Supply Chain Resilience: Evidence from Indian Firms

Gaurav Khanna [*]
Nicolas Morales[†]
Nitya Pandalai-Nayar[‡]

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Abstract

We characterize which features of supply chains make them more resilient to large shocks. Using a novel dataset on the universe of firm-to-firm transactions in an Indian state, we identify which firms were subject to a larger supplier risk, following the Covid-19 lockdowns in March 2020. We follow an event-study approach and find that firms whose suppliers were in strict-lockdown districts, experienced separation rates 8.8 pp higher than firms with suppliers in mild-lockdown districts (a 28% increase with respect to baseline). We then look into which characteristics make supply chains more resilient. Firms who buy more complex products, which have fewer suppliers in the market, are less likely to break links after the shock. On the contrary, firms who diversified, and purchased the same product from multiple suppliers, are more likely to break links. Finally, we explore how firms change the composition of their suppliers after the shock. Firms with higher supplier risk start sourcing from closer distances, and concentrate their purchases into larger and better connected suppliers.

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[*]University of California, San Diego, gakhanna@ucsd.edu
[†]Federal Reserve Bank of Richmond, nicolas.morales@rich.frb.org
[‡]University of Texas, Austin and NBER, npnayar@utexas.edu
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1 Introduction

The rise of supply chains, within and across borders, is one of the most striking features in the recent decades of economic transformation (Johnson, 2017). While the efficiency gains from complex supply chains have been established theoretically and empirically, a growing literature has also found that supply chains can transmit shocks across regions with significant economic consequences. For instance, following the 2011 Tohoku earthquake, supply chain disruptions for multinational affiliates operating in the US lead to a substantial decrease in 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 (LaBelle and Santacreu, 2022). This lead to an increased emphasis by policymakers to develop policies to make supply chains more resilient and robust.[1]

Despite their importance, we still lack empirical evidence on which features make supply chains resilient to external shocks. In this paper, we use a novel dataset of 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 or not it leads to a drop in input usage and output, whether or not supplier links are maintained following the shock, and third, 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 these supply chains made them more resilient.

Two particular features of our setting make it ideal to answer this question. First, we obtain unique daily establishment-to-establishment 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 the fact that India had a mosaic of Covid-19 restriction policies, generating variation in the impact on supply-chain links. Between March – May 2020 districts in India were alternatively 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 were almost double than those from green zone suppliers.

To first 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,

[1] The White House's 100-day review of America's Supply Chains in June 2021: "Building Resilient Supply Chains, Revitalizing American Manufacturing and Fostering Broad-Based Growth"

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

based on the existing supplier network before the shock and the exposure of suppliers to different lockdown policies across India. We then implement a differences-in-differences estimation to compare the resilience of firms with suppliers facing strict lockdowns to the resilience of firms with suppliers facing mild lockdowns, relative to the period before the pandemic. To control for own-demand shocks that affect separation rates, we control for a rich set of fixed effects such as firm, industry-time, and own-district-time. Such controls allow us to compare firms within a given industry, who face a similar lockdown policy themselves, but differ in their supplier composition before the shock.

We find that a one standard deviation increase in supplier risk was associated with an 2.8 pp higher separation rate. On average, the effects were persistent, lasting throughout the 2020 period. To put these magnitudes into context, a firm who had all of their suppliers in strict-lockdown zones experienced a separation rate 28% higher than a firm whose suppliers were in mild-lockdown zones. 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 who had all of their suppliers in strict-lockdown zones decreased their input purchases (output) by 58% (6.5%) more than firms with suppliers in mild lockdown zones.

Our varied measures of resilience present a similar picture: more exposed firms are more likely to break links with suppliers, find it harder to find new suppliers, and decrease their overall input purchases and output. We investigate the contribution of the intensive and extensive margins to the overall decline in input purchases when characterizing resilience. More than half of the observed drop in input purchases can be explained by the extensive margin, where firms break links with suppliers 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 measures of resilience 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, likely because their suppliers were more resilient themselves. Somewhat surprisingly, firms who buy more complex products were less likely to break links after the shock, perhaps as they might assign more value to supplier specific links, making them more resilient to disruptions.

To inform the largely theoretical literature on supply-chain resilience, we assess whether

[3]There is no consensus on the definition of supply-chain resilience. For instance, 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."*

the measures suggested by Elliot et al. (2022) are good proxies for resilience. We find those firms who sourced products that had many available suppliers in the market, and firms who 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 who buy products not easily available in the market.

Finally, we study the formation of new links following the lockdowns. We find that firms with a higher supplier risk concentrate more into larger and better connected suppliers. At the same time, supply chains get slightly less complex, as firms become more likely to source products that require fewer inputs. In summary, our evidence strongly suggests that the most resilient supply chains are when suppliers are larger, inputs being purchased are more differentiated, and the number of alternative suppliers in the market is low.

We build on an 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 with a focus on shock transmission (Bems et al., 2010; Burstein et al., 2008; Eaton et al., 2016; Johnson, 2014). Also related are recent papers on the short-run transmission and amplification 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 detail in the data, offers a unique opportunity to study how firm linkages and supply chain resilience are impacted by large shocks.

Supply chain resilience has been the focus of an emerging literature, which is primarily theoretical and quantitative (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 buyers and suppliers, but the focus is not on supply-chain resilience. In contrast, we use exogenous variation to identify characteristics of supply chains that make them more resilient to shocks, which is a useful input for models of supply- chain resilience.

While our focus is not the 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, 2020a,b; 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 or link formations. Closely related is Cevallos Fujiy et al. (2021), who use the same data to estimate firm-level elasticities of substitution following the shock, but do not study the extensive margin responses of supply chain linkages or emphasize supply chain resilience overall.

2 Data

Here we provide a general overview of our data and context.

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

The data contains daily transactions between all registered establishments in this state and all registered establishments in India and abroad, from April 2018 to October 2020. Each transaction reports a unique tax code identifier for both the selling and the buying establishments, together with all the items contained within the transaction, including 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 the mode of transportation.

Each transaction also reports the zip-code location of both the selling and buying establishments, which we use to merge with other geographic data. By law, any person dealing with the supply of goods and services whose transaction value exceeds Rs.50,000 ($700) has to generate eway-bills. Transactions with values lower than $700 can also be registered but it is not mandatory. This implies that our network is certainly 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 by firms. As a measure of output, we use the reported quantity of each transaction to calculate a unit value for each product, construct a price index and deflate the total firm level sales to obtain a measure of real output. 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 real sales, who buy inputs every period.

Geographic Variation in Lockdowns. On March 25th 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 between *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.[5] Districts in the red zone saw the strictest lockdown measures,

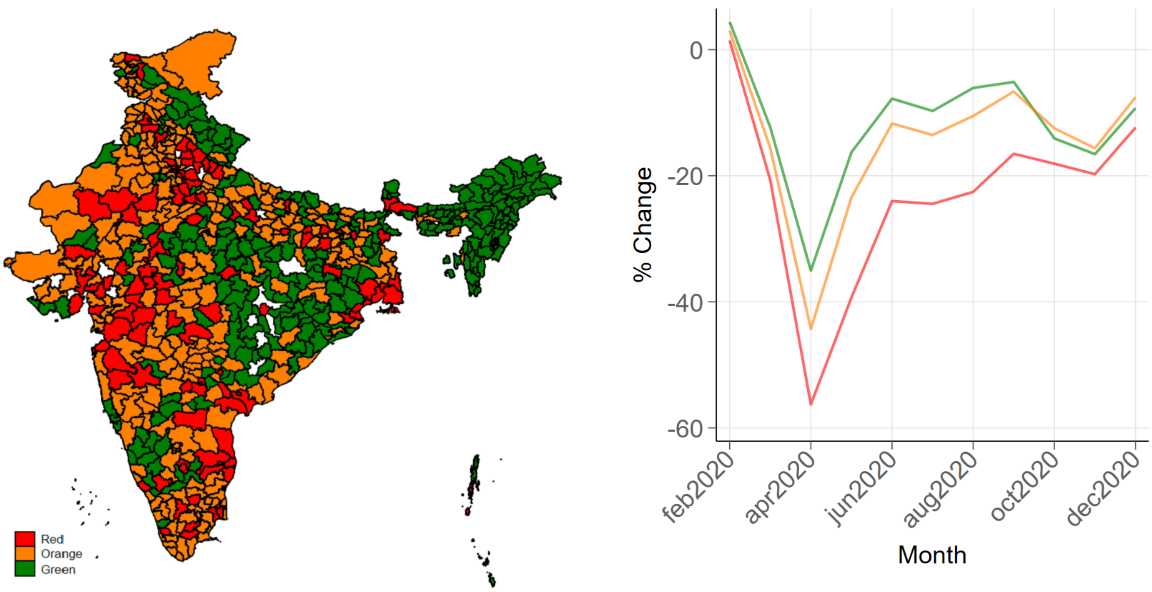
[4]While we use the term 'firm' in the paper, these data are at the granular establishment level.

[5]We use zone information from firms located all over the country as long as one node of the transaction

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, as well as the inter-district movement of individuals and vehicles for permitted activities. Additionally, in green zones, buses (and depots) were allowed to operate with up to 50% seating capacity.[6]

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 5-week period Jan 3 – Feb 6, 2020.

As shown in Figure 1b, lockdown stringency was strongly correlated with measures of economic activity and mobility. We further validate our measures of lockdown intensity using 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 several alternative measures that capture the ability of a firm to minimize output disruptions when buyer-supplier links experience a shock, and its ability to recover after receiving a shock. We consider the lockdowns to be an idiosyncratic shock to a

was in the state of our tax data.

[6]Source: Lockdown 3.0: Guidelines for red zone

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 begin by computing the supplier-separation rates as in equation 1.

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

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:

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

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 change in the total value of inputs purchased by firms, and the total value of inputs sold. Finally, we also compute output changes, although our sample for which output data are available is limited.[7]

3.1 Event-study Analysis

To evaluate how firms adapt to supply-chain disruptions created by the lockdowns, we need to quantify how such firms would have responded if no shock occurred. While there is a clear spike in the separation rates from suppliers in strict lockdown zones relative to other suppliers, 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 the behavior of its suppliers.

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

[7] 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.

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. Further, 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 lockdown shock as shown in equation 3.

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

where s_{ij} stands for the value of purchases that firm j buys from firm i, relative to firm j's total purchases; and N is the total number of firm j's suppliers. Time subscript t_0 stands for the period just before the lockdowns begun. 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, which do not correspond to any cardinal interpretation, 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:

$$y_{j,t,r,k} = \sum_{x=1}^{T} \gamma_x \left[\mathbb{1}\left(t = x\right)_t \times \left(\text{Supplier Risk}\right)_j \right] + \delta_j + \delta_{r,t} + \delta_{k,t} + \epsilon_{j,t,r,k} \qquad (4)$$

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 input values and real sales as additional outcomes.

Coefficients γ_x are time dummies that capture the differential separation/ net-separation/ nominal input value growth rate for buyers with supplier-risk one standard deviation above the mean.[8] We omit the interaction term for the period of December 2019 to February 2020, 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

[8] We use nominal input values as unit values (our measure of prices) spike up during the shock. As a result, the decline in real input values is much larger than nominal values.

own location lockdown which can also affect their disruption. We also include industry-time fixed effects, $\delta_{k,t}$, to control for industry-specific effects that might be contemporary to the lockdowns. For instance, if the shock increased demand for durable goods, 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 supplier lockdowns.

In Figure 2, we plot the 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 were following a similar trend in terms of their supply chain disruption measures before the shock. Consistent with Figure 2a, we see a persistent increase in supplier separations for firms most exposed to the lockdown shock. In the period of March to 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 14.5% increase with respect to baseline separation rates. The higher separation rates between high- and low- exposed firms remain through the 2020 period.

In Figure 2a, we also plot the net-separation rate: the difference between the separation and entry rate for a firm. The patterns follow closely those observed with separations, but the effects are slightly larger, as some firms increase separations and have a lower entry of new suppliers.[9] In the period of March to May 2020, firms with supplier risk of one standard deviation above the mean experienced an increase of 6pp in their net-separation rate from suppliers. Finally, in Figure 2b, we look at changes in input value, which combine the extensive and intensive margin responses of firms. Once again, we see that firms that have a one standard deviation higher supplier risk decrease their input value by 30% after the shock, and the drop is quite persistent throughout 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, highly exposed firms experience a drop in real sales of almost 4% for the period June-August 2020. In sum, our evidence suggests that Covid-19 was a salient shock to firms, and supply chain disruptions propagated to firm output.

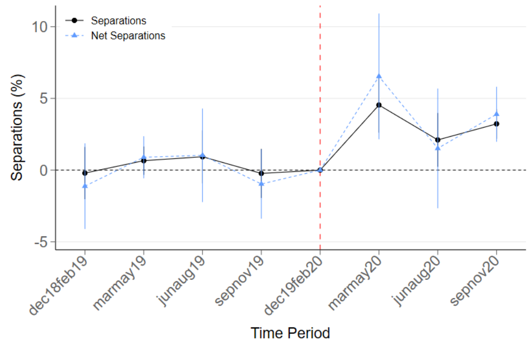
In Appendix Figure A3, we corroborate that our results truly capture links that get broken after the shock, and are not just reflecting changes in the frequency of purchases. When defining time periods as groups of 4 or 6 months, we still see a persistent increase in separation rates and net-separation rates after the shock. Such findings are also indicative that affected firms do not seem to return to their old suppliers whose links get broken. We

[9] Appendix Figure A6a plots entry rates.

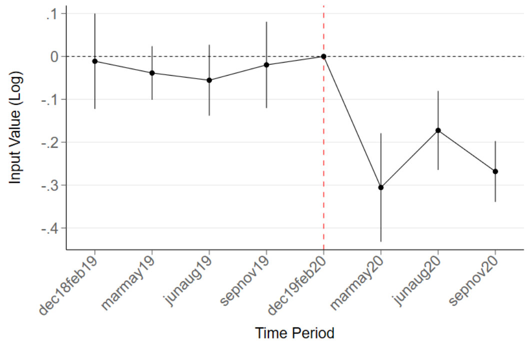
also present the estimates of our main outcomes using a difference-in-difference approach to summarize the estimated effects in Appendix Table A3.

Figure 2: Baseline Event Studies

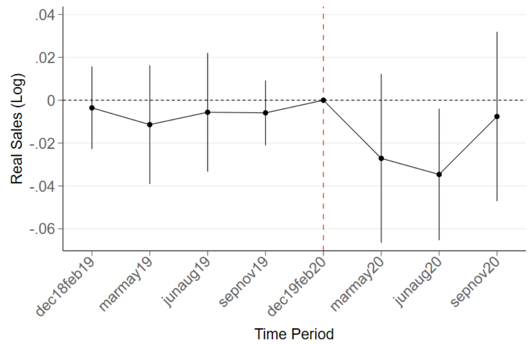
(a) Separations



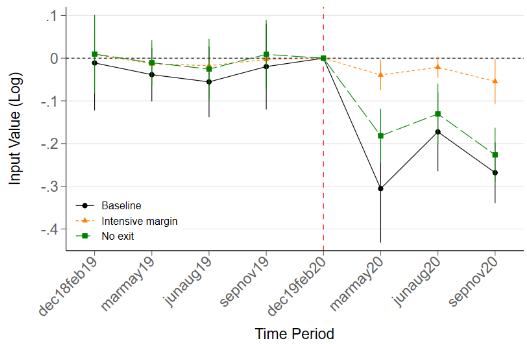
(b) Log Input Value



(c) Log Real Sales



(d) Extensive vs. Intensive Margin



Note. We plot the estimated coefficients γ_x 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%. Average log value of input purchases in the omitted period: 13.20. Number of observations: 946,665. Average real sales (log) in the omitted period: 16.817. In panel (c), the sample is restricted to include firms with positive real sales and who 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 who already supplied to the firm in the previous period (continuing relationships). Mean input purchases (log) in omitted period: 13.44688. N obs: 675,261. The green line presents the change in input purchases calculated using only firms who transact at least once in the post-shock periods (do not exit). Mean input purchases (log) in dec19feb20: 13.46411. N obs: 864,076. In Appendix Figure A6b, 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.

3.2 Intensive and Extensive Margins of Resilience

We investigate the role of the extensive margin on the total input value drop by quantifying the change in input purchases for alternative samples of firms. We begin by excluding from the sample those 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 in the post-period. As shown by the green line in Figure 2d, the drop in input purchases goes from 30% to 18% when excluding firms that exit. That is, a third of the total effect is driven by firms that stop purchasing inputs all together.

Finally, we calculate the total 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 who break links with the firm. The orange line in Figure 2d shows that firms with highly exposed continuing suppliers only decrease input purchases by 4%. This suggests that the extensive margin and firm entry and exit drive a majority of the observed supply-chain disruptions.

4 Characterizing Resilience

We now focus on our primary goal: understanding which firms exposed to the shock via their supply chains fared better or worse based on the characteristics of their supply chains. That is, we study which characteristics of supply chains more efficiently propagated or mitigated the effect of the shock. 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.

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 now 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 who 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. To present the results succinctly, we now estimate a triple difference-in-difference specification as opposed to the event studies shown in Section 3.1.[10] All characteristics Z_j are calculated for the period right before the shock December 2019 to February 2020. Our baseline results use standardized measures of all Z_j, but we also estimate differences by quantile. In alternative specifications, we add firm-level controls $X_{j,t}$, such as firm size interacted with the post-period indicator as

[10] 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.

well as the triple interaction between firm size, supplier risk, and the post-period. Overall, results are robust to accounting for firm characteristics.

4.1 Firm Characteristics

We begin by looking into attributes of firms that might make their supply chains more resilient. We follow the literature on networks and compute the indegree of the firm. We calculate the total purchases of buyer j from supplier s as a share of total sales from s. Then we 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 the role of 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 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 who 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 that are necessary to produce each product the firm produces. A higher number suggests a deeper, more complex supply chain. The second order depth measures whether the average product used to produce some of the firm's output itself has a high supply chain depth.

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 how dependent a firm is on its current suppliers. We calculate both 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.

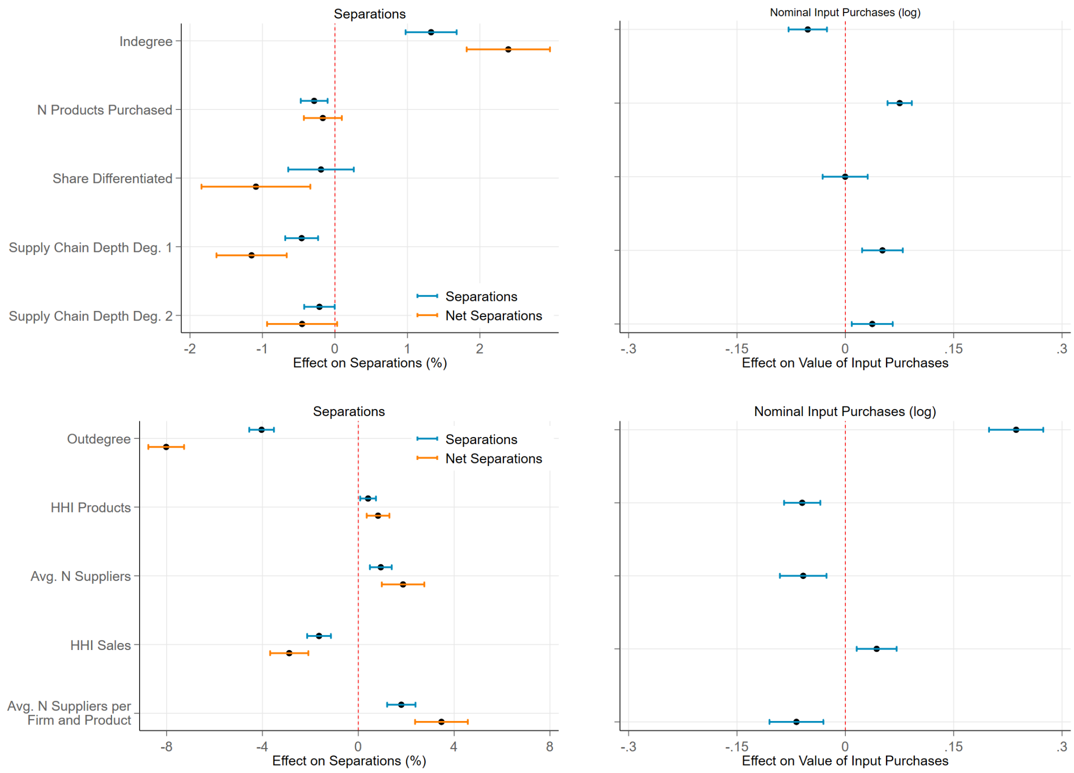
As a second metric, we also compute the number of suppliers per product and firm. A higher number would suggest that firms invested in relationships with multiple suppliers for a given product. After the shock, firms with multiple existing supplier relationships for a product might find it less costly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

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, and 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 our three measures of resilience 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

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 A4 and A5 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.

firm in the 90th indegree percentile would have a 1.1pp higher net-separation rate than a firm in the 10th indegree percentile. Considering that the baseline effect of the shock increased net-separation rates by 6pp, 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 change in net-separations for firms with higher supplier risk. 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.

The top right panel of Figure 3 considers the effect of firm characteristic heterogeneity on firm input purchases. The effect 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, who 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 important 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.

Finally, consistent with the predictions of Elliot et al. (2022), firms who buy products that have many suppliers in the market, exhibit higher separation rates than firms who buy products with fewer suppliers. For example a firm that is in the 90th percentile in terms of available suppliers for the products purchased have a separation rate that is 2.38pp higher than a firm in the 10th percentile. This suggests that investing in link-resiliency is less valuable for firms who 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.

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 A4 and A5 we show results controlling for firm size (interacted with post dummies), and then the entire range of results controlling for every other firm characteristic (interacted with post dummies). We find the results remain very similar.[11]

5 Changes in Supplier Composition

Finally, we look into how firms re-build 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.

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

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 that takes the value of one if the time period occurs after February 2020. We also 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 baseline sample. First, we limit the sample to firms that are 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 of December 2019 to February 2020. Effectively, we are comparing firms that bought from a given state, but from districts with different lockdown degrees. Finally, we restrict the sample to firms that are 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 ($\bar{y}^{q4}_{j,t,r,k}$)

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

[11]Table A7 pairwise correlates all metrics. Barring a few obvious correlations such as a 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. It is worth mentioning that supply-chain depth is negatively correlated with the number of suppliers in the market, as expected.

deviation above the mean buy from suppliers who 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 who were the most concentrated in their largest supplier prior to the shock, concentrate even more, as evidenced by the 4th 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 A8b we present the event study specification of equation 6 for selected outcomes, and show that highly exposed firms reduce their supply chain depth 6 months after the initial shock.

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 4th 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. $***p < 0.01, **p < 0.05, *p < 0.1$, Standard errors clustered at buyer district level. Outcomes include the average of a given characteristic across suppliers of a firm j. We separately run the analysis for the full sample and the 4th quartile of the outcome.

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 who buy more from large and well-connected suppliers are more resilient to the shock. Firms who buy products that are more complex are also less likely to break links. On the other hand, firms who buy products that are easily available 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 who buy inputs from suppliers who 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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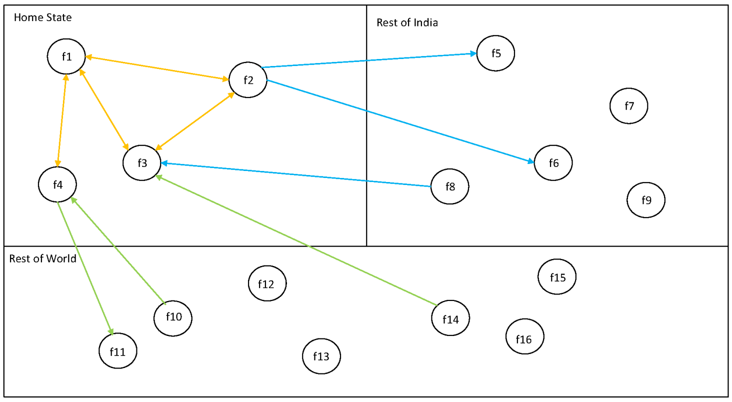
Appendix for online publication only

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 or outflows from and 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 reports value and quantity of traded items, so we can construct unit values. To do this, we aggregate values and quantities at the 4-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 our firm-to-firm dataset that we use in the analysis. Additionally, we can aggregate this 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 shows 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
Input Value (log)	13.20	11.78	13.07	14.50
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 (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

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. 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 – Feb 6, 2020.[12] As is clear from Figure A2b, we see that there is a substantial increase in staying at home in red zones compared to green zones. Such differences also exist between orange and green zones. People in red zones also spend more time at home compared to people in either orange or green zones. By December 2020 these differences become smaller.

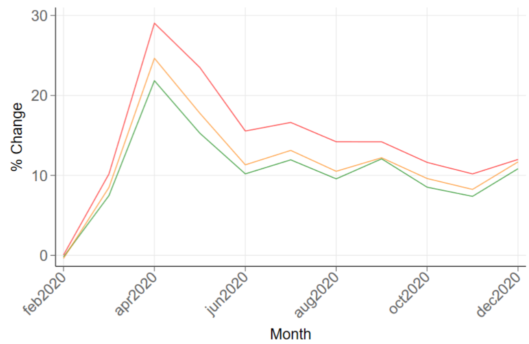
In Figure A2a, we follow past research in using nighttime lights from the VIIRS system, as a proxy for economic activity (Henderson et al., 2012). More recently, this has been used in India (Chodorow-Reich et al., 2019), where high-frequency, high-spatial resolution economic data is rare. These data 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.

[12] Source: https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927

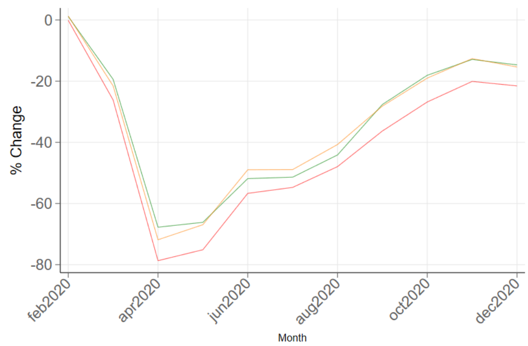
Figure A2: Alternative Lockdown Measures

(a) VIIRS Nighttime Lights

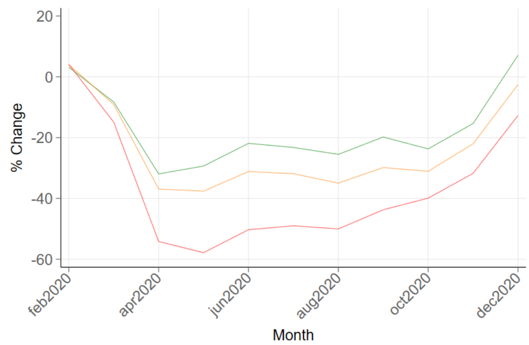
(b) Place of Residence



(c) Retail and Recreation

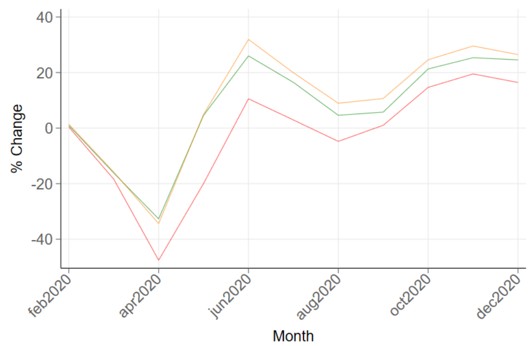


(d) Parks



(e) Transit Stations

(f) Grocery and Pharmacy

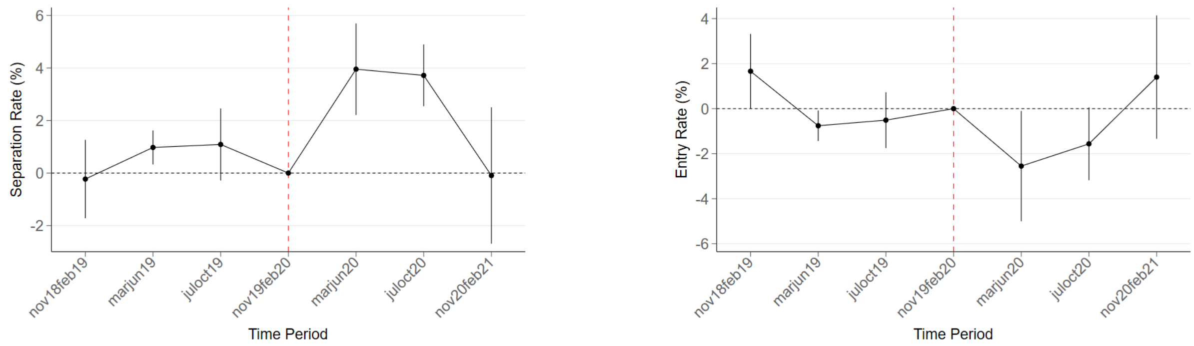


Note: We validate our lockdown measures using he VIIRS Satellite Nighttime lights data in panel (a) and Google Mobility data in panels (b)-(f). Google mobility data shows how the number of visitors to (or the time spent in) categorized places change compared to the period Jan 3 – Feb 6, 2020. Source: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

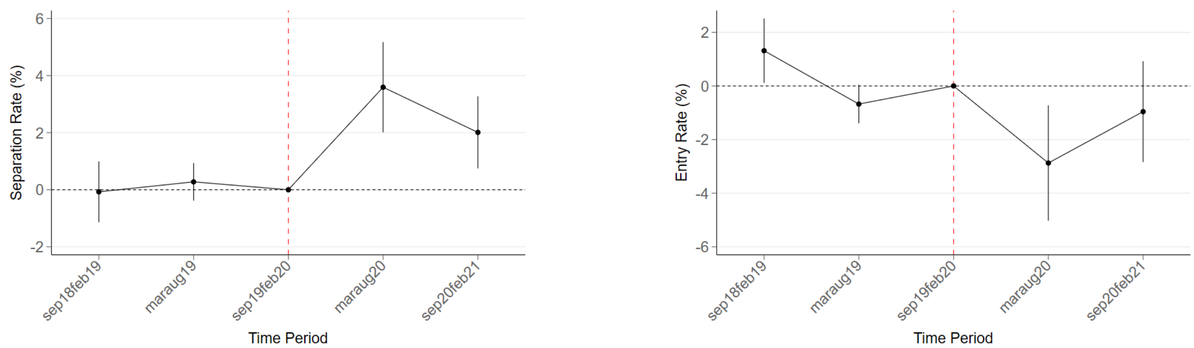
C Alternative Specifications and Robustness

Figure A3: Baseline event studies with alternative time periods.

(a) Separation Rate - 4 month periods (b) Entry Rate - 4-month periods



(c) Separation Rate - 6 month periods (d) Entry Rate - 6 month periods



Note. We compute separation and entry rates for periods of 4 and 6 months. For the 4-month analysis the number of observations is 843,910; mean entry rate in omitted period: 71.8%; mean separation rate in omitted period: 33.0%. For the 6-month analysis, the number of observations: 625,686; mean entry rate in omitted period: 68.1%; mean separation rate in omitted period: 37.5%.

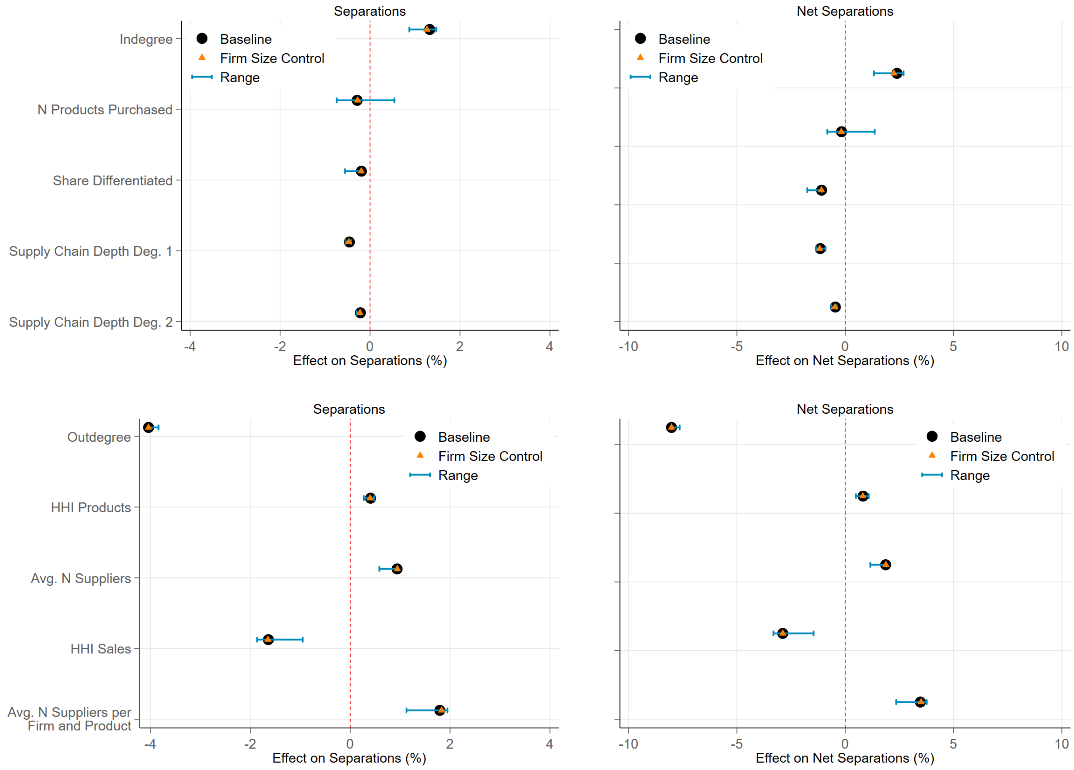
In Table A3, we present the difference in difference estimates for the outcomes in Figure 2. These estimates come from a similar regression as in equation 4 but instead of year dummies we just interact the treatment with a dummy for periods after March 2020. As shown in columns 5 and 6 of Table 2, firms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

Table A3: Difference-in-differences estimates for key outcomes.

	Separation Rate	Entry Rate	Net Separations	Input purchases (log)	Real Sales (log)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	2.778***	-0.959	3.737***	-0.185***	-0.0205**
	(0.394)	(0.784)	(1.150)	(0.0251)	(0.00768)
Observations	946,665	946,665	946,665	946,665	214,412
R-squared	0.321	0.285	0.183	0.531	0.861

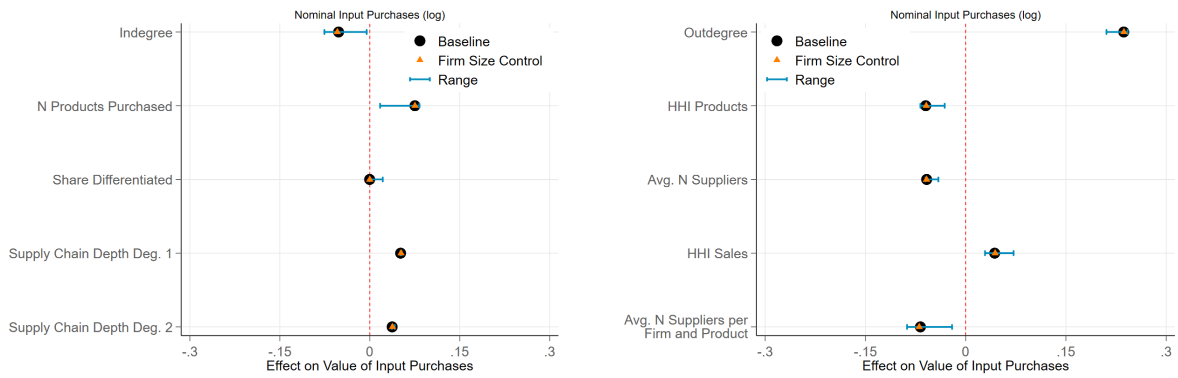
Note. Table presents results from Equation 4 for key outcomes. $***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors clustered at buyer district level in parentheses.

Figure A4: Effect of Firm Characteristics on Separations; Robustness



Note. We plot the triple-interaction coefficients β for each of the characteristics described in Section 4. The baseline point estimate is plotted in black. The point estimate when controlling for firm size is plotted in orange. We control for each firm characteristic individually and plot the minimum and maximum values of β in blue. Standard errors clustered at buyer district level.

Figure A5: Effect of Firm Characteristics on Input Value; Robustness

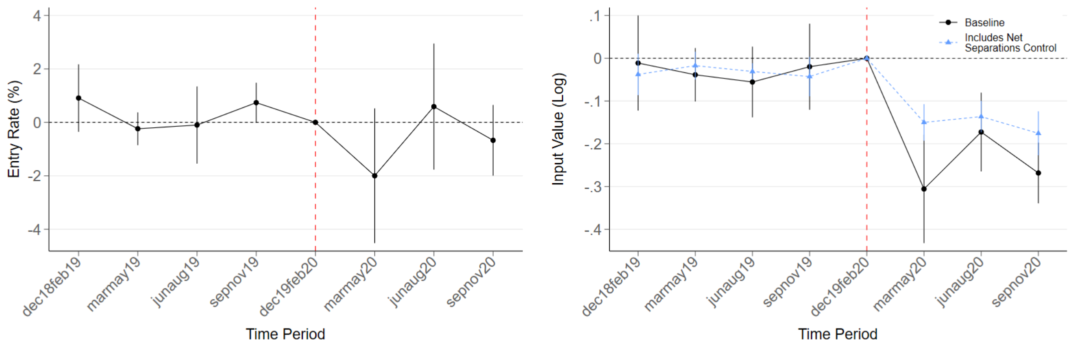


Note. We plot the triple-interaction coefficients β for each of the characteristics described in Section 4. The left panels present the results for separation rate, and the right panels for net separations. The baseline point estimate is plotted in black. The point estimate when controlling for firm size is plotted in orange. We control for each firm characteristic individually and plot the minimum and maximum values of β in blue. Standard errors clustered at buyer district level.

We complete the baseline analysis by running regression 4 with the entry rate as the outcome. As shown in Figure A6a, the overall entry rate of suppliers for firms with a standard deviation above the mean risk was 2 pp lower than for firms with the 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 these numbers into context, if we compare a firm whose suppliers were located in strict-lockdown (red) areas with a firm whose suppliers were located in mild-lockdown (green) areas, the most exposed firm experienced a separation rate 8.8 pp higher than the least exposed firm (or a 28% higher separation rate). For the entry rate, the most exposed firm experienced a rate 6.3 pp (or an 8.5%) lower than the least exposed firm.

Figure A6: Baseline Event Studies

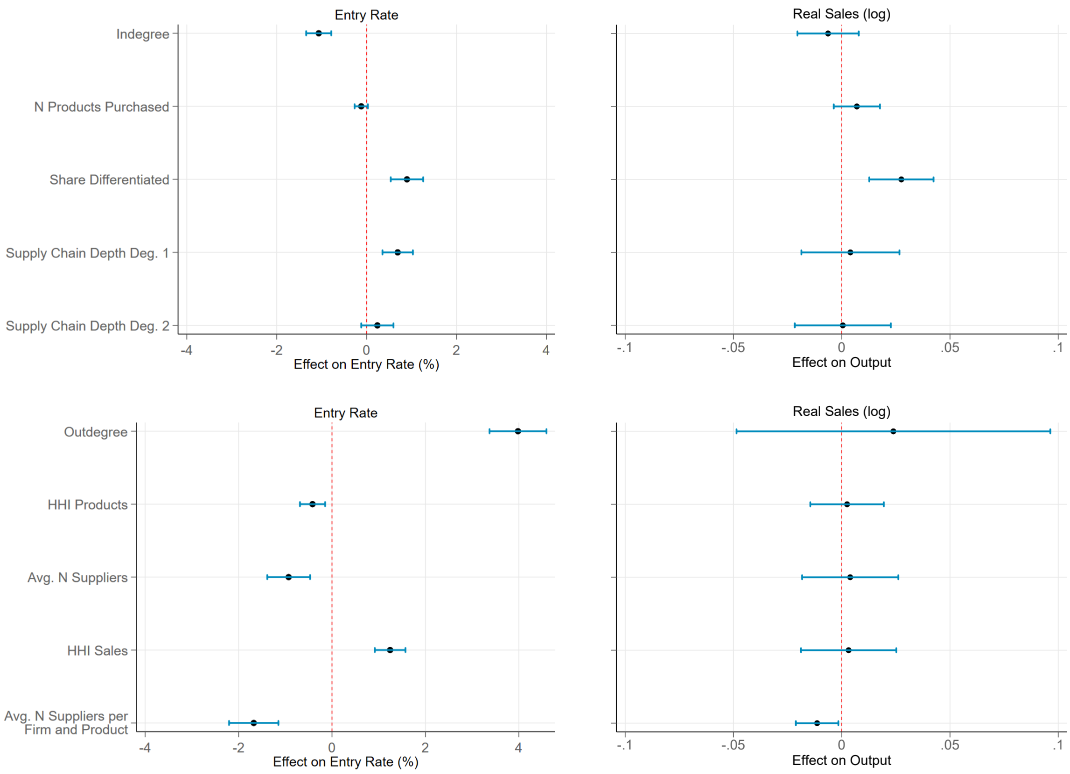
(a) Entry Rate (b) Controlling for Net-Separations



Note. We plot the estimated coefficients γ_x and their 95% confidence intervals. 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: 13.20. In panel (b), the purple line captures the input drop when controlling for net separations. Standard errors 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 as a control the net separations experienced by the firm. Such analysis quantifies what is the residual response in input purchases after we account for the extensive margin response experienced by the firm. As shown in Figure A6b, 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 30% to a drop of 15%. This finding suggests that the extensive margin is an important channel to measure supply chain disruptions.

Figure A7: 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 entry rate and the right panels for output. 95% confidence intervals reported. Standard errors clustered at buyer district level.

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

	Supply Chain Depth 1st Degree	**Supply Chain Depth 2nd Degree**	**Outdegree**	**Share Largest Supplier**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	1.094**	1.099**	2.112***	2.790***
	(0.440)	(0.439)	(0.444)	(0.341)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$	2.573***	2.508***	-3.191***	4.012***
	(0.238)	(0.235)	(0.348)	(0.208)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	-0.459***	-0.214*	-4.036***	-1.043***
	(0.116)	(0.107)	(0.263)	(0.213)
Observations	856,855	856,855	946,665	946,665
R-squared	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.
$***p < 0.01, **p < 0.05, *p < 0.1$ 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
		Supply Chain Depth 1st Degree	**Supply Chain Depth 2nd Degree**	**Outdegree**	**Share Largest Supplier**
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$		1.020	1.013	2.649*	3.670***
		(1.263)	(1.260)	(1.271)	(1.015)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Characteristic})_j$		4.013***	3.505***	-4.004***	9.010***
		(0.430)	(0.422)	(0.542)	(0.366)
$\mathbb{1}(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		-1.150***	-0.453*	-8.017***	-1.792***
		(0.247)	(0.247)	(0.381)	(0.393)
Observations		856,855	856,855	946,665	946,665
R-squared		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. $***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors 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**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.1849***	-0.192***	-0.184***	-0.163***	-0.177***
	(0.0250)	(0.0237)	(0.0239)	(0.0217)	(0.0285)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$		0.171***	0.114***	0.378***	-0.196***
		(0.0339)	(0.0250)	(0.0294)	(0.0128)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$		-0.0520***	0.0376**	0.0752***	-0.000238
		(0.0135)	(0.0151)	(0.00858)	(0.0159)
Observations	946,665	946,665	946,665	946,665	908,630
R-squared	0.530	0.531	0.531	0.533	0.534

	Supply Chain Depth 1st Degree	**Supply Chain Depth 2nd Degree**	**Outdegree**	**Share Largest Supplier**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.0698**	-0.0704**	-0.154***	-0.161***
	(0.0280)	(0.0278)	(0.0274)	(0.0164)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.173***	-0.168***	0.104***	-0.677***
	(0.0139)	(0.0139)	(0.0179)	(0.0117)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	0.0514***	0.0373**	0.236***	0.0240**
	(0.0144)	(0.0145)	(0.0192)	(0.00955)
Observations	856,855	856,855	946,665	946,665
R-squared	0.535	0.535	0.531	0.535

	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**
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j$	-0.147***	-0.185***	-0.176***	-0.176***
	(0.0224)	(0.0252)	(0.0168)	(0.0220)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Characteristic})_j$	-0.533***	0.0646***	-0.568***	0.285***
	(0.00958)	(0.0114)	(0.0153)	(0.00993)
$\mathbb{1}\,(t > \text{Feb2020}) \times (\text{Supplier Risk})_j \times (\text{Characteristic})_j$	-0.0597***	-0.0583***	0.0434***	-0.0677***
	(0.0128)	(0.0165)	(0.0141)	(0.0190)
Observations	946,665	946,665	946,665	946,665
R-squared	0.534	0.531	0.534	0.532

Note. Table presents difference-in-difference results from Equation 5 for the log nominal input value outcome. $***p < 0.01, **p < 0.05, *p < 0.1$ Standard errors clustered at buyer district level in parentheses.

Table A7: Pairwise correlation between supply-chain characteristics

	Buyer Size	Buyer Indegree	Share of purchases - largest supplier	Share of purchases - differentiated prod.
Buyer Size	1.00	-	-	-
Buyer Indegree	0.47	1.00	-	-
Share of purchases - largest supplier	-0.05	-0.21	1.00	-
Share of purchases - differentiated prod.	-0.02	0.00	0.04	1.00
Average Supplier Indegree	-0.02	-0.07	0.11	0.02
Number of products purchased	0.42	0.58	-0.30	0.06
Concentration of products purchased (HHI)	-0.03	-0.15	0.51	-0.06
Number of suppliers in market	-0.01	0.04	-0.10	0.11
Concentration on suppliers (HHI)	-0.10	-0.20	0.72	0.04
Number of suppliers per product	0.24	0.48	-0.41	-0.03
1st degree supply chain depth	0.04	0.04	0.03	0.21
2nd degree supply chain depth	0.04	0.05	0.03	0.12
	Average Supplier Indegree	**Number of products purchased**	**Concentration of products purchased (HHI)**	**Number of suppliers in market**
Average Supplier Indegree	1.00	-	-	-
Number of products purchased	-0.01	1.00	-	-
Concentration of products purchased (HHI)	0.00	-0.44	1.00	-
Number of suppliers in market	-0.07	-0.06	0.14	1.00
Concentration on suppliers (HHI)	0.08	-0.14	-0.04	-0.23
Number of suppliers per product	-0.09	0.23	0.03	0.26
1st degree supply chain depth	0.00	0.21	-0.28	-0.40
2nd degree supply chain depth	-0.04	0.20	-0.25	-0.37
	Concentration on suppliers (HHI)	**Number of suppliers per product**	**1st degree supply chain depth**	**2nd degree supply chain depth**
Concentration on suppliers (HHI)	1.00	-	-	-
Number of suppliers per product	-0.59	1.00	-	-
1st degree supply chain depth	0.20	-0.17	1.00	-
2nd degree supply chain depth	0.18	-0.14	0.96	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.

To explore the new-link formation more in detail, we use an event study approach as in equation 7, to compare the supplier composition of high- and low-supplier-risk firms over time.

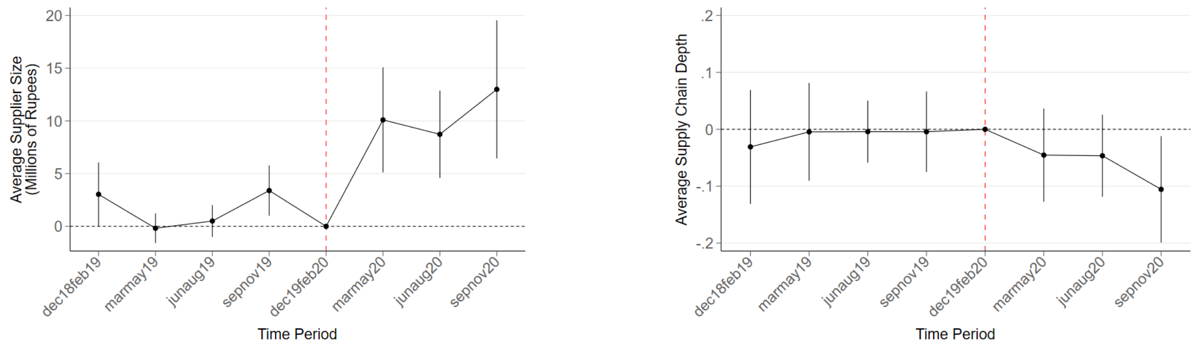
$$\bar{y}_{j,t,r,k} = \sum_{x=1}^{T} \gamma_x \left[\mathbb{1} \left(t = x \right)_t \times (\text{Supplier Risk})_j \right] + \delta_j + \delta_{r,t} + \delta_{k,t} + \delta_{s,t} + \epsilon_{j,t,r,k} \tag{7}$$

In Figure A8, we plot the event studies for two specific outcomes: Average supplier size and the average supply chain depth. As shown in Figure A8a, 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 who are 10% larger than firms with an average supply chain risk. Figure A8b, 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 A8b shows that firms with higher supplier risk decrease their average supply chain depth, buying products that are, on average, slightly less complex.

Figure A8: 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. 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 clustered at buyer district level.