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 risk following the Covid-19 lockdowns. Using an event-study design we find firms with suppliers in strict-lockdown districts experienced 4.5pp higher separation rates (a 15% increase relative to baseline). We study which characteristics increase supply-chain resilience. Firms that buy more complex products, with fewer available suppliers, are less likely to break links. We explore how firms change post-shock supplier composition. Firms with higher supplier risk 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., 2019a). 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 use new data on daily firm-to-firm transactions from India, coupled with a large exogenous shock that disrupted supply chains to varying degrees. There are at least three dimensions along which supply-chain resilience can be studied following disruptions: 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. We measure resilience along all three 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 and input usage. We then assess which characteristics of supply chains made them more resilient.

Two particular features of our setting make it ideal to answer this question. First, we obtain 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.[2] 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 than those from green-zone suppliers.

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 risk, 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,

[1] 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."

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

comparing the resilience of firms whose suppliers faced strict lockdowns to firms whose suppliers faced mild lockdowns, relative to the period before the pandemic. To control for own-demand shocks, we include a rich set of fixed effects such as firm, industry-time, and own-district-time. Therefore, we compare firms within a given industry that face similar lockdown policies but differ in their pre-shock supplier compositions.

We find that a one standard deviation increase in supplier risk was associated with a 4.5pp higher separation rate three months after the lockdowns started. On average, the effects were persistent, lasting throughout 2020. Firms with high supplier risk also exhibited lower entry rates, lower net-separations (separations minus entries), lower input values, and lower output in response to the shock. For instance, firms with one standard deviation higher supplier risk decreased their input purchases (output) by up to 31% (2.7%) after the lockdowns.

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 are unable to find replacements.

The second part of our analysis uncovers which features of supply chains make them more resilient. As our three 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.[3] 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-separation. Somewhat surprisingly, firms that buy more complex products were less likely to break links after the shock, perhaps as they might assign more value to supplier-specific links, increasing resilience. To inform the largely 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 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 risk concentrate into larger and better connected suppliers. At the same time, supply chains

[3] There is little consensus on the definition of supply-chain resilience. The Brookings Institution defines 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."*

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 more differentiated, and the number of alternative suppliers is low.

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), and a focus on shock transmission (Bems et al., 2010; Burstein et al., 2008; Johnson, 2014). Also related are recent papers on the short-run transmission of natural disasters through trade links (Barrot and Sauvagnat, 2016; Boehm et al., 2019a; Carvalho et al., 2021). In contrast, the heterogeneous incidence of Covid-19 lockdowns across Indian districts, coupled with the size of the shock and detailed data, offers a unique opportunity to study how large shocks impact firm linkages and supply-chain resilience.

The resilience of supply chains has been the focus of an emerging theoretical and quantitative literature (Elliot et al., 2022; Grossman et al., 2021). A few papers leverage firm-to-firm data to calibrate models studying production networks (Arkolakis et al., 2021; Dhyne et al., 2020). Some model the formation of links between firms, but the focus is not 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 of economic resilience.

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.

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

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, 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. By law, any goods transaction with value over Rs.50,000 ($700) has to generate eway-bills, which populate our data. Transactions with values lower than $700 can also optionally be registered. As such, our network is representative of relatively larger firms, but the threshold is sufficiently low to capture small firms as well. More information is in Appendix A, with summary statistics in Table A1.

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 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 and purchases every period.

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.

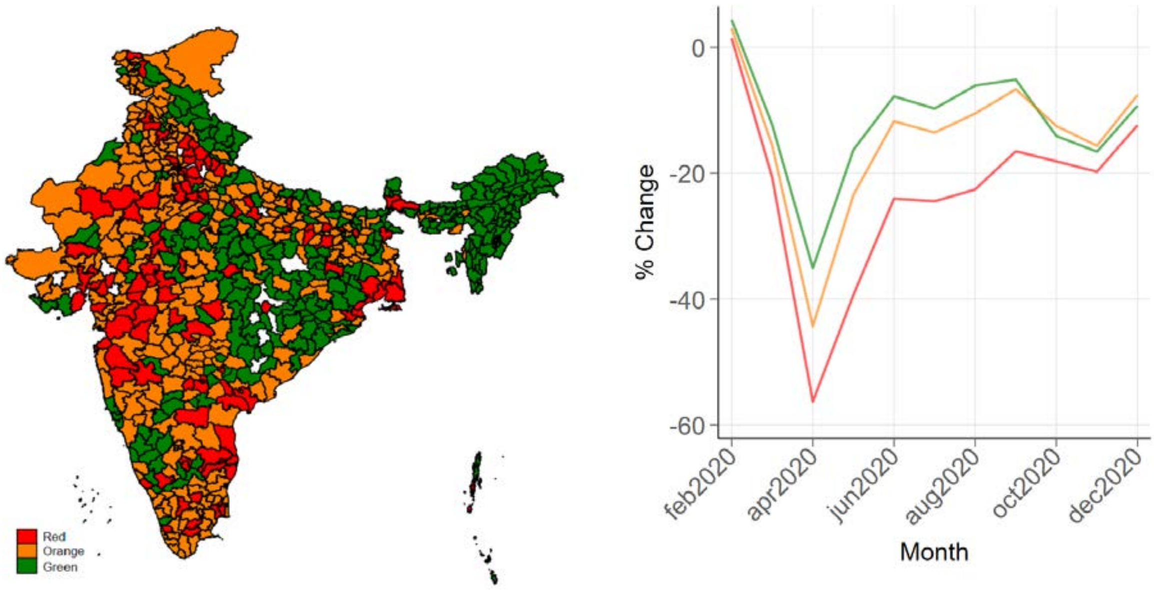
Districts in the red zone saw the strictest lockdowns, with rickshaws, taxis, public transport, barber shops, spas, and salons remaining shut. E-commerce was allowed for essential services. Orange and green zone districts saw fewer restrictions. In addition to the activities allowed in red zones, orange 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]

As shown in Figure 1b, lockdown stringency was strongly correlated with measures of economic activity and mobility. We validate our measures of lockdown intensity using

[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 five-week period Jan. 3 to Feb. 6, 2020.

Google Mobility data, and satellite nighttime luminosity in Appendix B.

3 The Impact of Lockdowns on Supply-Chain Resilience

We begin our analysis by measuring how the March 2020 lockdowns affected supply-chain resilience. Since no conventional economic definition of supply-chain resilience exists, we define alternative measures that capture a firm's ability to minimize output disruptions and recover after a shock. We view the lockdowns as an idiosyncratic shock to a buyer-supplier relationship. A firm which 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. 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. Finally, we also compute output changes, although our sample for which output data are available is limited.[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 A3), it is possible that those buying from suppliers in red zones were following different trends than those buying from suppliers in green zones. Also, 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 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-risk index to identify the exposure of the firms in our sample to the lockdowns as shown:

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

where s_{ij} stands for the value of purchases that firm j buys from firm i, relative to firm j's

[6] Boehm et al. (2019b) show that output falls with inputs in the short run in response to a shock. We validate this result with output data where available.

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 risk index to make it easier to interpret. A higher value of the index implies firm j faces a higher "supplier-risk," 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:

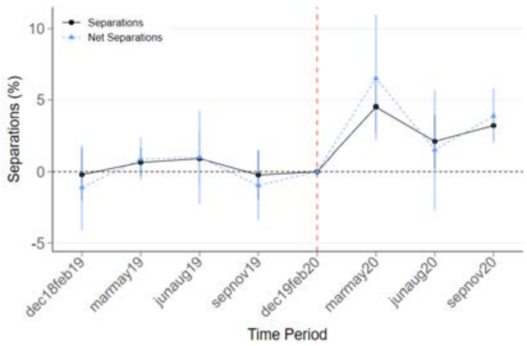
$$y_{j,t,r,k} = \sum_{x=t_0-4,\neq t_0}^{t_0+3} \gamma_x \left(\text{Supplier Risk}\right)_j + \delta_j + \delta_{r,t} + \delta_{k,t} + \epsilon_{j,t,r,k} \ , \tag{4}$$

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 rates as defined in equations 1 and 2. We also use real inputs and 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-risk 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-time fixed effects $\delta_{r,t}$, which control for a firm's own location lockdown, which can also affect their disruption. We control for industry-specific effects that might be contemporary to the lockdowns using industry-time fixed effects, $\delta_{k,t}$. For instance, if the shock increased demand for durable goods, such changes should be captured by industry-time 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.

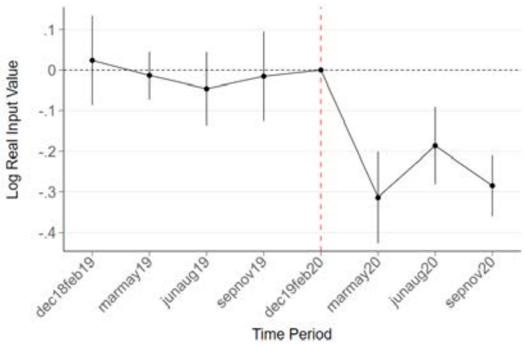
Figure 2 plots γ_x over time for our measures of supply-chain resilience. Reassuringly, the coefficients in the pre-periods are not statistically significant, implying that high- and low-exposed firms had similar trends in terms of their pre-shock supply-chain disruption measures. Consistent with Figure 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 risk of one standard deviation above the mean experienced an increase of 4.5pp in their separation rate from suppliers. The effect is economically significant, as it corresponds to a 15% increase with respect to baseline separation rates. The higher separation rates between high- and low-exposed firms remain through the 2020 period.

Figure 2: Baseline Event Studies

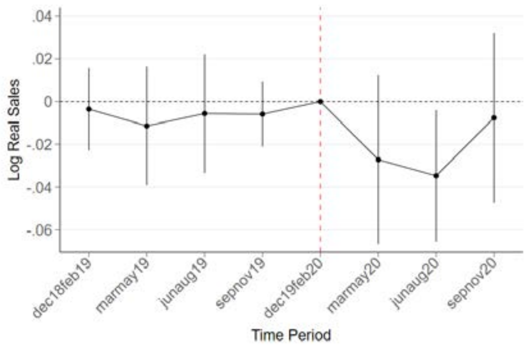
(a) Separations



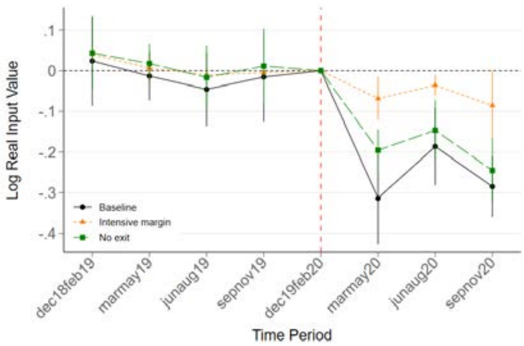
(b) Log Real Input Value



(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. Omitted period is December 2019 to February 2020. Average separation rate in the omitted period: 30.9%. Mean net separations in the omitted period: -43.1%. Number of observations: 946,665. In panel (c), the sample is restricted to include firms with positive real sales and that are observed making purchases in every period. Number of observations: 165,645. 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: 675,256. 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: 864,076. In Appendix Figure A4b, 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. Standard errors clustered at buyer-district level.

In Figure 2a, we also plot effects on 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 A4a plots entry rates. Between March and May 2020, firms with supplier risk 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 higher supplier risk decrease input values by 31% 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. As shown in Figure 2c, output responds with a lag, where highly-exposed firms experience a drop in real sales of almost 4% for the period June to August 2020. In sum, our evidence suggests that Covid-19 was a salient shock to firms, and supply-chain disruptions propagated to firm output.[7]

In Figure A5, 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 return to their old suppliers shortly after the shock. In Figure A6, we corroborate that the shock is not coming from a firm's buyers, and that the separations results are robust to weighting broken links by supplier size. Finally, we present the estimates of our main outcomes using a difference-in-difference approach to summarize the estimated effects in Table A3.

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 31% 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 7%. This suggests that the extensive margin and entry and exit drive approximately 77% of the observed supply-chain disruptions.

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

[7]The output decline is smaller than inputs as our baseline output sample (firms with positive sales and transactions every period) corresponds to firms with the least separation/smallest input declines. In this sub-sample input declines are similar to output declines.

supply-chain disruptions for which our data are most comprehensive: separation rates, net-separation rates, and total input purchases.[8]

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

$$\begin{aligned} y_{j,t,r,k} =& \gamma \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times (\text{Supplier Risk})_j \right] + \alpha \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times Z_j \right] + \\ & \beta \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times (\text{Supplier Risk})_j \times Z_j \right] + \delta_j + \delta_{r,t} + \delta_{k,t} + \zeta X_{j,t} + \epsilon_{j,t,r,k} \ , \end{aligned} \tag{5}$$

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-risk that are also one standard deviation higher in terms of characteristic of interest Z_j. As before, we include firm, district-time, and industry-time fixed effects. That is, we now estimate a triple difference-in-difference specification as opposed to the event studies shown in Section 3.1.[9] 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.

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.

[8] We also consider output in Figure A7, 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.

[9] We interact our supplier risk 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.

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 one hand, the low substitutability of inputs in production documented by Boehm et al. (2019a) 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.

Finally, 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.

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.

We analyze measures of concentration to quantify firm 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.

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 more spatially concentrated might have fewer alternative suppliers and exhibit more disruptions.

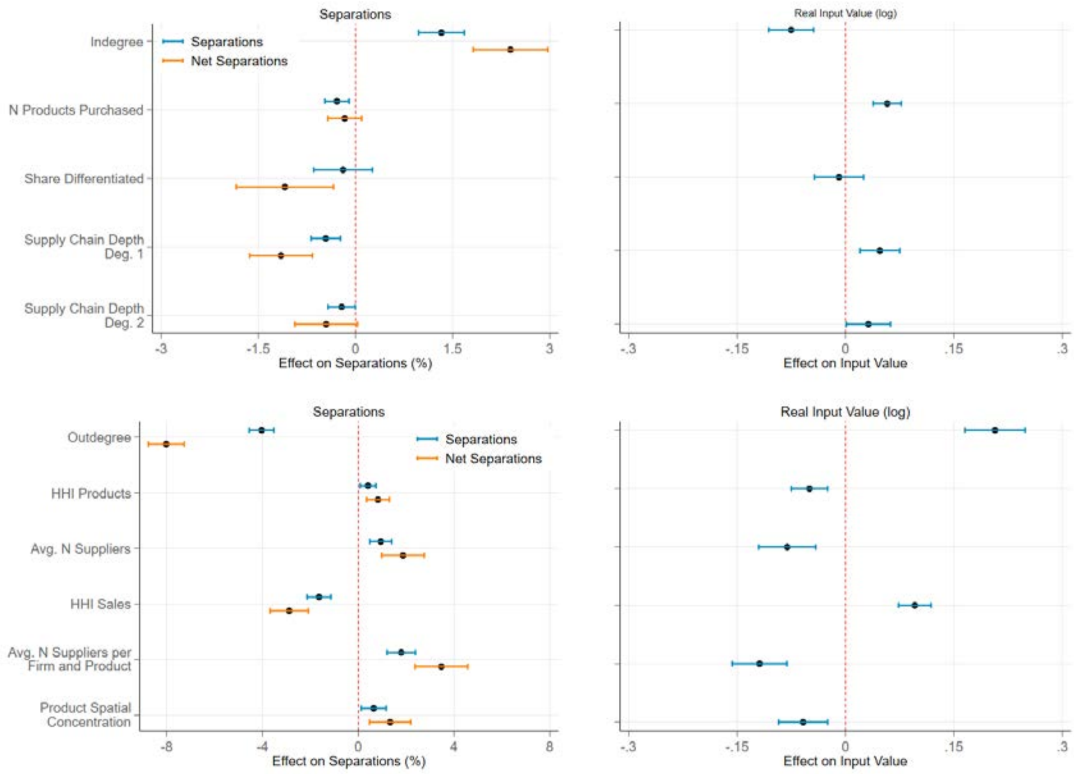
4.3 Results: What Characteristics Determine Resilience?

The left panel of Figure 3 shows the coefficient estimates of β in equation 5 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, and supply-chain depth (of degrees 1 or 2). 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 risk. 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 risk measures and characteristics are standardized, comparing magnitudes requires care. The 2.39pp coefficient on the indegree interaction implies that a firm in the 90th indegree percentile would have a 1.1pp higher net-separation rate than a firm in the 10th indegree percentile. Since the baseline effect of the shock increased net-separation rates by 3.7pp (Table A3), the 1.1pp difference is large.

We also find that the share of differentiated products a firm purchases, and its supply-chain complexity of degrees 1 and 2 significantly decrease its net-separation rate, suggesting that more complex supply chains are more resilient. A firm in the 90th percentile of these characteristics decreases net-separation rates by 2.69pp (share differentiated), 2.52pp (supply-chain depth of degree 1) and 0.98pp (supply-chain depth of degree 2) percentage points relative to firms in the 10th percentile. 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 risk. The result on supply-chain complexity suggests that

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 buyer-district level. In Figures A8 and A9 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.

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.

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 2, 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 highest supplier risk, 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 an increase in the number of suppliers per product aligns with this intuition: An increase in the number of suppliers leads to an increase in the separation rate for higher supplier-risk firms. 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 high-risk zone 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 2.38pp 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 net-separations as alternative resilience measures. Finally, 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.

In Appendix Tables A4-A6, 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 A7.

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 A8-A9, 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.[10]

[10]Table A7 pairwise correlates all metrics. Barring a few obvious correlations, we do not find much correlation across characteristics, suggesting most of the Z_j considered above are useful metrics of resilience

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 6.

$$\bar{y}_{j,t,r,k} = \gamma \left[\mathbb{1}\left(t > \text{Feb2020}\right)_t \times \left(\text{Supplier Risk}\right)_j \right] + \delta_j + \delta_{r,t} + \delta_{k,t} + \delta_{s,t} + \epsilon_{j,t,r,k} \ , \qquad (6)$$

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-risk measure with a post-period dummy taking the value one for the period after February 2020. We include firm, own-district-time, and industry-time fixed effects as in equation 4. As we want to track how the supplier composition changes over time, we add a few restrictions to the sample. First, we limit the sample to firms observed buying from at least one other firm every period to keep a consistent sample of firms. Second, we add an additional set of fixed effects $\delta_{s,t}$, which are time dummies interacted with the share of purchases firm j bought from state s in the period December 2019 to February 2020. Effectively, we are comparing firms that bought from suppliers in a given state but in districts with different lockdown degrees. Finally, we restrict the sample to firms observed selling their products to other firms, to ensure the firms remain active throughout the period. We also estimate a specification using the top quartile of the outcome ($\bar{y}^{q_4}_{j,t,r,k}$).

In Table 1, 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 risk one standard deviation above the mean buy from suppliers that are 5.6% larger than firms with an average supply-chain risk, 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 the most concentrated in their largest supplier prior to the shock, concentrate even more, as evidenced by the fourth quartile analysis.

From the second panel of Table 1, we see that firms do not significantly change the number of products they purchase. When looking at product complexity measures, we can see a slight increase in the share spent in differentiated products and a slight decrease in the average supply-chain depth. However, in Appendix Figure A10b, we present the event-study specification of equation 6 for selected outcomes, and show that highly exposed firms reduce their supply-chain depth six months after the initial shock.

in themselves.

Finally, in the third panel we look at 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 4%. 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.

Table 1: 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
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	6.029***	5.918**	1.247***	1.411**	0.144	0.255*
	(1.064)	(2.073)	(0.264)	(0.596)	(0.120)	(0.132)
Pre-period mean	106.4	387.83	43.04	69.25	52.39	89.82
Observations	249,346	51,083	264,648	56,761	264,648	66,136

	Number Products		Share Purch. Diff products		Supply Chain depth	
	Baseline	Quartile 4	Baseline	Quartile 4	Baseline	Quartile 4
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.0155	-0.180	0.183**	0.104	-0.0210	-0.0705
	(0.0421)	(0.152)	(0.0639)	(0.140)	(0.0233)	(0.0732)
Pre-period mean	12.05	31.09	60.19	99.65	32.32	42.35
Observations	264,648	65,920	259,630	65,048	264,648	66,144

	Number of Suppliers		Avge Distance to suppliers		Share Purch: non-home state	
	Baseline	Quartile 4	Baseline	Quartile 4	Baseline	Quartile 4
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.124*	-1.335***	-1.535	-16.32***	-0.256**	-0.163
	(0.0594)	(0.369)	(1.963)	(2.543)	(0.113)	(0.230)
Pre-period mean	12.35	34.32	486.71	1288.13	38.54	94.63
Observations	264,648	60,960	264,648	66,136	264,648	66,144

Note. Estimates from equation 6. 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. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$, Standard errors clustered at buyer district level.

6 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.

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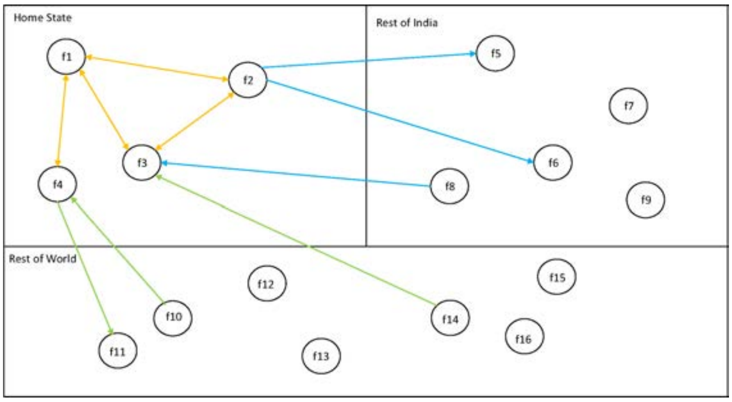
Appendix for online publication only

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



Notes: 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.

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 A2.

The mobility data show how the number of visitors to (or the time spent in) categorized

Table A1: Summary Statistics for Main Variables

Outcome	Mean	p25	p50	p75
Separation Rate (%)	30.9	0	16.67	52.78
Entry Rate (%)	74.06	0	50	106.67
Net Separations (%)	-43.12	-70	0	0
Real Input Value (log)	14.91	12.48	14.55	16.96
Real Sales (log)	16.33	13.57	16.05	18.66
Avg. Supplier Size (millions of rupees)	106.42	9.65	34.04	127.49
Avg. Supplier Outdegree	43.04	3.3	10.97	31.99
Share Purch. Lgst. Supplier (%)	52.39	31.06	47.84	71.82
Number Products	12.05	3	7	14
Share Purch. Diff. Prod. (%)	60.19	21.25	72.78	97.81
Supply Chain Depth	32.32	28.15	31.46	36.35
Number Suppliers	12.35	3	7	14
Avg. Distance (km)	486.71	97.13	251.65	712.75
Share Purch. Non-Home State (%)	38.54	0	24.42	78.48

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. Number of firms included in calculations: 136,562.

Table A2: Summary Statistics by District Lockdown Degree

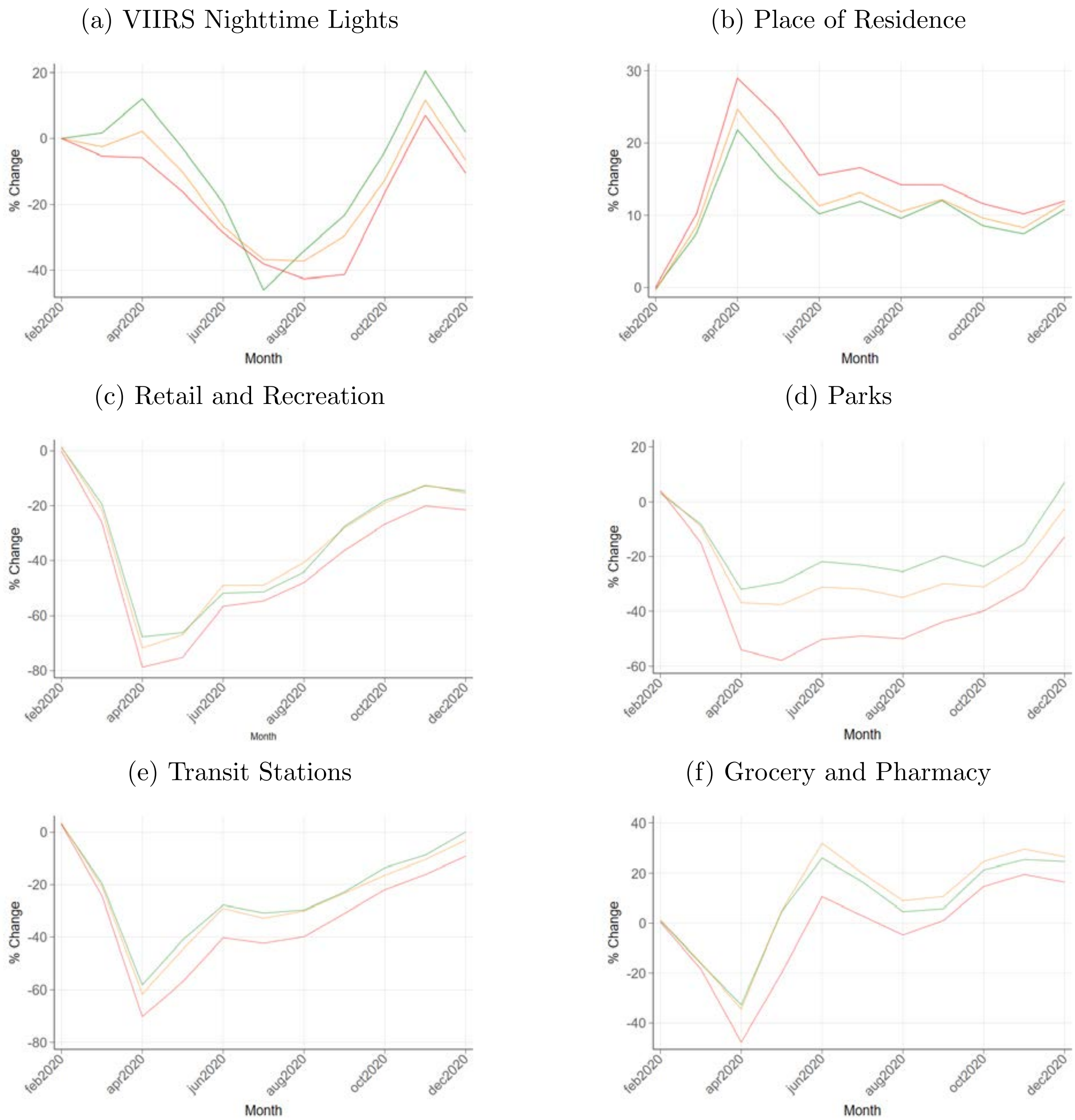
Zone	Avg. Cases/Million	Avg. Deaths/Million	Avg. Population	Total Cases	Total Deaths	Total Population
Green	26.316	0.1865	1,135,294	7,533	50	287,229,399
Orange	69.841	0.9236	1,990,250	24,713	364	469,698,944
Red	369.80	10.901	3,196,090	143,828	4,796	354,766,033

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.

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 A2b, 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 A2c to A2e. Such differences also exist between orange and green zones. By December 2020, these differences become smaller.

In Figure A2a, 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.

Figure A2: Alternative Lockdown Measures



(a) VIIRS Nighttime Lights (b) Place of Residence (c) Retail and Recreation (d) Parks (e) Transit Stations (f) Grocery and Pharmacy

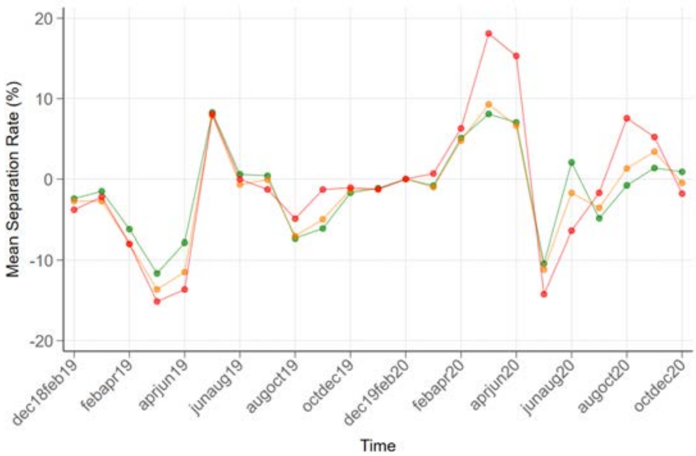
Note: We validate our lockdown measures using he VIIRS Satellite Nighttime lights data in panel (a) and Google Mobility data in panels (b)-(f). Google mobility data shows how the number of visitors to (or the time spent in) categorized places change compared to the period Jan 3 – Feb 6, 2020. Source: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

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.

To corroborate lockdowns indeed caused supply-chain disruptions, in Figure A3, 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 A3 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.

Figure A3: Mean separation rate by supplier location (relative to Dec 2019 - Feb 2020).



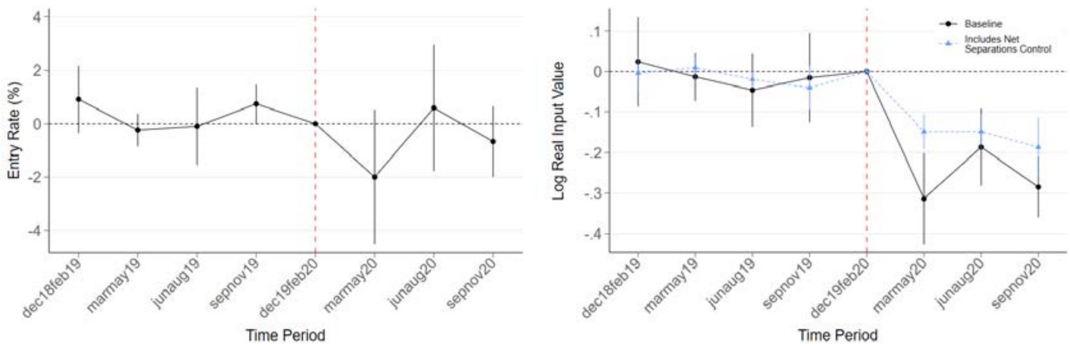
Note. We plot the mean separation rate across the firms in our sample, separating their suppliers by their district's lockdown stringency. We restrict the sample of buyers to firms in our state who are located in districts with medium-stringency. Separation rates are defined using three-month periods 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 A4a, 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 risk, 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 8.8pp higher than the less exposed firm (or a 28% higher separation rate). For the entry rate, the more exposed firm experienced a rate 6.3pp (or 8.5%) lower than the less exposed firm.

Figure A4: Baseline Event Studies

(a) Entry Rate (b) Controlling for Net-Separations



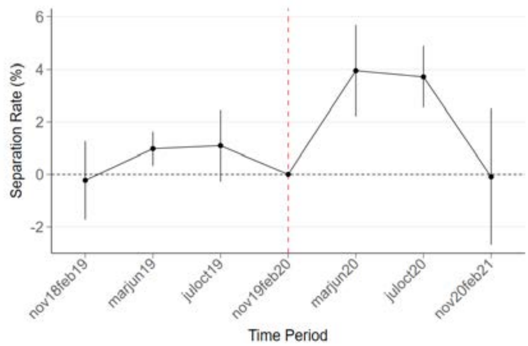
Note. We plot the estimated coefficients γ_x from estimating equation 4 for alternative outcomes (entry rate, panel (a)) and with alternate controls (panel (b)). Confidence intervals are 95%. Omitted period is December 2019 to February 2020. Average entry rate in the omitted period: 74.1%. Average log value of input purchases in the omitted period: 14.91. In panel (b), the purple line captures the input drop when controlling for net separations. Standard errors are clustered at buyer-district level

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 A4b, the drop in input value for firms with high supplier risk gets slashed by half once we control for net separations, going from a drop of 31% to a drop of 15%. This finding suggests that the extensive margin is an important channel to measure supply-chain disruptions.

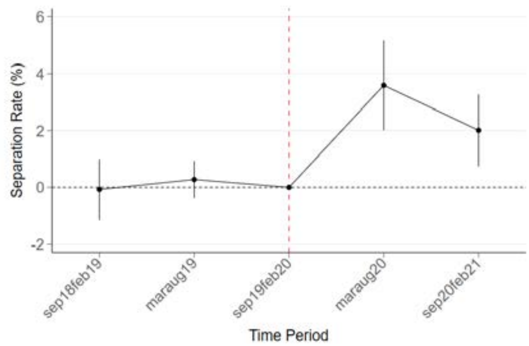
In Figure A5, we compute separation rates, net-separation rates, and total input purchases in periods of 4-months (left panels) or periods of 6-months (right panels). The finding that the separations and net-separations keep the same pattern, even with longer time periods, indicates that the separation rates in Figure 2, are not a product of firms changing the frequency of their purchases, and maintaining their previous suppliers.

Figure A5: Baseline Event Studies with Alternative Time Periods

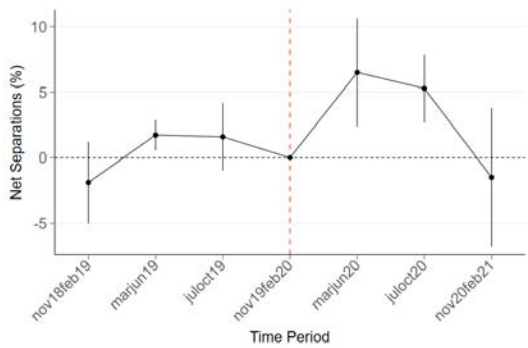
(a) Separation Rate - 4-month periods



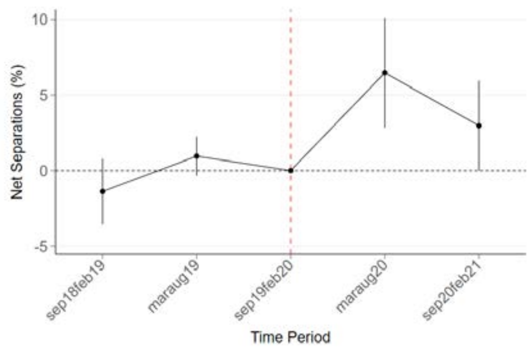
(b) Separation Rate - 6-month periods



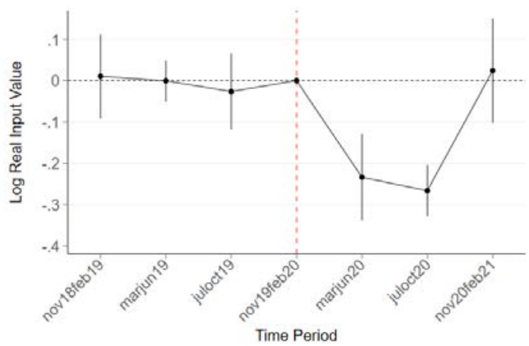
(c) Net Separation Rate - 4-month periods



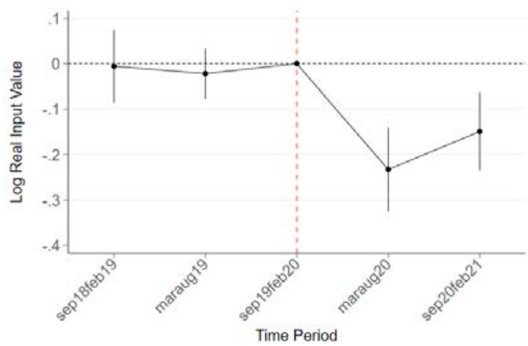
(d) Net Separation Rate - 6-month periods



(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 843,910, the mean net-separation rate in the omitted period is -38.7% and the mean separation rate in the omitted period is 33.0%. For the six-month analysis, the number of observations is 625,686, the mean net-separation rate in the omitted period is -30.6% and the mean separation rate in the omitted period is 37.5%. Confidence intervals are at the 95 percent level. Standard errors are clustered at the buyer-district level.

In Figure A6 we run robustness checks on our main results in Figure 2. As a first step, we want 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. To test for this, we add to equation 4 a demand control, which consists of time dummies interacted with a "consumer risk measure" calculated as in equation 7.

$$(\text{Consumer Risk})_j = \sum_{i}^{N} c_{j,i,t_0-1} \times (\text{Consumer } i\text{'s lockdown stringency in } t_0) \ , \tag{7}$$

where the consumer risk is calculated as a weighted average of firm j consumers in $t_0 - 1$ lockdown risk, using the share of sales to i in the pre-period as weights (c_{j,i,t_0-1}). Reassuringly, when we add the consumer risk as a control, our results are almost identical, which means that the supplier shock we defined is uncorrelated with shocks to consumers.

As a second step, we want to 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 A6c and A6d, the separation and net-separation rates are slightly higher when using weights, but the estimates are not statistically different from each other.

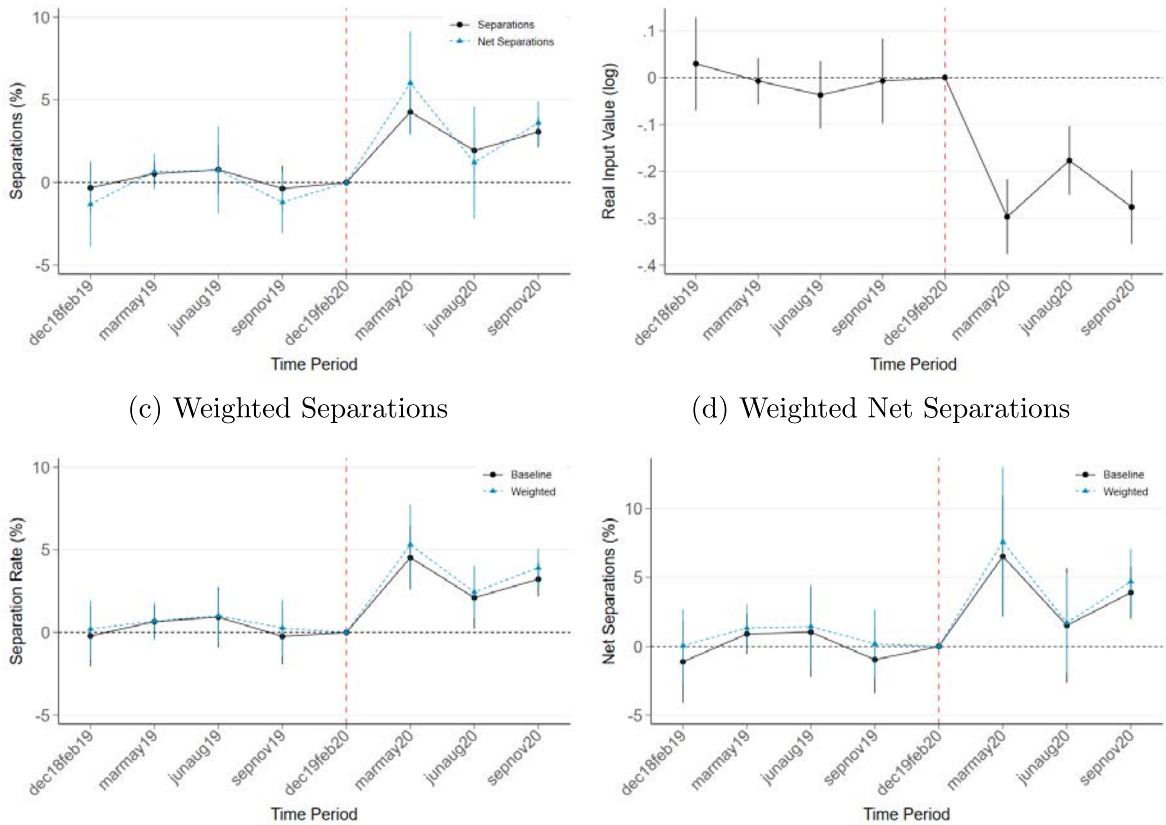
In Table A3, we present the difference-in-difference estimates for the outcomes in Figure 2. These estimates come from a similar regression as in equation 4, but instead of year dummies, we interact the treatment with a dummy for periods after March 2020. As shown in columns 5 and 6 of Table 2, firms with supplier risk of one standard deviation above the mean experienced a decrease in inputs of 20% and decrease sales by 2%.

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

	Separation Rate	Entry Rate	Net Separations	Real Input Value (log)	Real Sales (log)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	2.778***	-0.959	3.737***	-0.204***	-0.0205**
	(0.394)	(0.784)	(1.150)	(0.024)	(0.0077)
Observations	946,665	946,665	946,665	946,665	214,412
R-squared	0.321	0.285	0.183	0.563	0.861

Note. Table presents results from the difference in difference version of equation 4 for key outcomes. Supplier risk 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 district level in parentheses.

Figure A6: Demand Controls and Weighted Separations



(a) Separations with Demand Control

(b) Input Value with Demand Control

(c) Weighted Separations

(d) Weighted Net Separations

Note. We plot the estimated coefficients γ_x from estimating equation 4 with demand controls (a) and (b)) and with alternate outcomes (weighted separations and weighted net separations) (panels (c) and (d)). 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 log value of input purchases in the omitted period: 14.9. Average weighted separation rate in the omitted period: 19.5%. Average weighted net separation rate in the omitted period: -39.7%. In panels (a) and (b), the demand control is the exposure risk of the buyer. In panels (c) and (d), the shares of a firm's suppliers in total purchases are used as weights. Standard errors are clustered at buyer-district level.

D Characterizing resilience - additional results

We run our triple difference estimation from equation 5 for two additional outcomes: entry rates and log real output. The estimates on entry rates, presented in the left panels of Figure A7, 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 A7, 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 A4 - A6, we present the full triple difference estimates for our main outcomes: separations, net-separations, and log inputs.

Table A4: Triple Difference Results for Separation Rate

	Baseline	**Indegree**	**Firm Size**	**Number of Products Purchased**	**Share Differentiated**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	2.778***	2.827***	2.764***	2.625***	2.738***
	(0.394)	(0.406)	(0.379)	(0.367)	(0.459)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$		-0.986***	-1.412***	-3.148***	2.528***
		(0.230)	(0.291)	(0.269)	(0.167)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		1.327***	-0.389*	-0.287***	-0.192
		(0.180)	(0.203)	(0.0945)	(0.231)
Observations	946,665	946,665	946,665	946,665	908,6305
R-squared	0.321	0.321	0.321	0.322	0.324

	Product Spatial Concentration	**Supply Chain Depth 1st Degree**	**Supply Chain Depth 2nd Degree**	**Outdegree**	**Share Largest Supplier**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	2.843***	1.094**	1.099**	2.112***	2.790***
	(0.382)	(0.440)	(0.439)	(0.444)	(0.341)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	0.549**	2.573***	2.508***	-3.191***	4.012***
	(0.193)	(0.238)	(0.235)	(0.348)	(0.208)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	0.645**	-0.459***	-0.214*	-4.036***	-1.043***
	(0.266)	(0.116)	(0.107)	(0.263)	(0.213)
Observations	946,665	856,855	856,855	946,665	946,665
R-squared	0.321	0.318	0.318	0.322	0.322

		HHI of Value of Different Products	**Average Number of Suppliers**	**HHI of Sales of Suppliers for Each Product**	**Average Number of Suppliers per Firm and Product**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$		2.493***	2.772***	2.836***	2.574***
		(0.376)	(0.391)	(0.308)	(0.354)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$		4.131***	-0.0378	4.073***	-3.254***
		(0.174)	(0.174)	(0.233)	(0.150)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		0.408**	0.940***	-1.638***	1.796***
		(0.168)	(0.232)	(0.253)	(0.302)
Observations		946,665	946,665	946,665	946,665
R-squared		0.322	0.321	0.322	0.322

Note. Table presents difference-in-difference results from equation 5 for the separation rate outcome. Supplier risk is calculated following equation 3. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$ Standard errors clustered at buyer district level in parentheses.

Table A5: Triple Difference Results for Net Separations

	Baseline	**Indegree**	**Firm Size**	**Number of Products Purchased**	**Share Differentiated**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	3.737***	3.841***	3.713***	3.489***	3.883**
	(1.15)	(1.173)	(1.127)	(1.108)	(1.294)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$		-2.224***	-2.437***	-5.739***	4.805***
		(0.483)	(0.510)	(0.480)	(0.363)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		2.392***	-0.535	-0.167	-1.090**
		(0.293)	(0.350)	(0.134)	(0.383)
Observations	946,665	946,665	946,665	946,665	908,630
R-squared	0.182	0.183	0.183	0.184	0.185

	Product Spatial Concentration	**Supply Chain Depth 1st Degree**	**Supply Chain Depth 2nd Degree**	**Outdegree**	**Share Largest Supplier**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	3.801***	1.020	1.013	2.649*	3.670***
	(1.062)	(1.263)	(1.260)	(1.271)	(1.015)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$	2.786***	4.013***	3.505***	-4.004***	9.010***
	(0.324)	(0.430)	(0.422)	(0.542)	(0.366)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	1.333***	-1.150***	-0.453*	-8.017***	-1.792***
	(0.439)	(0.247)	(0.247)	(0.381)	(0.393)
Observations	946,665	856,855	856,855	946,665	946,665
R-squared	0.183	0.176	0.176	0.184	0.185

		HHI of Value of Different Products	**Average Number of Suppliers**	**HHI of Sales of Suppliers for Each Product**	**Average Number of Suppliers per Firm and Product**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$		3.181**	3.724***	3.800***	3.335***
		(1.100)	(1.145)	(0.968)	(1.058)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$		7.994***	-0.0369	8.850***	-7.097***
		(0.253)	(0.315)	(0.433)	(0.302)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		0.825***	1.868***	-2.882***	3.471***
		(0.242)	(0.453)	(0.407)	(0.562)
Observations		946,665	946,665	946,665	946,665
R-squared		0.184	0.183	0.185	0.185

Note. Table presents difference-in-difference results from equation 5 for the net-separations outcome. Supplier risk is calculated following equation 3. $***\ p < 0.01$, $**\ p < 0.05$, $*\ p < 0.1$ Standard errors are clustered at buyer-district level in parentheses.

Table A6: Triple difference results for Input Purchases

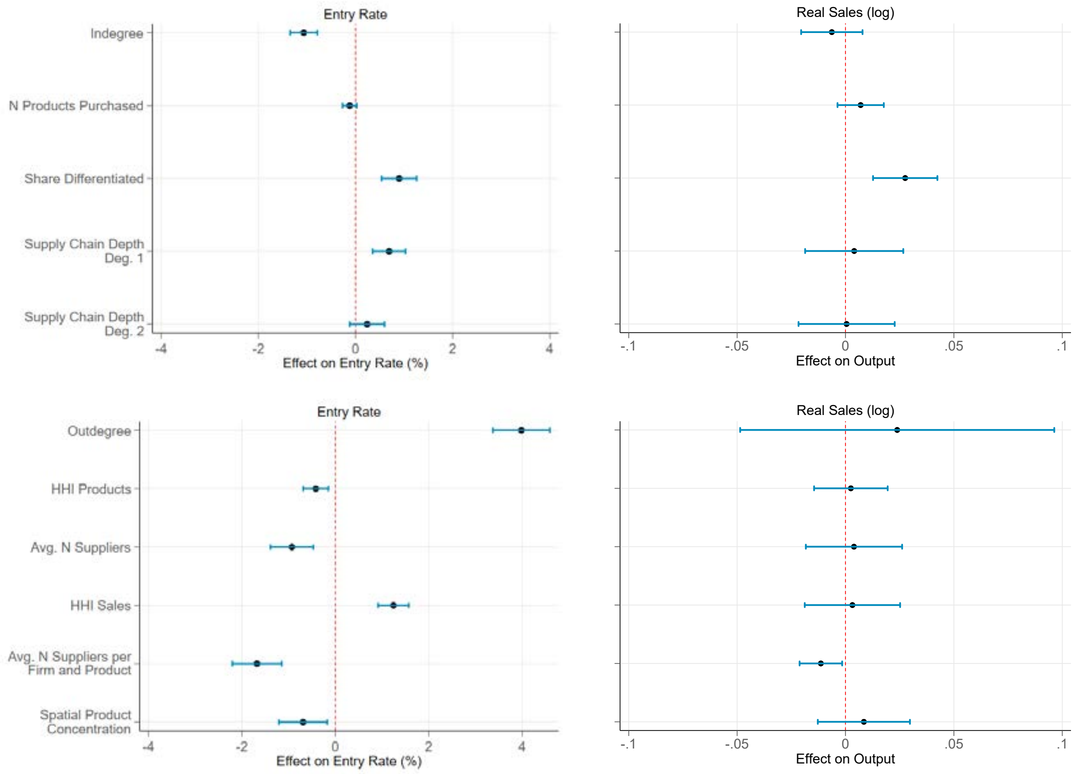
	Baseline	**Indegree**	**Firm Size**	**Number of Products Purchased**	**Share Differentiated**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.204***	-0.210***	-0.203***	-0.185***	-0.195***
	(0.024)	(0.023)	(0.023)	(0.021)	(0.026)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$		0.158***	0.108***	0.352***	-0.163***
		(0.032)	(0.022)	(0.030)	(0.015)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		-0.075***	0.036**	0.058***	-0.009
		(0.016)	(0.014)	(0.010)	(0.017)
Observations	946,665	946,665	946,665	946,665	908,630
R-squared	0.626	0.627	0.627	0.630	

	Product Spatial Concentration	**Supply Chain Depth 1st Degree**	**Supply Chain Depth 2nd Degree**	**Outdegree**	**Share Largest Supplier**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.210***	-0.090***	-0.091***	-0.178***	-0.188***
	(0.024)	(0.026)	(0.026)	(0.026)	(0.017)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.055***	-0.215***	-0.207***	0.081***	-0.646***
	(0.016)	(0.016)	(0.016)	(0.020)	(0.009)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	-0.059***	0.047***	0.032*	0.207***	0.064***
	(0.017)	(0.014)	(0.016)	(0.021)	(0.009)
Observations	946,665	856,855	856,855	946,665	946,665
R-squared	0.627	0.632	0.632	0.627	0.629

	HHI of Value of Different Products	**Average Number of Suppliers**	**HHI of Sales of Suppliers for Each Product**	**Average Number of Suppliers per Firm and Product**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.169***	-0.205***	-0.201***	-0.190***
	(0.021)	(0.024)	(0.017)	(0.021)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.515***	0.128***	-0.512***	0.248***
	(0.011)	(0.014)	(0.012)	(0.010)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	-0.050***	-0.081***	0.096***	-0.119***
	(0.013)	(0.020)	(0.011)	(0.019)
Observations	946,665	946,665	946,665	946,665
R-squared	0.628	0.627	0.628	0.627

Note. Table presents difference-in-difference results from equation 5 for the log real input value outcome. Supplier risk is calculated following equation 3. $***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors are clustered at buyer-district level in parentheses.

Figure A7: Effect of Firm Characteristics on Separations/Input Purchases



Note. We plot the triple-interaction coefficients β from estimating equation 5 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-district level.

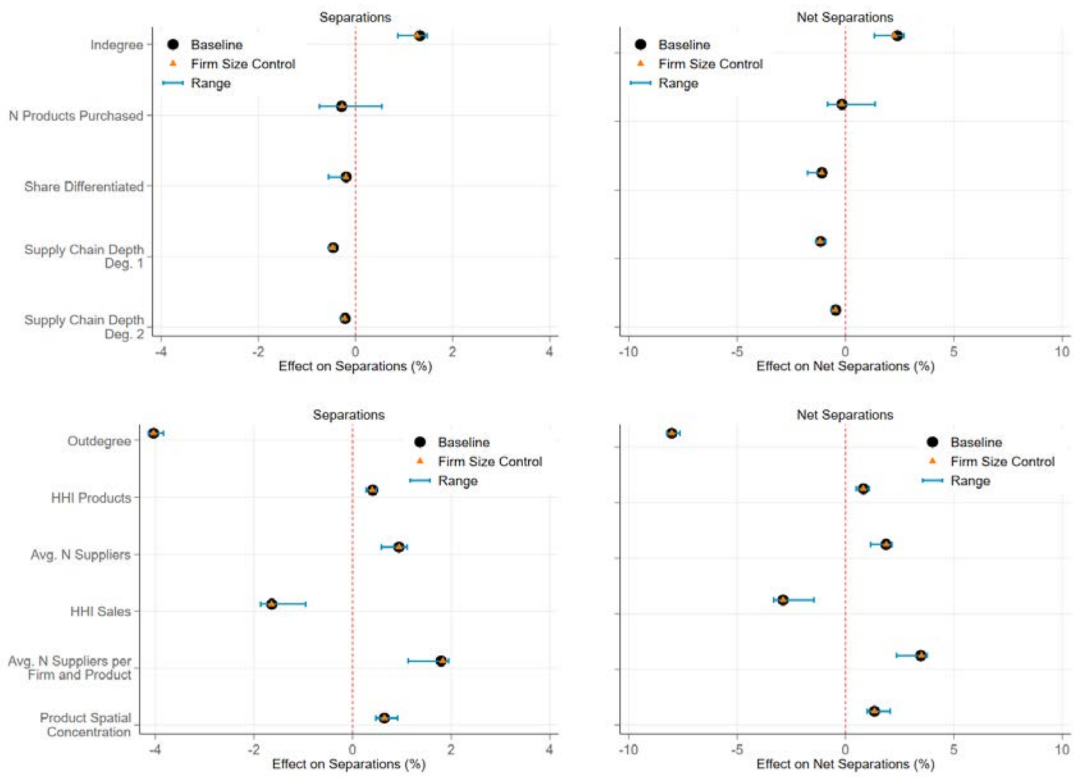
Next, we investigate whether supply chain characteristics might be correlated with each other, which might explain the pattern of results. Further, supply chains might typically be characterized by several of these metrics at once in the data. Running a horse-race between all of these metrics is computationally 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 5 for each characteristic and add as controls the interaction coefficients between firm size, supplier risk, 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 A8, 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 A9, presents the results for log inputs which also shows results are robust.

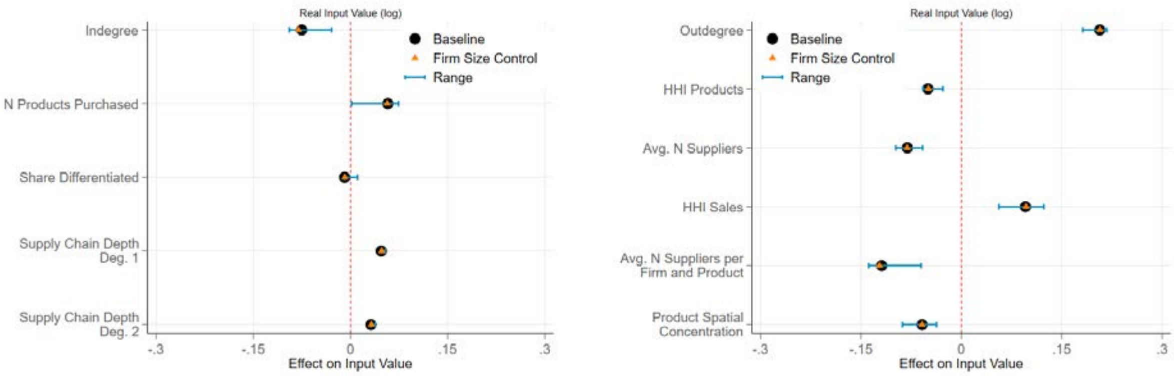
To further asses the degree of correlation among the supply-chain characteristics, Table A7 correlates some of our key metrics. Overall, barring a few obvious correlations such as a high positive correlation between buyer size and buyer indegree, or between product concentration and the share of the 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 A8: Separation/Net-Separation Results Controlling for Other Characteristics



Note. We plot the triple-interaction coefficients β from estimating equation 5 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-district level.

Figure A9: 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 5 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-district level.

Table A7: 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
	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
	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

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

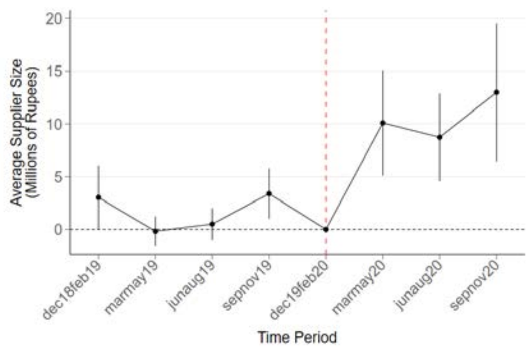
To explore the new-link formation in more detail, we use an event-study approach as in equation 8 to compare the supplier composition of high- and low-supplier-risk firms over time.

$$\bar{y}_{j,t,r,k} = \sum_{x=t_0-4,\neq t_0}^{t_0+3} \gamma_x \left(\text{Supplier Risk}\right)_j + \delta_j + \delta_{r,t} + \delta_{k,t} + \delta_{s,t} + \epsilon_{j,t,r,k} \tag{8}$$

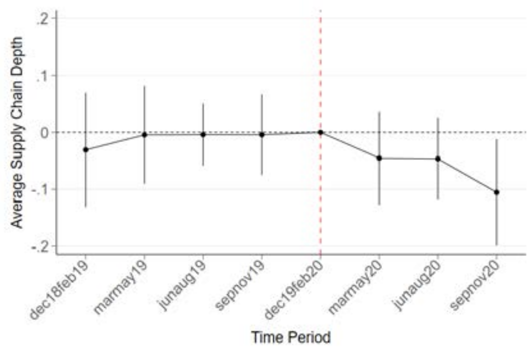
In Figure A10, we plot the event studies for two specific outcomes: average supplier size and the average supply-chain depth. As shown in Figure A10a, firms seem to significantly concentrate into larger suppliers after the shock. By May 2020, firms with supplier risk one standard deviation above the mean buy from suppliers that are 10% larger than firms with an average supply-chain risk. Figure A10b 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 A10b shows that firms with higher supplier risk decrease their average supply-chain depth, buying products that are, on average, slightly less complex.

Figure A10: Changes in Composition of New Suppliers

(a) Average Supplier Size



(b) Supply Chain Depth



Note. We plot the interactions between time dummies and our supplier-risk measure estimated in equation 8. Average supplier size in omitted period: 106.42 (millions of rupees). Average supply-chain depth in omitted period: 32.32. Number of observations: 249,346. Standard errors are clustered at buyer-district level. Confidence intervals shown are 95%