2020, when separations from suppliers in red zones more than double the separations from suppliers in green zones. After April 2020, the separation rates for red zones decreases relative to green/orange zones to later increase again towards the end of 2020. We should note that some amount of the separation rates rebounding is mechanical, as it depends on the number of suppliers in the previous period. In subsequent figures we show balance in the characteristics of the network, industry composition, firm size, and prices.

Figure A7: Mean separation rate by supplier location (relative to Dec 2019 - Feb 2020).



Note. We plot the mean separation rate across the firms in our sample, separating their suppliers by their district's lockdown stringency. We restrict the sample of buyers to firms in our state who are located in districts with medium-stringency. Separation rates are defined using three-month periods and computed for every month, such that the plotted rates capture the rolling average across time. To adjust for seasonality, we regress the firm-level separation rates on month-zone dummies and take the residual. Then, we calculate the average residual separation rate across firms in each period relative to the average in December 2019-February 2020.

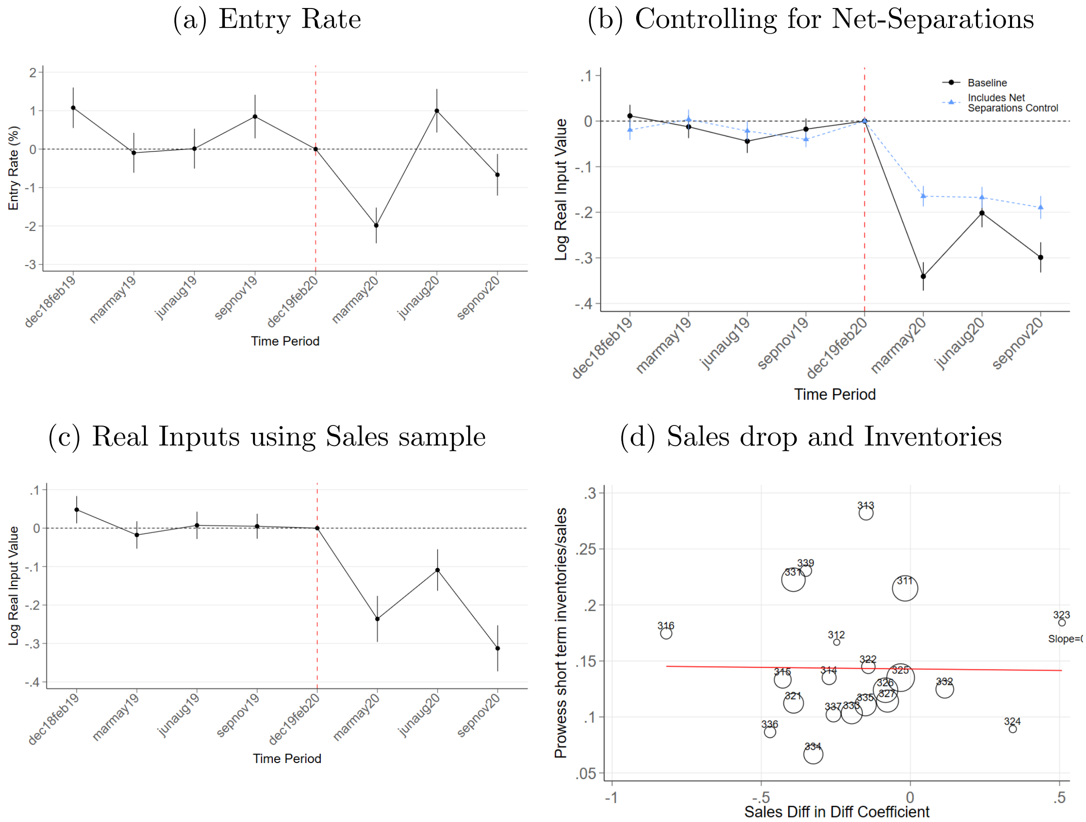
C Alternative Specifications and Robustness

We complement the baseline analysis by running regression 4 with the entry rate as the outcome. As shown in Figure A8a, the overall entry rate of suppliers for firms with one standard deviation above the mean risk was 2pp lower than for firms with average supplier exposure, a 2.7% decrease with respect to baseline. However, the decrease in the entry rate in the post period is not statistically different from zero. To put the separation and entry numbers into context, if we compare a firm with suppliers located in strict-lockdown (red) areas with a firm with suppliers in mild-lockdown (green) areas, the more exposed firm experienced a separation rate 15.4pp higher than the less exposed firm (or a 50% higher separation rate). For the entry rate, the more exposed firm experienced a rate 8.3pp (or 11%) lower than the less exposed firm. To further study the role of the extensive margin, we run our baseline specification with the log input value as the dependent variable, but add the net separations experienced by the firm as a control. Such analysis quantifies the residual response in input purchases after we account for the extensive margin response experienced by the firm. As shown in Figure A8b, the drop in input value for firms with high supplier exposure gets slashed by half once we control for net separations, going from a drop of 34% to a drop of 16%. This finding suggests that the extensive margin is an important channel to measure supply-chain disruptions.

We run two additional checks related to our real sales results. First, in Figure A8c, we run our real input event study for the same sample used for real sales, where we restrict to firms that are observed selling something every period prior to the shock. Real inputs drop in a similar magnitude than the full baseline sample. Second, we investigate whether the milder response in terms of real sales is driven by firms using inventories to mitigate the shock. To do so, we merge our transaction data with the corporate dataset Prowess, which provides for a subgroup of Indian firms, information on sales, short-term inventories and other financial at the firm level. Overall, 1,830 parent firms are matched from Prowess to our transaction dataset. We proceed to run our real sales regression separately by industry in a difference in difference regression, and correlate the drop in sales after the shock with the average short term inventories to sales ratio in the industry. As shown in Figure A8d there is no relationship between the inventory to sales ratio and the post-shock drop in sales. This is suggestive that firms are not using inventories to meet demand, and consistent with the low inventory ratios for this sample of firms in 2019 discussed in Castro-Vincenzi et al. (2024).

In Figure A9, we evaluate if there is a differential separation rate for suppliers of higher importance in a firm's purchases. To do so we compute the separation and net-separation rates by weighting each supplier link by the total input sales of each supplier to firm j. As shown in Figures A9a and A9b, the separation and net-separation rates are slightly higher

Figure A8: Baseline Event Studies



(a) Entry Rate

(b) Controlling for Net-Separations

(c) Real Inputs using Sales sample

(d) Sales drop and Inventories

Note. We plot the estimated coefficients γ_x from estimating equation 4 for alternative outcomes (entry rate, panel (a)) and with alternate controls (panel (b)). Confidence intervals are 95%. Omitted period is December 2019 to February 2020. Average entry rate in the omitted period: 74.1%. In panel (b), the purple line captures the input drop when controlling for net separations. Standard errors are clustered at buyer level. Sample size for panels a and b is 930,501. Panel (c) estimates the drop in real inputs once we make the same restriction as in the same sample, keeping only firms that have positive sales every period before the shock. Sample size is 166,906 observations. Finally, panel (d) plots the correlation between the drop in real sales by industry and the mean ratio of short-term inventories to sales by industry taken from the Prowess database.

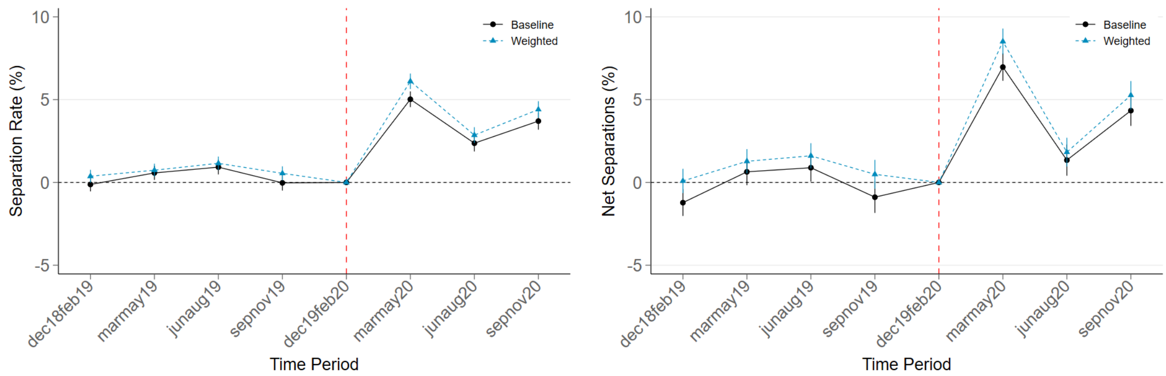
when using weights, but the estimates are not statistically different from each other.

In Table A3, we present the difference-in-difference estimates for the outcomes in Figure 2. These estimates come from a similar regression as in equation 4, but instead of year dummies, we interact the treatment with a dummy for periods after March 2020. As shown in columns 5 and 6 of Table 2, firms with supplier exposure of one standard deviation above the mean experienced a decrease in inputs of 27% and decrease sales by 16%. We also show in Table A3 how our standard errors change when showing a more conservative clustering at the buyer-district level.

We perform a series of robustness checks to ensure that our results are not sensitive to the choice of exposure measure to the lockdowns. In Table A4, we show how our main results change when we define the exposure as a binary variable instead of continuous. To do this, we define dummy variables for exposure larger than median, 75th percentile and 90th percentile. As expected, the most exposed firms tend to have larger effects and while

Figure A9: Weighted Separations

(a) Weighted Separations (b) Weighted Net Separations



Note. We plot the estimated coefficients γ_x from estimating equation 4 with alternate outcomes (weighted separations and weighted net separations). Confidence intervals are 95%. Omitted period is December 2019 to February 2020. Average separation rate in the omitted period: 30.9%. Average net-separation rate in the omitted period: -43.1%. Average weighted separation rate in the omitted period: 19.5%. Average weighted net separation rate in the omitted period: -39.7%. The shares of a firm's suppliers in total purchases are used as weights. Standard errors are clustered at buyer-level.

Table A3: Difference-in-Differences Estimates for Key Outcomes.

	Separation Rate	Entry Rate	Net Separations	Real Input Value (log)	Real Sales (log)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.649***	-1.129***	4.778***	-0.270***	-0.157***
(Firm Clustering)	(0.141)	(0.139)	(0.214)	(0.011)	(0.028)
(District Clustering)	(0.241)	(0.731)	(0.892)	(0.023)	(0.022)
Observations	823,395	823,395	823,395	823,395	143,643
R-squared	0.351	0.318	0.217	0.652	0.740

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents results from the difference-in-differences version of equation 4 for key outcomes. Supplier exposure is calculated following equation 3. The post-period includes March 2020 to August 2020. Standard errors clustered at buyer and buyer-district levels in parentheses.

the coefficient interpretation changes, the results are qualitatively similar. In Table A5 we define exposure based on the change in the Google mobility index on time spent in place of residence between February 2020 and April 2020. We assign each supplier district the corresponding change in the Google mobility index and aggregate at the buyer level using pre-period purchases as weights. We then standardize the new exposure index. Since the index is quite different, the magnitudes are not directly comparable. However, we can see that the results are consistent with our baseline results. Finally, we separate the exposure shares of red suppliers and orange suppliers by running equation 8:

$$\begin{aligned} y_{j,t,r,k} = \gamma_{red}\mathbb{1}(t > \text{Feb2020}) \times (\text{Share Purchases from Red Zones})_j + \\ \gamma_{orange}\mathbb{1}(t > \text{Feb2020}) \times (\text{Share Purchases from Orange Zones})_j \\ +\delta_j + \delta_{r,k,t} + \beta X_{j,t} + \epsilon_{j,t,r,k}\ , \end{aligned} \tag{8}$$

where the specification follows closely the difference-in-difference version of equation 4 with the difference that instead of our standardized exposure measure we separately include the pre-period share of purchases from red zones and orange zones. Perhaps not surprisingly, as shown in Table A6, exposure from red zones have the stronger impact on our resilience outcomes, particularly for separations and net separations. The inputs and sales drop, however, also have a significant impact in response to being exposed to orange zones.

Table A4: Supplier Exposure Using Binary Indicators

	Separations			
	Continuous	Median	75th Percentile	90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.649***	8.067***	12.006***	16.244***
	(0.141)	(0.263)	(0.406)	(0.531)
N	823,395	823,395	823,395	823,395
R-sq	0.351	0.351	0.351	0.351
	Net Separations			
	Continuous	Median	75th Percentile	90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	4.778***	12.957***	16.706***	24.497***
	(0.214)	(0.398)	(0.625)	(0.822)
N	823,395	823,395	823,395	823,395
R-sq	0.217	0.217	0.217	0.217
	Log Real Inputs			
	Continuous	Median	75th Percentile	90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.270***	-0.741***	-1.035***	-1.553***
	(0.011)	(0.020)	(0.032)	(0.040)
N	823,395	823,395	823,395	823,395
R-sq	0.652	0.652	0.652	0.653
	Log Real Sales			
	Continuous	Median	75th Percentile	90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.157***	-0.433***	-0.398***	-1.001***
	(0.028)	(0.056)	(0.085)	(0.144)
N	143,653	143,643	143,643	143,643
R-sq	0.740	0.740	0.740	0.740

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents results for the equation 4 for key outcomes, but using binary above/below indicators instead of continuous. Standard errors clustered at buyer level in parentheses.

We proceed to investigate whether specific type of firms or transactions drive our results. A novel feature of our data is that it includes establishment level information and it also records transactions within establishments of a same firm. In our pre-period, intra-firm transactions account for 30.1% of the total transaction value recorded. However, the total establishments that engage in intra-firm transactions is small. Throughout our analysis

Table A5: Difference-in-Differences Estimates with Google Mobility Measure of High Risk

	Separation Rate	Net Separations	Log Real Input Value	Log Real Sales
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Google Mobility Supplier Exposure})_j$	0.948***	1.848***	-0.129***	-0.092***
	(0.117)	(0.178)	(0.009)	(0.020)
N	820,057	820,057	820,057	143,085
R-sq	0.351	0.217	0.652	0.740

	Separation Rate	Net Separations	Log Real Input Value	Log Real Sales
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.649***	4.778***	-0.270***	-0.157***
	(0.141)	(0.214)	(0.011)	(0.028)
N	823,395	823,395	823,395	143,643
R-sq	0.351	0.217	0.652	0.740

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents results from the difference in difference version of equation 4. The top panel uses the change in the Google Mobility Place of Residence trend from February-April 2020 as the supplier exposure. The bottom panel presents the baseline results. The post-period includes March 2020 to August 2020. Standard errors clustered at buyer level in parentheses.

Table A6: Categorical Risk Measurement

	Separation Rate	Net Separations	Log Real Input Value	Log Real Sales
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Share of Purchases from Orange Zones})_j$	0.669*	1.516***	-0.158***	-0.344***
	(0.389)	(0.582)	(0.031)	(0.089)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Share of Purchases from Red Zones})_j$	11.976***	14.277***	-0.919***	-0.482***
	(0.477)	(0.727)	(0.037)	(0.101)
N	842,635	842,635	823,395	143,643
R-sq	0.351	0.216	0.652	0.740

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents results for impact in orange and red zones. Standard errors clustered at buyer level in parentheses.

we focus on establishments and include same firm suppliers into the computation of the supplier exposure and the outcomes. However, when excluding intra-firm transactions, the results are quantitatively very similar as shown in Table A7.

As a second step, we want to make sure our results are not driven by retailer or wholesaler firms, who might behave somewhat differently than the manufacturing firms generally focused on by the literature. While we don't directly observe whether firms are retailers or wholesalers, we can use their observed transaction patterns to predict likely-retailers and likely-wholesalers. For retailers we consider two approaches. First, a pure retailer would sell all their goods to consumers so we shouldn't observe them selling to other firms in our data. If a firm is never observed making any sales, we assume it is a likely-retailer. Second, a firm who buys many different products might also be a retailer. We exclude firms above the 90th and 95th percentile in terms of product purchased as additional checks. As shown in Table A8, excluding likely retailers does not change our baseline results significantly, indicating these firms are not providing an important part of the variation.

To understand whether wholesalers drive our results, we predict likely-wholesalers by looking at which products are bought and sold by firms. If a firm buys and sells the same products, then it is possible that they are a wholesaler who doesn't transform the products they buy. We run our results for the sample excluding firms who buy and sell identical 4-digit products and also evaluate excluding firms whose products bought and sold overlap by more than 90%. As shown in Table A9, our results don't significantly change when excluding these firms.

We also evaluate the robustness of our results if we exclude suppliers with high outdegrees. Given the highly skewed distribution of supplier outdegree presented in Table A10, we want to understand if these nodal suppliers are driving our separation results. When constructing our exposure measure, we exclude suppliers that are above the 90th percentile in the outdegree distribution. Results are quite consistent when excluding these particular suppliers.

Table A7: Excluding Intra-Firm Transactions

	Baseline Separations	Remove Intra-Firm Separations	Baseline Net Separations	Remove Intra-Firm Net Separations
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.649***	4.027***	4.778***	5.014***
	(0.141)	(0.149)	(0.214)	(0.220)
N	823,395	809,646	823,395	809,646
R-sq	0.351	0.375	0.217	0.259

	Baseline Log Real Inputs	Remove Intra-Firm Log Real Inputs	Baseline Log Real Sales	Remove Intra-Firm Log Real Sales
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.270***	-0.274***	-0.157***	-0.166***
	(0.011)	(0.011)	(0.028)	(0.028)
N	823,395	809,646	143,643	137,176
R-sq	0.652	0.652	0.740	0.735

Note. $*** \; p < 0.01$, $** \; p < 0.05$, $* \; p < 0.1$. Columns 1 and 3 present our baseline results while columns 2 and 4 present results after we remove intra-firm transactions. In our pre-period, 30.1% of transaction value comes from intra-firm shipments. Standard errors clustered at buyer level in parentheses.

As a final check to our baseline specification, we want to understand whether firms break their links with suppliers in a permanent or transitory way. In Figure A10, we compute separation rates, net-separation rates, and total input purchases in periods of 4-months (left panels) or periods of 6-months (right panels). The finding that the separations and net-separations keep the same pattern, even with longer time periods, indicates that the separation rates in Figure 2, are not a product of firms changing the frequency of their purchases, and maintaining their previous suppliers. In Figure A11, we define the entry rate of specific suppliers: suppliers who never transacted with the firm before time t (New supplier), suppliers who transacted with the firm in the six months prior to period t, and

Table A8: Excluding Likely Retailers

Separations	Baseline	Excluding 0 Sales	Excluding 95th Percentile	Excluding 90th Percentile	Excluding 0 Sales and 90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.649***	2.872***	3.663***	3.698***	2.906***
	(0.141)	(0.190)	(0.145)	(0.150)	(0.208)
N	823,395	346,031	780,012	733,695	288,028
R-sq	0.351	0.350	0.348	0.346	0.339

Net Separations	Baseline	Excluding 0 Sales	Excluding 95th Percentile	Excluding 90th Percentile	Excluding 0 Sales and 90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	4.778***	3.741***	4.741***	4.720***	3.722***
	(0.214)	(0.281)	(0.220)	(0.227)	(0.307)
N	823,395	346,031	780,012	733,695	288,028
R-sq	0.217	0.198	0.217	0.216	0.194

Log Real Inputs	Baseline	Excluding 0 Sales	Excluding 95th Percentile	Excluding 90th Percentile	Excluding 0 Sales and 90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.270***	-0.233***	-0.272***	-0.272***	-0.231***
	(0.011)	(0.016)	(0.011)	(0.012)	(0.017)
N	823,395	346,031	780,012	733,695	288,028
R-sq	0.652	0.683	0.630	0.617	0.639

Log Real Sales	Baseline	Excluding 0 Sales	Excluding 95th Percentile	Excluding 90th Percentile	Excluding 0 Sales and 90th Percentile
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.157***	-0.157***	-0.147***	-0.132***	-0.132***
	(0.028)	(0.028)	(0.029)	(0.030)	(0.030)
N	143,643	143,643	126,899	114,112	114,112
R-sq	0.740	0.740	0.713	0.708	0.708

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents results for equation 4 for key outcome variables but excluding various definitions of likely retailers. Column 1 presents the baseline results, column 2 excludes firms with no recorded sales, columns 3 and 4 exclude firms in the 95th and 90th percentile of products purchased, respectively. Column 5 includes only firms that sell their goods and are below the 90th percentile in terms of products purchased. Standard errors clustered at buyer level in parentheses.

suppliers who transacted with the firm in the nine months prior to period t. Overall, we don't find a statistically different entry rate responses across measures, indicating that while there might be some return to old suppliers, the net effects also include entry of new suppliers.

Table A9: Excluding Likely Wholesalers

	Separations			Net Separations		
	Baseline	Wholesalers, 90%	Wholesalers, 100%	Baseline	Wholesalers, 90%	Wholesalers, 100%
$\mathbb{1}\left(t > \text{Feb2020}\right) \times \left(\text{Supplier Exposure}\right)_j$	3.649***	3.694***	3.693***	4.778***	4.778***	4.778***
	(0.141)	(0.145)	(0.145)	(0.214)	(0.220)	(0.220)
N	823,395	790,403	790,757	823,395	790,403	790,757
R-sq	0.351	0.351	0.351	0.217	0.218	0.218

	Log Real Inputs			Log Real Sales		
	Baseline	Wholesalers, 90%	Wholesalers, 100%	Baseline	Wholesalers, 90%	Wholesalers, 100%
$\mathbb{1}\left(t > \text{Feb2020}\right) \times \left(\text{Supplier Exposure}\right)_j$	-0.270***	-0.270***	-0.270***	-0.157***	-0.167***	-0.166***
	(0.011)	(0.011)	(0.011)	(0.028)	(0.030)	(0.030)
N	823,395	790,403	790,757	143,643	124,494	124,760
R-sq	0.652	0.652	0.652	0.740	0.745	0.745

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents results for equation 4 for key outcome variables but excluding various definitions of wholesalers. "Wholesalers 90%" excludes firms whose input and output product codes overlap by more than 90%. "Wholesalers 100%" Standard errors clustered at buyer level in parentheses.

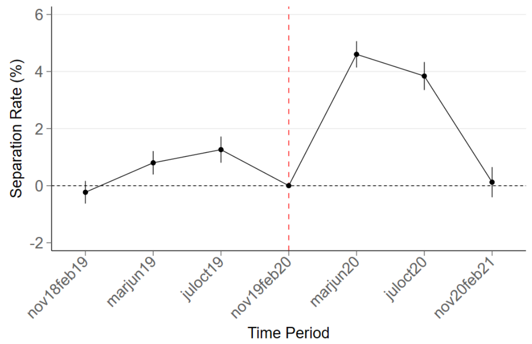
Table A10: Excluding Suppliers with Outdegree > 90th Percentile

Excluding $> 90^{th}$ percentile	Separation Rate	Entry Rate	Net Separations	Real Input Value (log)	Real Sales (log)
$\mathbb{1}\left(t > \text{Feb2020}\right) \times \left(\text{Supplier Exposure}\right)_j$	4.567***	-2.295***	6.862***	-0.354***	-0.162***
	(0.137)	(0.135)	(0.209)	(0.011)	(0.029)
Observations	781,216	781,216	781,216	781,216	143,082
R-squared	0.350	0.316	0.216	0.653	0.740
Full Sample	Separation Rate	Entry Rate	Net Separations	Real Input Value (log)	Real Sales (log)
$\mathbb{1}\left(t > \text{Feb2020}\right) \times \left(\text{Supplier Exposure}\right)_j$	3.649***	-1.129***	4.778***	-0.270***	-0.157***
	(0.141)	(0.139)	(0.214)	(0.011)	(0.028)
Observations	823,395	823,395	823,395	823,395	143,643
R-squared	0.351	0.318	0.217	0.652	0.740

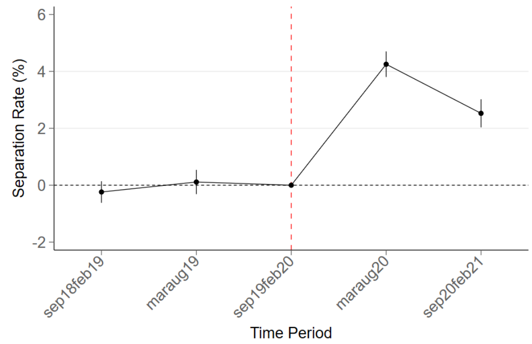
Note. Table presents results from the difference-in-differences version of equation 4 for key outcomes, but excluding all suppliers with outdegree above the 90th percentile, in comparison with the full sample results. Supplier exposure is calculated following equation 3. The post-period includes March 2020 to August 2020. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$ Standard errors clustered at buyer level in parentheses.

Figure A10: Baseline Event Studies with Alternative Time Periods

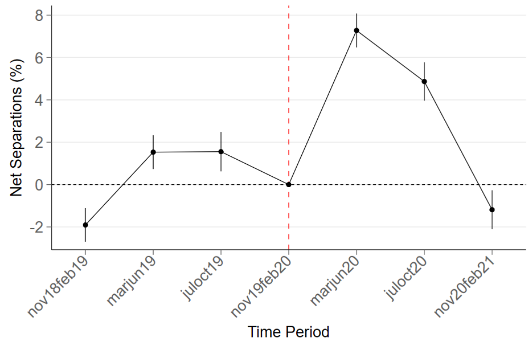
(a) Separation Rate - 4-month periods



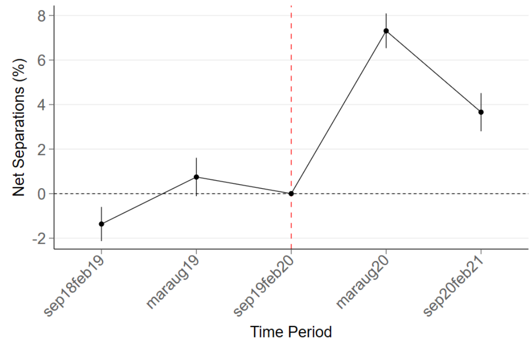
(b) Separation Rate - 6-month periods



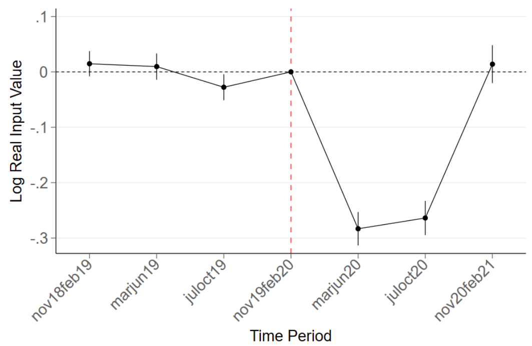
(c) Net Separation Rate - 4-month periods



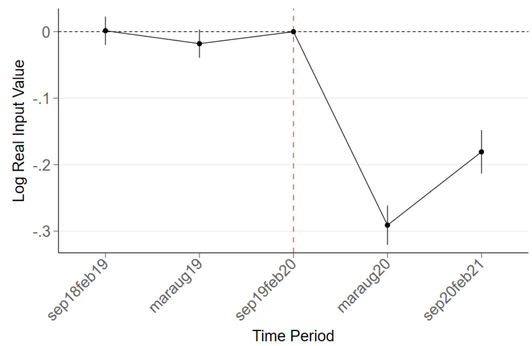
(d) Net Separation Rate - 6-month periods



(e) Real Input Value - 4-month periods

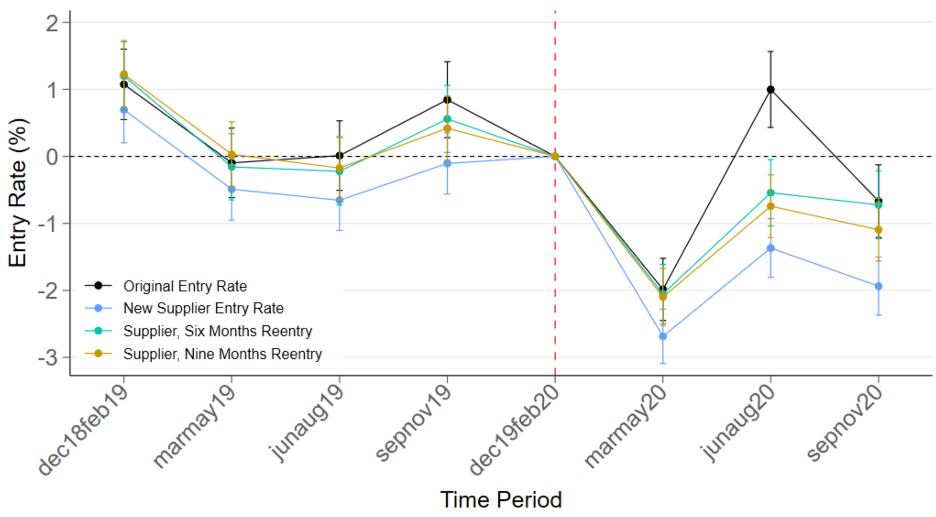


(f) Real Input Value - 6-month periods



Note. Panels (a) and (b) extend the baseline event-study estimation in equation 4 to separation rates, panels (c) and (d) for net-separation rates, and panels (e) and (f) for real input value, where the time period over which the measures are computed is alternatively four months or six months. For the four-month analysis, the number of observations is 879,376, the mean net-separation rate in the omitted period is -39.9% and the mean separation rate in the omitted period is 33.7%. For the six-month analysis, the number of observations is 702,379, the mean net-separation rate in the omitted period is -32.4% and the mean separation rate in the omitted period is 39.0%. Confidence intervals are at the 95 percent level. Standard errors are clustered at the buyer level.

Figure A11: Comparison of Entry Rate Definitions



Note. We plot our event study results for alternative definitions of the entry rate. "Original Entry Rate" refers to the baseline. "New supplier" is the entry rate for suppliers who never transacted with the firm up to that point. Six and nine month re-entry is the entry rate for suppliers that transacted with the firm six or nine months before the current period. 95% confidence intervals reported. Standard errors clustered at the buyer level.

D Characterizing resilience - additional results

We run our triple difference estimation from equation 6 for two additional outcomes: entry rates and log real output. The estimates on entry rates, presented in the left panels of Figure A12, have the expected opposite direction as the estimates on separations presented in Figure 3. The point estimates for output, shown in the right panel of Figure A12, follow a similar direction as inputs, but given the more stringent sample used for firm output the point estimates tend to be imprecise. In Tables A11 - A13, we present the full triple difference estimates for our main outcomes: separations, net-separations, and log inputs.

Table A11: Triple Difference Results for Separation Rate

	Indegree	Number of Products Purchased	Share Differentiated	Supply Chain Depth 1st Degree	Supply Chain Depth 2nd Degree
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.665***	3.455***	3.611***	1.892***	1.874***
	(0.141)	(0.140)	(0.144)	(0.152)	(0.152)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.272***	-2.923***	2.697***	2.504***	2.521***
	(0.081)	(0.152)	(0.163)	(0.182)	(0.193)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	0.721***	-0.583***	-0.068	-0.197	0.035
	(0.133)	(0.149)	(0.143)	(0.157)	(0.158)
Observations	823,395	823,315	789,648	744,821	744,821
R-squared	0.351	0.351	0.353	0.346	0.346
	Stickiness	**Downstreamness**	**Outdegree**	**Share Largest Supplier**	**HHI of Value of Different Products**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	1.843***	3.673***	2.850***	3.570***	3.294***
	(0.165)	(0.142)	(0.144)	(0.137)	(0.140)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.635***	0.543***	-4.703***	3.453***	4.180***
	(0.151)	(0.206)	(0.191)	(0.127)	(0.133)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	-0.776***	-0.177	-4.025***	-0.466***	0.598***
	(0.147)	(0.142)	(0.194)	(0.138)	(0.138)
Observations	694,944	823,395	823,395	823,395	823,315
R-squared	0.348	0.351	0.351	0.351	0.352
	Average Number of Suppliers	**HHI of Sales of Suppliers for Each Product**	**Average Number of Suppliers per Firm and Product**	**Product Spatial Concentration**	**Number of Transactions**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	3.641***	3.672***	3.506***	3.758***	3.643***
	(0.141)	(0.139)	(0.143)	(0.143)	(0.141)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	0.290*	3.410***	-2.802***	-0.361**	-0.708***
	(0.150)	(0.117)	(0.113)	(0.160)	(0.198)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	0.578***	-1.110***	1.309***	0.771***	0.115
	(0.128)	(0.130)	(0.133)	(0.151)	(0.120)
Observations	823,315	823,315	823,395	823,315	823,395
R-squared	0.351	0.351	0.351	0.351	0.351

Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents difference-in-difference results from equation 6 for the separation rate outcome. Supplier exposure is calculated following equation 3. Standard errors clustered at buyer level in parentheses.

Table A12: Triple Difference Results for Net Separations

	Indegree	**Number of Products Purchased**	**Share Differentiated**	**Supply Chain Depth 1st Degree**	**Supply Chain Depth 2nd Degree**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	4.823***	4.481***	5.057***	2.006***	1.940***
	(0.214)	(0.213)	(0.213)	(0.229)	(0.230)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.941***	-5.094***	5.351***	3.745***	3.296***
	(0.188)	(0.257)	(0.246)	(0.273)	(0.287)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	1.382***	-0.435*	-0.557***	-0.910***	-0.172
	(0.272)	(0.254)	(0.213)	(0.232)	(0.232)
Observations	823,395	823,315	789,648	744,821	744,821
R-squared	0.217	0.217	0.219	0.209	0.209

	Stickiness	**Downstreamness**	**Outdegree**	**Share Largest Supplier**	**HHI of Value of Different Products**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	2.769***	4.815***	3.435***	4.557***	4.112***
	(0.248)	(0.216)	(0.216)	(0.211)	(0.212)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-1.701***	1.352***	-6.997***	8.418***	8.110***
	(0.226)	(0.321)	(0.256)	(0.194)	(0.203)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	-1.316***	-0.249	-8.475***	-0.968***	0.962***
	(0.217)	(0.218)	(0.277)	(0.216)	(0.211)
Observations	694,944	823,395	823,395	823,395	823,315
R-squared	0.212	0.217	0.218	0.218	0.218

	Average Number of Suppliers	**HHI of Sales of Suppliers for Each Product**	**Average Number of Suppliers per Firm and Product**	**Product Spatial Concentration**	**Number of Transactions**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	4.764***	4.786***	4.474***	4.876***	4.764***
	(0.214)	(0.213)	(0.217)	(0.218)	(0.214)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	0.506**	7.962***	-6.463***	0.875***	-1.075***
	(0.226)	(0.179)	(0.229)	(0.247)	(0.283)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	1.282***	-2.101***	2.732***	0.927***	0.255
	(0.194)	(0.205)	(0.260)	(0.239)	(0.182)
Observations	823,315	823,315	823,395	823,315	823,395
R-squared	0.217	0.218	0.218	0.217	0.217

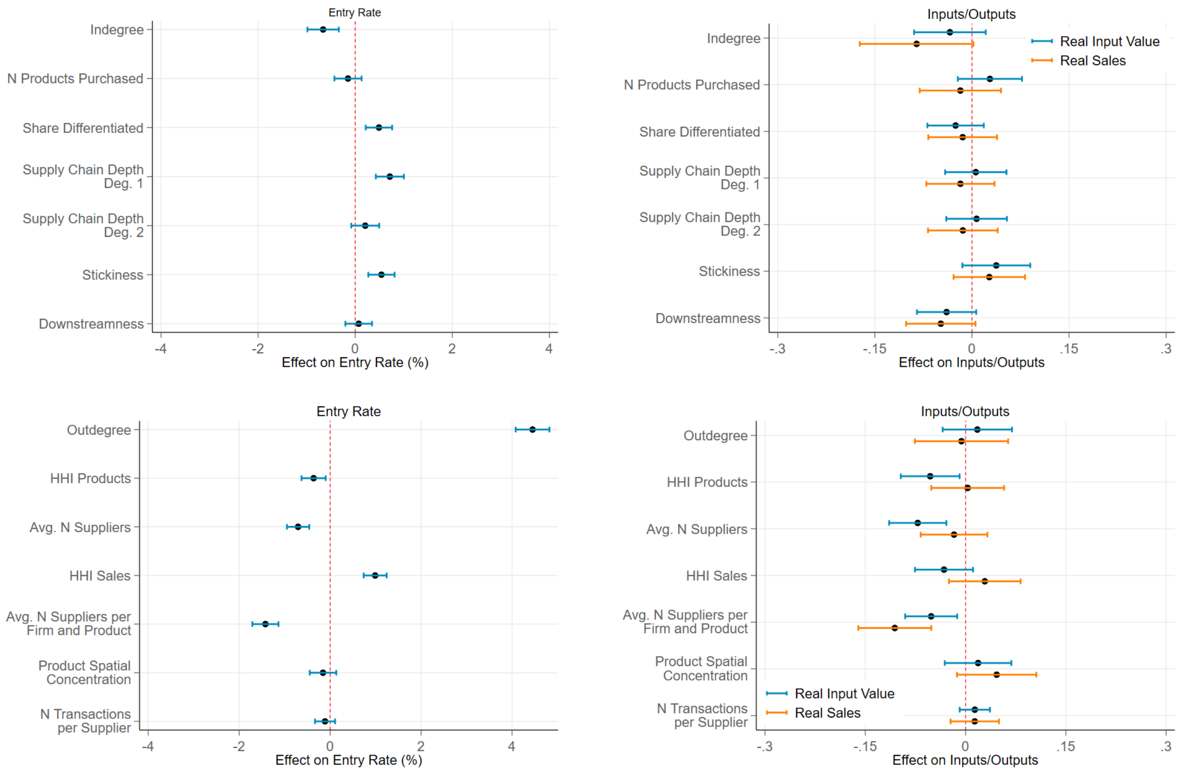
Note. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$. Table presents difference-in-difference results from equation 6 for the net-separations outcome. Supplier exposure is calculated following equation 3. Standard errors are clustered at buyer level in parentheses.

Table A13: Triple difference results for Input Purchases

	Indegree	**Number of Products Purchased**	**Share Differentiated**	**Supply Chain Depth 1st Degree**	**Supply Chain Depth 2nd Degree**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.274***	-0.245***	-0.265***	-0.154***	-0.152***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$	0.116***	0.358***	-0.170***	-0.231***	-0.227***
	(0.020)	(0.015)	(0.013)	(0.014)	(0.015)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	-0.032*	0.080***	-0.010	0.027**	0.006
	(0.018)	(0.014)	(0.011)	(0.012)	(0.012)
Observations	823,395	823,315	789,648	744,821	744,821
R-squared	0.652	0.653	0.655	0.657	0.657
	Stickiness	**Downstreamness**	**Outdegree**	**Share Largest Supplier**	**HHI of Value of Different Products**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.057***	-0.271***	-0.238***	-0.246***	-0.226***
	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.103***	-0.092***	0.159***	-0.663***	-0.549***
	(0.012)	(0.017)	(0.014)	(0.010)	(0.010)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	0.080***	0.005	0.216***	0.036***	-0.057***
	(0.012)	(0.011)	(0.014)	(0.011)	(0.011)
Observations	694,944	823,395	823,395	823,395	823,315
R-squared	0.663	0.652	0.652	0.654	0.654
	Average Number of Suppliers	**HHI of Sales of Suppliers for Each Product**	**Average Number of Suppliers per Firm and Product**	**Product Spatial Concentration**	**Number of Transactions**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j$	-0.271***	-0.264***	-0.259***	-0.276***	-0.270***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$	0.125***	-0.500***	0.210***	-0.010	0.031***
	(0.012)	(0.009)	(0.008)	(0.012)	(0.008)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Exposure})_j \times (\text{Characteristic})_j$	-0.072***	0.067***	-0.100***	-0.054***	-0.002
	(0.010)	(0.011)	(0.010)	(0.012)	(0.005)
Observations	823,315	823,315	823,395	823,315	823,395
R-squared	0.652	0.653	0.652	0.652	0.652

Note. $***p < 0.01, **p < 0.05, *p < 0.1$. Table presents difference-in-difference results from equation 6 for the log real input value outcome. Supplier exposure is calculated following equation 3. Standard errors are clustered at buyer level in parentheses.

Figure A12: Effect of Firm Characteristics on Entry/Output



Note. We plot the triple-interaction coefficients β from estimating equation 6 with alternative outcome variables for each of the characteristics described in Section 4. The left panels present the results for the entry rate and the right panels for output. 95% confidence intervals reported. Standard errors are clustered at buyer level.

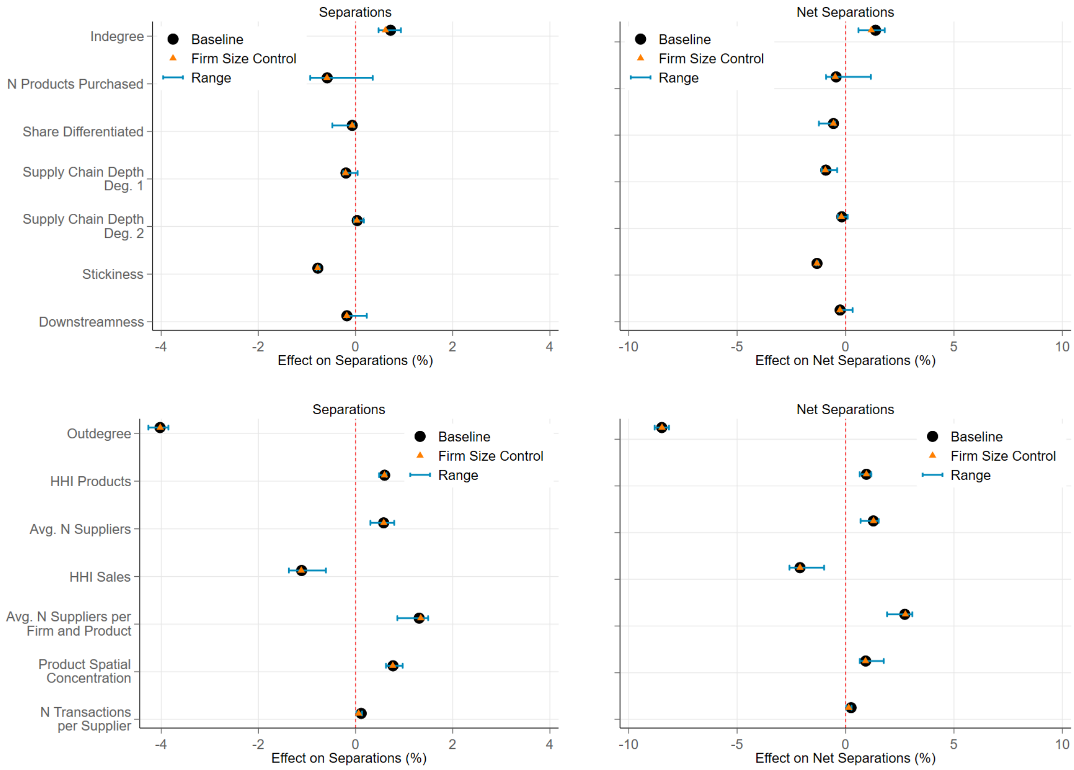
Next, we investigate whether supply chain characteristics might be correlated with each other, which might explain the pattern of results. Further, supply chains might typically be characterized by several of these metrics at once in the data. Running a horse-race between all of these metrics is computationally challenging, but we take multiple steps to address this issue. We begin by looking at firm size, which is measured as the total value of inputs the firm purchases in the period before the shock. It is well known that firm size tends to be correlated with multiple characteristics such as input complexity, length of the supply chain, likelihood to engage in international trade among may other supply chain features. Hence, we begin by running the regression in equation 6 for each characteristic and add as controls the interaction coefficients between firm size, supplier exposure, and the post period, as well as the triple interaction coefficient among the three.

We also run the triple-difference regression for each characteristic and control for the interaction terms with each of the other characteristics. If two characteristics are significantly correlated, we would expect the point estimates to change when adding both characteristics in the same regression.

In Figure A13, we plot the baseline triple difference estimates for separations and net-separations together with the point estimates of the triple interaction when controlling for firm size. We also plot the maximum and minimum of estimates of the triple interaction when controlling for each of the other characteristics in the regression. It is reassuring to see that none of the estimated coefficients of the triple interaction change significantly when controlling for firm size and other characteristics. For the case of supply-chain depth 1 and 2, we do not include them as a control for each other since, by construction, they are significantly correlated. Figure A14, presents the results for log inputs which also shows results are robust.

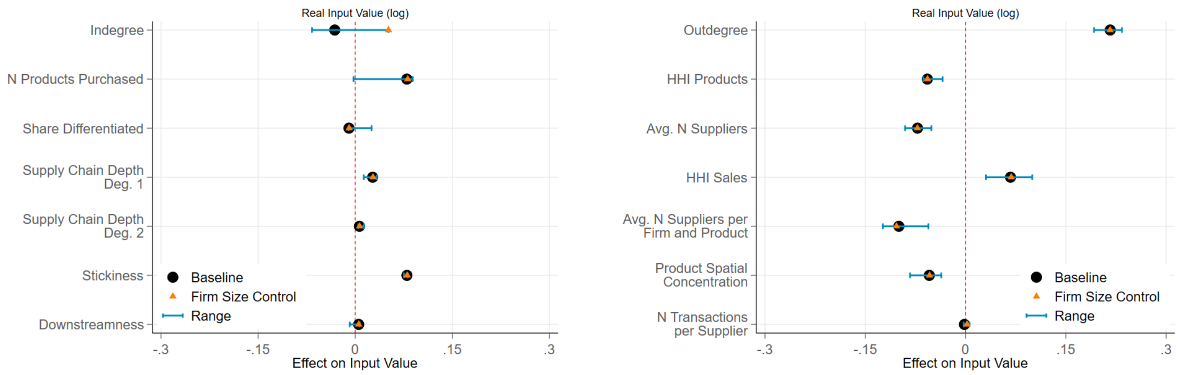
To further asses the degree of correlation among the supply-chain characteristics, Table A14 correlates some of our key metrics. Overall, barring a few obvious correlations such as a high positive correlation between buyer size and buyer indegree, or between product concentration and the share of the largest supplier in total purchases, we do not find much correlation across characteristics, suggesting most of the Z_j considered above are useful metrics of resilience in themselves.

Figure A13: Separation/Net-Separation Results Controlling for Other Characteristics



Note. We plot the triple-interaction coefficients β from estimating equation 6 for each of the characteristics described in Section 4 with additional controls. The baseline point estimate is plotted in black. The point estimate when controlling for firm size is plotted in orange. The additional controls are each possible firm characteristic— that is not the coefficient of interest — individually. We plot the minimum and maximum values of β in blue. Standard errors are clustered at buyer level.

Figure A14: Log Input Purchases Results Controlling for Other Characteristics



Note. We plot the triple-interaction coefficients β for each of the characteristics described in Section 4. The left panels present the input-value results for firm characteristics, and the right panels for supplier characteristics when estimating equation 6 with additional controls. The baseline point estimate is plotted in black. The point estimate when controlling for firm size is plotted in orange. The additional controls are each possible firm characteristic— that is not the coefficient of interest — individually. We plot the minimum and maximum values of β in blue. Standard errors are clustered at buyer level.

Table A14: Pairwise Correlation Between Supply-Chain Characteristics

	Buyer Size	Buyer Indegree	Number of Products Purchased	Share of Purchases - Differentiated Prod.
Buyer size	1.00	-	-	-
Buyer indegree	0.48	1.00	-	-
Number of products purchased	0.36	0.51	1.00	-
Share of purchases - differentiated prod.	-0.02	-0.01	-0.01	1.00
1st degree supply chain depth	0.01	0.01	0.15	0.10
2nd degree supply chain depth	0.01	0.02	0.15	0.02
Average Supplier outdegree	-0.02	-0.06	-0.07	0.12
Concentration on suppliers (HHI)	-0.11	-0.21	-0.20	0.05
Concentration of products purchased (HHI)	-0.03	-0.13	-0.50	0.02
Number of suppliers in market	-0.01	0.03	-0.03	0.17
Number of suppliers per product	0.24	0.48	0.26	-0.03
Product spatial concentration	0.02	0.00	-0.02	-0.28
Stickiness	-0.04	-0.04	-0.06	0.06
Downstreamness	0.00	0.00	0.06	0.28
N transactions per Supplier	0.29	0.16	0.25	0.01

	1st Degree Supply Chain Depth	2nd Degree Supply Chain Depth	Average Supplier Outdegree	Concentration on Suppliers (HHI)
1st degree supply chain depth	1.00	-	-	-
2nd degree supply chain depth Number of products purchased	0.96	1.00	-	-
Average supplier outdegree	0.10	0.02	1.00	-
Concentration on suppliers (HHI)	0.17	0.14	0.13	1.00
Concentration of products purchased (HHI)	-0.19	-0.18	0.08	0.08
Number of suppliers in market	-0.38	-0.34	-0.18	-0.15
Number of suppliers per product	-0.14	-0.11	-0.10	-0.60
Product Spatial Concentration	0.07	0.10	0.24	0.00
Stickiness	-0.02	-0.14	0.11	0.06
Downstreamness	0.35	0.38	-0.10	0.09
N transactions per Supplier	0.03	0.03	0.00	-0.02

	Concentration of Products Purchased (HHI)	Number of Suppliers in Market	Number of suppliers per Product	Product Spatial Concentration
Concentration of products purchased (HHI)	1.00	-	-	-
Number of suppliers in market	0.05	1.00	-	-
Number of suppliers per product	-0.06	0.18	1.00	-
Product spatial concentration	0.02	-0.28	0.03	1.00
Stickiness	0.02	-0.13	-0.10	0.02
Downstreamness	-0.05	-0.08	-0.07	-0.20
N transactions per Supplier	-0.03	-0.01	0.04	-0.01

	Stickiness (HHI)	Downstreamness in Market	N transactions per supplier
Stickiness	1.00	-	-
Downstreamness	0.04	1.00	-
N transactions per Supplier	-0.01	0.03	1.00

Note. We compute pairwise correlations among the different characteristics described in Section 4. All characteristics and correlations are computed for the period December 2019 to February 2020.

E New Buyer-Supplier Links

To explore the new-link formation in more detail, we use an event-study approach as in equation 9 to compare the supplier composition of high- and low-supplier-exposure firms over time.

$$\bar{y}_{j,t,r,k} = \sum_{x=t_0-4,\neq t_0}^{t_0+3} \gamma_x \left(\text{Supplier Exposure}\right)_j + \delta_j + \delta_{r,k,t} + \zeta X_{j,t} + \epsilon_{j,t,r,k} \tag{9}$$

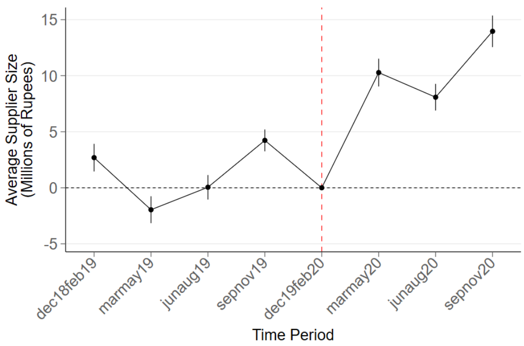
In Figure A15, we plot the event studies for four selected outcomes: average supplier size, average outdegree, supply chain depth of products purchased and the number of suppliers. As shown in Figure A15a, firms seem to significantly concentrate into larger suppliers after the shock. By May 2020, firms with supplier exposure one standard deviation above the mean buy from suppliers that are 10% larger than firms with an average supply-chain risk. Similarly, the average outdegree of suppliers increases after the shock meaning that firms not only transact more with bigger suppliers but also more central ones to the network.

Figure A15c measures how the average supply-chain depth changes over time. As mentioned in Section 4.2, the supply-chain depth measure captures how many products are needed to produce a given product. We compute the average supply-chain depth across products bought by the firm in each time period. The event-study plot in Figure A15c shows that firms with higher supplier exposure decrease their average supply-chain depth, buying products that are, on average, slightly less complex. Finally, firms also reduce the number of suppliers they transact with after the shock.

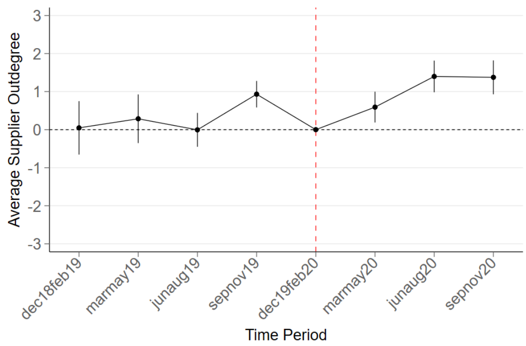
As additional checks, we explore whether the frequency of transactions changes after the shock. We count, for each supplier, the total number of shipments recorded in each time period and calculate the simple average across all suppliers. As shown in Figure A16, firms make on average, 1 fewer shipment from their suppliers per period. However, as shown in Figure A16, the total value per transaction does not change while total inputs purchased does decrease. This suggests that part of the observed input decrease is driven by having fewer transactions with suppliers.

Figure A15: Changes in Composition of New Suppliers

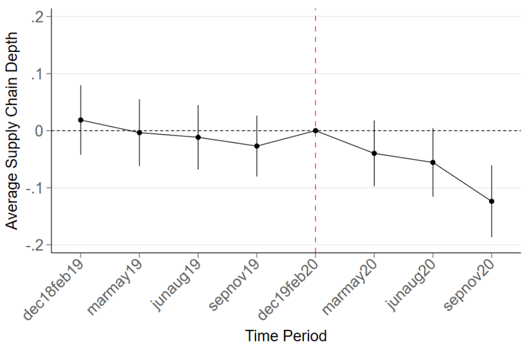
(a) Average Supplier Size



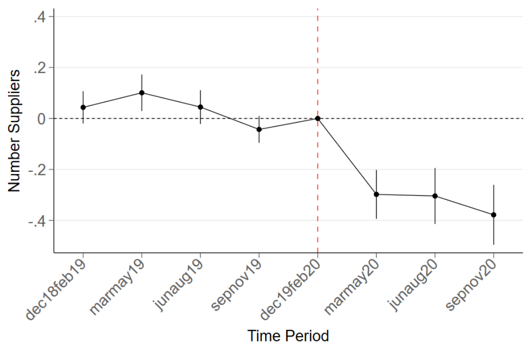
(b) Average Outdegree



(c) Supply Chain Depth

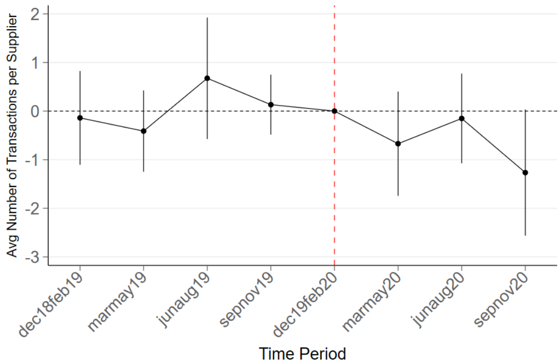


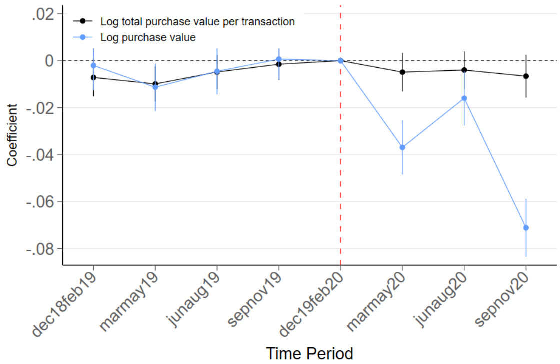
(d) Average Number of Suppliers



Note. We plot the interactions between time dummies and our supplier-risk measure estimated in equation 9. Average supplier size in omitted period: 112.38 (millions of rupees). Average supply-chain depth in omitted period: 32.31. Average number of suppliers: 12.20. Average outdegree of firms in our sample in pre-period: 42.37. Standard errors are clustered at buyer level. Confidence intervals shown are 95%

Figure A16: Event study: Transaction frequency





Note. We plot the interactions between time dummies and our supplier-exposure measure estimated in equation 9. Confidence intervals shown are 95%. Standard errors are clustered at the buyer level.