Trade Disruptions and Reshoring*

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Abstract

Firms are increasingly concerned about the resilience of their sales and sourcing decisions as conflicts, natural disasters, and labor disputes frequently disrupt trade. Using administrative tax data, we show that a temporary disruption in trade due to state border closures in India led to a persistent trade collapse within the country – inter-state trade relative to intra-state remains 4% lower even six months after all the restrictions were lifted. We show that reshoring explains this phenomenon as plants more dependent on inter-state sales (input-sourcing) shift from inter- to intra-state sales (input-sourcing). We find that state borders rather than distance are salient in explaining the observed reshoring. Finally, we propose a novel product-level measure, incorporating demand and supply characteristics, that determines the extent of reshoring.

JEL Codes: F14, E32, L23, L6

Keywords: Domestic trade, Reshoring, Scope for Home Expansion, Trade collapse

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1 Introduction

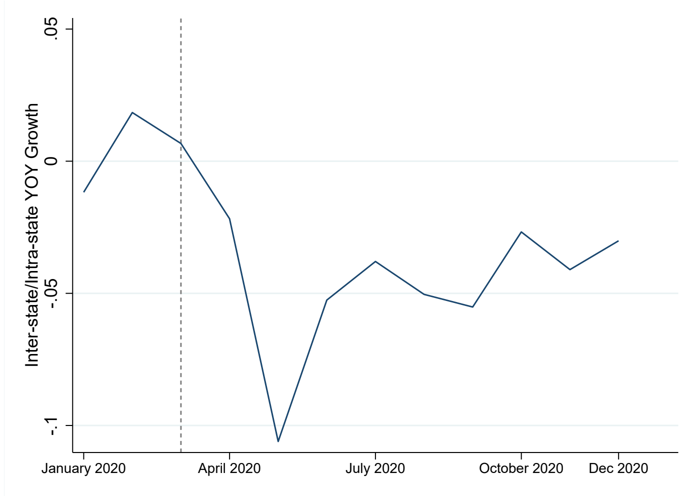
Delays in input sourcing and sales due to disruptions arising from natural disasters, labor disputes, and conflicts, among other factors are some of the major current challenges affecting timely sales and procurement by firms (Business Continuity Institute's reports for 2019 and 2021). Existing literature examines output losses for firms having linkages to regions affected by such disruptions (Barrot and Sauvagnat, 2016; Carvalho et al., 2021). However, there is little research on whether firms change where they sell and source from, to mitigate similar disruptions in the future.

We examine this question in the context of the COVID-19 induced national lockdown in India, which led to a strict closure of all inter-state borders during March 2020 - May 2020.[1] Apart from providing a unique natural experiment to examine how intra-national trade responds to temporary disruptions, the Indian context is advantageous for two additional reasons. First, India is a large country with *35* states and with an average state population comparable to countries like Spain. Second, novel administrative data on intra-national trade flows from the Goods and Service tax Network (GSTN) track inter- and intra-state sales for plants at a monthly frequency in India. This allows us to study the changes in domestic trade at a granular level.

The first national lockdown in India started on March 25, 2020, and was in place until May 2020. The sudden lockdown curtailed movement of goods as inter-state borders were closed and freight services reduced during this period. A comparison of inter- vs. intra-state trade pre- and post-lockdown shows a clear inter-state trade collapse – a phenomenon where both inter-state trade and output collapse, but trade recovers slower than output. Figure 1 traces this domestic trade collapse over time. We see a drastic decline of more than 10 percent in inter- to intra-state sales growth immediately after the lockdown. This ratio remains 4 percent lower relative to the pre-lockdown level even towards the end of 2020, signifying that inter-state sales recovery has been slower than intra-state sales. Given the administrative restrictions on cross-state transportation, the immediate decline in inter-state trade until May 2020 is not surprising. However, this does not explain the slower recovery in inter-state vis-a-vis intra-state sales in the latter half of 2020, when the restrictions were completely removed.

[1] In India, there are police check posts at state borders to monitor movement of goods and people, which makes the enforcement of such border closures possible.

Figure 1: Domestic Trade Collapse: Inter- to Intra-State Sales Ratio Growth (YoY)



Notes: The figure plots the evolution of inter- to intra-state sales ratio growth (year-on-year) in India. The inter-state (intra-state) sales is the sum of inter-state (intra-state) sales of all regions. There are 35 states/union territories in India. The vertical line corresponds to the first national lockdown in India. The sales data comes from E-Way Bills information collected by the GSTN and primarily captures the sales in the manufacturing sector.

We show that reshoring of sales and input sourcing by plants, a previously undocumented channel, explains this phenomenon. We find that plants more dependent on inter-state trade before the shock shift to intra-state trade, thus, leading to reshoring or shift in sales and input sourcing from inter to intra-state.[2] Multiple other channels (like changes in demand, or financial constraints) can also explain the observed trade collapse. In our analyses, we control for or rule out these channels and find causal evidence in favor of the reshoring channel. Moreover, we find that state borders rather than distance are salient in explaining the observed reshoring. This shows that a rise in trade cost associated with border closures primarily explains the reshoring rather than an increased cost of transportation. Lastly, we define a new product attribute, called *Scope for Home Expansion*, which captures the extent to which production within the state can be diverted towards within state consumption. We find that this is an important product attribute that explains reshoring.

We use the administrative data on E-Way Bills collected by the GSTN of India for the analyses. As per law, every establishment in India is required to generate an

[2]There can be other channels that can explain the reported trade collapse. For instance, increase in intra-state sales and input sourcing by plants selling more in their home state (or sourcing more within the state) before the shock by utilizing their pre-existing intra-state connections, while those selling inter-state failing to recover. Our results rule out such channels.

E-Way Bill for shipments above INR 50,000 ($\approx$ USD 700) in value. We observe the data at plant$\times$state and product$\times$state level with monthly frequency for 2019–2020 for the top thousand plants and products in each state. The sales data include both intermediate and final goods, as the shipments can go to either downstream plants or consumers, while the inputs data consists exclusively of intermediate goods. For both plants and products, we observe the values of inter- and intra-state sales and inputs.

To test the reshoring channel, we use an event study design around the first national lockdown, akin to a difference-in-differences (DID) estimation strategy. We examine if the change in plant level inter- and intra-state sales post the lockdown varies by their pre-pandemic dependence on inter-state sales, with January 2020 as our baseline month, relative to the change in the plant outcomes between the same months in 2019. We measure a plant's inter-state sales dependence as the fraction of its inter-state sales to total sales in 2019, i.e., prior to the shock. We control for unobserved heterogeneity at plant-month level that rules out plant specific seasonality. Additionally, we control for demand shocks by using a rich set of fixed effects on industrial sector of a plant by time. We, therefore, compare plants before and after the lockdown, within a given industry that differ in their pre-lockdown exposure to inter-state sales.

We find a 6 percent decline in inter-state sales and a simultaneous 8 percent increase in intra-state sales for a one-standard-deviation increase in plants' inter-state sales dependence until December 2020. This persistent shift in plant-level trade lasts much beyond the administrative border closure policy that ended in May 2020. The reshoring is on account of change in trade volumes as we control for changes in sectoral prices throughout our analyses. A direct test using the count of shipments (proxy measure for quantity) also shows that changes in trade volume drive reshoring. Additionally, these results are not driven by the entry-exit of plants in the sample as we use a balanced set of plants for which total sales information is available for each month. We find analogous results on reshoring in plant inputs, i.e., intermediate goods trade. The plants more dependent on inter-state inputs switch to sourcing more inputs from home state until the end of the year.

Given the role of reshoring in explaining the trade collapse, we investigate its main determinants. First, we disentangle the role of state administrative boundaries in determining reshoring vis-á-vis an average increase in trade cost (analogous to iceberg trade cost over distance) after the lockdown. If trade costs per unit distance increase uniformly, then plants located inland would reshore more relative to those on the border. This is because for the plants located on the state border selling across the border could be geographically closer than selling to far-away areas within their state. Alternatively, if there is uncertainty about state administrative border closures, then expected trade costs would increase only for cross-border trade after the shock. It would result in similar reshoring outcomes for inland and border plants.[3] We find no difference in reshoring between the two sets of plants, thereby confirming the salience of state administrative boundaries in determining reshoring.

Second, on the products side, we show that *Scope for Home Expansion (SHE)*, a new measure that we define in the paper, is the key product characteristic that determines reshoring. A product in a given state has high *SHE* if the product has high inter-state sales in the pre-pandemic period and this state also imports sufficient value of this product from other states. A high *SHE* allows for excess production (sold inter-state before the lockdown) to be diverted towards the home state. We find that products with a high *SHE* not only reshore their sales more but also witness higher growth in their total sales until the end of the year. Other product-level characteristics like product differentiation (Rauch, 1999) do not explain reshoring. Overall, the reshoring channel contributes 7.6 percent towards the aggregate sales growth (year-on-year) in India during October–December 2020. However, there is significant heterogeneity in its contribution to sales growth across states due to variation in state-level *SHE*.

We include a range of fixed effects in our empirical specification to control for alternate channels that can explain the trade collapse. Since the pandemic and the associated lockdowns also impact demand, differential changes in demand across industrial-sectors can affect plant outcomes. To account for changes in demand, we include sector$\times$month$\times$year fixed-effects, at the National Industry Classification (NIC) five-digit level for plant data and product$\times$month$\times$year fixed-effects for product data (Levchenko et al., 2010; Bricongne et al., 2012; Behrens et al., 2013). These fixed effects also rule out the possibility that changes in aggregate product prices drive our results. Our results are also invariant to controlling for alternate channels, like firms' financial conditions, that explain the collapse in international trade after the Global Financial Crisis (GFC) (Amiti and Weinstein, 2011; Chor and Manova, 2012). We also directly test and rule out the existence of any pre-trends in inter and intra-state trade by inter-state dependence of plants, before the lockdown.

[3] While there were some restrictions on within-state trade, the closures of state borders completely blockaded inter-state trade.

Our results hold under a variety of alternative specifications. We control for the effect of other plant-level characteristics like plant size and location on plant outcomes; use district×month×year fixed-effects to control for variation in movement restrictions across districts over time.[4] We also drop plants that import or export internationally to rule out any spillover effects from international trade disruption during the pandemic (Chacha et al., 2021).

Our paper makes three contributions to the literature. First, we causally examine how reshoring can explain trade collapse resulting from temporary transport disruptions. While the existing literature documents output losses due to supply disruptions arising from natural disasters (Barrot and Sauvagnat, 2016; Carvalho et al., 2021), the adjustment by firms in response to such shocks remains under studied. In the aftermath of the COVID-19 pandemic, Antràs (2020) and Bonadio et al. (2020) warn of reshoring in international trade. However, to the best of our knowledge, evidence on reshoring is non-existent. Our results on reshoring, while based on a within country setting, have crucial implications for international trade where disruptions are likely to occur more frequently. Our findings of persistent changes in trade patterns due to reshoring in a domestic trade setting, where the uncertainty is likely to be lower, show that reshoring may be larger in international trade in response to temporary disruptions. In fact, within country setting provides cleaner identification since confounding factors such as changes in protectionism or exchange rates can be ruled out.

Second, we find that plants are flexible in choosing their sales destination over a two-three quarter period. These results mirror the "vent-for-surplus" channel discussed in Almunia et al. (2021). They document a high degree of substitutability between firm-level exports and domestic sales as firms switch to selling abroad after a fall in local demand. Our results show that this channel works in the opposite direction as well. We find that plants substitute outside home sales (inputs) with sales (inputs) within home after suffering a decline in inter-state trade. Figuratively, one can refer to it as the "venting-in" mechanism.[5]

Third, we find that high *SHE* products are more likely to undergo reshoring

[4] A district is a smaller administrative unit within a state in India. The 35 states were divided into 723 districts in 2019.

[5] Studies also document how shocks to exports due to changes in international demand affect domestic sales of firms. The evidence here is mixed. While some studies find complementarities between the two (Berman et al., 2015; Erbahar, 2020), others find that such complementarities are limited due to capacity constraints (Vannoorenberghe, 2012; Soderbery, 2014).

suggesting significant substitutability across these products. In the context of international trade, Boehm et al. (2019) estimate how the US affiliates of Japanese multinational firms respond to the Tōhoku earthquake in Japan and find near-zero elasticity of substitution for intermediate imports across countries. They cannot directly test the substitution of imports by domestic inputs due to unavailability of domestic trade data. Similarly, using data from one state in India Fujiy et al. (2021) find low substitutability across inputs during the lockdown period.[6] However, using data from all the Indian states and over a longer time horizon we find that high *SHE* products witness reorientation in their sales towards the home state, therefore displaying high substitutability between home and inter-state sales of these products.[7]

Our work is also related to recent studies examining the impact of the pandemic on international trade (Bonadio et al. (2020); Liu et al. (2021); Lafrogne-Joussier et al. (2022), among others). Similar analyses on within-country trade, however, are non-existent. Therefore, our work contributes to the emerging literature on domestic trade issues (Atkin and Donaldson, 2015; Donaldson, 2018; Atkin and Khandelwal, 2020). The rest of the paper is structured as follows. In Section 2, we describe the timeline of COVID-19 associated lockdown in India, and the datasets. We discuss the estimation strategy and main results on trade collapse and reshoring in Section 3. Section 4 tests for the main determinants of reshoring. Section 5 estimates the impact on the aggregate sales due to the reshoring channel, and Section 6 concludes.

2 Background and Data

2.1 Timeline of the Shock

Figure 2 describes the timeline of the COVID-19 pandemic and the associated economic disruptions in India. India reported its first case of COVID-19 on January 30, 2020 (Andrews et al., 2020), while it announced its first lockdown in response to the

[6] Given the data available to them, they cannot test the reshoring channel over a longer period and multiple states. In a recent paper, Khanna et al. (2022) examine the resilience of supply chains after the lockdown in India. They find that firm-to-firm links are less likely to break when suppliers are larger, inputs more differentiated, and the number of alternative suppliers is low.

[7] The flexibility in organizing supply chains is also documented in Bernard et al. (2019), who examine the impact of the opening of high-speed trains in Japan on the formation of buyer-seller relationships and firm performance. Korovkin and Makarin (2020) use simulation to calculate how new network formation across firms compensates for the network destruction after the Ukraine-Russia war in 2014.

pandemic on March 24, 2020. This lockdown was in force from March 25 to April 14, 2020. In fact, with just 500 reported Covid cases at the time of the lockdown announcement, India imposed one of the world's strictest shutdowns, restricting all economic activities except those deemed essential like food and medicine, all within 24 hours (Balajee et al., 2020). However, the severity and sudden enforcement of the lockdown led to uncertainty in these essential commodity markets too, since permits and licenses were to be obtained for operations during the lockdown (Mahajan and Tomar, 2021).

The impact of the lockdown was more severe for inter-state trade, as restrictions on truck movement led to the choking of inter-state borders (Appendix Figure A.1). It had a significant impact on inter-state trade as freight movement is dominated by road transport in India, accounting for 75% of the volume in 2019.[8] The closure of inter-state borders for non-essential products continued until May 17, 2020.[9] After April 14, the federal government issued color-coded district-level restrictions - wherein the extent of restrictions across districts were imposed based on reported district level COVID-19 cases - as discussed in Beyer et al. (2021) and Fujiy et al. (2021). These district-level restrictions were mostly phased out by the end of May 2020, with a gradual easing of mobility restrictions on people.

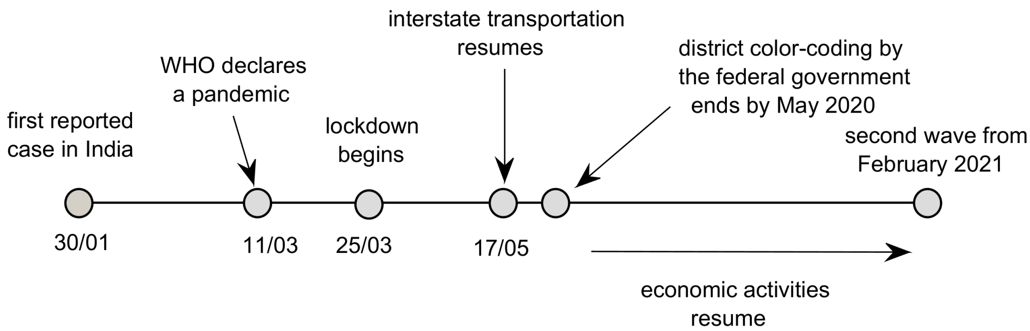
The economic activity in India followed the above timeline closely. The GDP contracted by 23.9 percent (April–June 2020) and 7.5 percent (July–September 2020) in comparison to 4.2 percent growth in the previous year (April 2019–March 2020). The economic recovery picked up in the October–December 2020 quarter, with the GDP registering a 0.4 percent growth.

The first wave of infections was much smaller than expected, making the lockdown a more significant factor behind the loss in output in 2020 rather than the health shock. Appendix Figure A.2 shows that the second and more infectious wave hit the country in February 2021, leading to a resumption of lockdowns and significant disruption in economic activity thereafter.

[8]See: India Transport Report. The lockdown negatively impacted the movement of freight by railways as well (Business Standard).

[9]See Business Standard. The restrictions on the movement of people in the early phase of the lockdown negatively impacted manufacturing activity, as a large fraction of manufacturing activity cannot be done from home. As we discuss in the next section, our data mainly pertains to this sector.

Figure 2: Timeline of COVID-19 in India



Notes: Timeline of Covid-related major events in India in 2020. The first case was noted on 30^{th} January in India. On 11^{th} March 2020, the WHO declared COVID-19 to be a pandemic. India entered into the first national lockdown on 25^{th} March which included a ban on inter-state transportation except for goods deemed essential. On May 12^{th}, a set of fiscal and monetary stimulus were announced (not shown above). On 17^{th} May, inter-state transportation began with limited scope. From 1^{st} July, restrictions on domestic flights and trains were gradually relaxed. By August 1, all inter-state movement restrictions were fully lifted. Thereafter, further unlockdowns gradually relaxed restrictions placed on schools, gymnasiums and other public spaces (The Indian Express). By 13^{th} September, Nomura India Business Resumption Index indicated that the economic activities reached almost the pre-pandemic level (The Economic Times). On 12^{th} October and 12^{th} November, further additions to economic stimulus packages were announced. The second infectious wave hit India in February 2021.

2.2 Data

We use data on Electronic-Way (E-Way) Bills collected by the Goods and Services Tax Network (GSTN) in India. The GSTN implemented the E-Way Bills system in April 2018, whereby plants are legally required to generate an E-Way Bill before transporting goods above INR 50,000 (around USD 700), irrespective of the mode of transport. This threshold for generating E-Way Bills is very small, especially for the large plants considered in our analyses. The E-Way Bills allow the GSTN to collect real-time information on the sales of goods. The data, however, includes information mainly for the manufacturing sector since an E-Way Bill is required only for the movement of physical goods. We observe the following datasets from January 2019 to December 2020.

Plant Data: It has plant-level monthly sales and input information.[10] On the sales side there are two datasets that record sales by the destination type – inter-state and intra-state.[11] The first data record inter-state plant sales for the top 1,000 plants by inter-state sales in a given state and month. Similarly, the second one records intra-state plant sales for the top 1,000 plants by intra-state sales in a given state and month. Each plant has a unique identifier at the state level and can be tracked over time and across the two datasets.

These data cover a significant portion of manufacturing sales in India and adequately capture domestic economic activities. The top 1,000 plants contribute on average 59 percent to the aggregate state level sales, while the top 200 plants contribute 42 percent. Given that there are more than 1,000 plants in most states for each destination type, the set of reported plants changes each month.[12] However, a significant fraction of plants are present for the entire duration.

The two input sourcing datasets are similar and provide monthly information on intra- and inter-state input sourcing for the top 1,000 plants. The unique plant identifier allows us to track a plant across the sales and the inputs data. One crucial difference between the sales and inputs is that the former consists of both business-to-business (B2B) and business-to-consumer (B2C) transactions, while the latter captures only B2B transactions, i.e., the value of intermediate goods. The B2C transactions roughly account for one-third of the total sales. This ratio is similar to the corresponding measure reported in global trade (UNCTAD, 2020).

The summary statistics of plant data are provided in Panel (a) of Table 1. We calculate total monthly sales (inputs) of a plant as the sum of intra- and inter-state sales (inputs) in a given month. We keep a balanced set of plants for which we observe total sales in every month. As discussed later, all our results are robust to various subsets of plants chosen on the basis of their frequency of appearance in our data. The balanced dataset ensures that our main results are not driven by the entry and

[10] The time frame of the data used is limited by its availability to the authors. Though the collection of data started in April 2018, it only stabilized by the end of 2018.

[11] In this paper, we use the word 'state' to denote both states and union territories within India. There were 27 states and 8 union territories in India during the time-frame of this study.

[12] It is possible that some plants may not be observed in both the datasets in a given month. For instance, a plant may lie in the top 1,000 for inter-state sales in a month but have low intra-state sales and never lie in the top 1,000 plants by intra-state sales in that state. In this case, we only observe its inter-state sales. See Chakrabarti and Tomar (2021) for more details on the coverage of E-Way Bills data.

exit of plants from the set of top 1,000 plants.[13] The first four rows of Table 1, Panel (a), show the summary statistics for the sales data—number of plants per state (row (1)), average total monthly sales (row (2)) and average monthly sales by type (row (3) and row (4)). On average there are 272.1 plants from each state, i.e., a total of 9,252 plants from 34 states. We use data for 34 states in our main analyses as one of the states is very small and has no plants in the balanced sample. The average total sales of these plants is INR 355.8 million per month in 2019, which falls to 337.1 million in 2020. This corresponds to a 5.2 percent fall in average monthly sales between 2019 and 2020. We also see a fall in the average inter- and intra-state sales. The former falls by 7.9 percent and the latter by 3.4 percent. These statistics immediately highlight a larger negative impact of the lockdown on inter-state sales.

Next, we show information on plants that report total inputs for all 24 months in our data (the last four rows of Panel (a)). There are on average 265.6 such plants from each state (row (5)) i.e., in total 9,029 plants. The input side also presents a similar pattern—a fall in average monthly total inputs in 2020 vis-à-vis 2019 by 5.2 percent, and a higher fall in inter-state (6.4%) than intra-state inputs (4%).

The above administrative data do not provide information on the sector of each plant. We use the publicly available data with the Ministry of Corporate Affairs (MCA) to map each plant to its industrial sector (NIC five-digit). The MCA database provides the industrial sector of the parent company. We match the parent company name for a plant and are able to map 83 percent and 72 percent of the plants in the total sales and inputs data, respectively. The balanced set of plants constitute 52 percent of total plant sales in 2019, and after matching with MCA data this reduces to 47 percent of total sales. Hence, we continue to capture a large fraction of plant sales even after losing some plants in the merged data.[14]

Product Data: The E-Way Bills data also provide product level (at HSN four-digit level) data for every state and month. It records three types of sales—inter-state sales,

[13]This restriction minimizes concerns that our results on total sales are driven by entry and exit of plants. However, results are robust to inclusion of plants that appear in our dataset for fewer months as well as those that strictly report both intra-state and inter-state sales (inputs) for each of the 24 months.

[14]Of the total plants matched, we are able to match the exact firm name in 85 percent of plant names, while the remaining are obtained using a fuzzy match based on word occurrences—exact match with first three–four words (3%) and first two words (12%). All the results presented in the paper are robust to restricting the analyses to the set of plants whose parent firm names could be matched exactly with the MCA database.

Table 1: Summary Statistics

Panel (a): Plant Data (Sales and Inputs)						
	2019			2020		
	Obs.	Mean	S.D.	Obs.	Mean	S.D.
(1) Number of plants (Sales data)	408	272.1	151.9	408	272.1	151.9
(2) Total Sales	111024	355.8	1342.6	111024	337.1	1410.3
(3) Inter-State Sales	81092	309	1238.5	81983	285.4	1368.5
(4) Intra-State Sales	80685	179.1	493.9	81041	173.1	460.1
(5) Number of plants (Inputs data)	408	265.6	85.1	408	265.6	85.1
(6) Total Inputs	108348	223.9	802.6	108348	212.2	982.4
(7) Inter-State Inputs	81883	200.8	597.3	83113	187.2	913.1
(8) Intra-State Inputs	65204	120.0	589.9	64715	115.0	547.0

Panel (b): Product Data (Production and Sales)						
	2019			2020		
	Obs.	Mean	S.D.	Obs.	Mean	S.D.
(1) Number of Products (Sales data)	408	409.4	273.2	408	409.4	273.2
(2) Total Sales	167028	669.6	2504.3	167028	613.1	2515.8
(3) Inter-State Sales	162252	360.6	1612.4	160179	329.7	1640.5
(4) Intra-State Sales	161793	329.6	1259.4	160322	309.3	1253.1
(5) Inter-State Receivables	164161	343.4	1079.9	162318	313.9	1161.0

Panel (c): Inter-State Dependence (2019)						
	Obs.	Mean	Median	S.D.	Min	Max
(1) Plants: Inter-State Sales Fraction	9252	0.53	0.59	0.40	0.00	1.00
(2) Plants: Inter-State Inputs Fraction	9029	0.64	0.84	0.40	0.00	1.00
(3) Products: Inter-State Sales Fraction	13912	0.53	0.55	0.27	0.00	1.00
(4) Products: Inter-State Receivables Fraction	13912	0.65	0.68	0.23	0.00	1.00
(5) Products: Scope for Home Expansion	13912	0.47	0.46	0.26	0.00	1.00

Notes: Panel (a) shows the mean plant sales and inputs (in INR million), in years 2019 and 2020, for the balanced set of plants i.e. for plants for which total sales (for sales data) and total inputs (for inputs data) data is available for all the 24 months of data in our analyses respectively. The mean number of balanced plants in each state across the 12 months (408 observations for 34 states) for each category (Sales and Inputs) are also provided. The 'Total Sales (Inputs)' is further divided into Intra-State and Inter-State Sales (Inputs) in Panel (a). Panel (b) shows the mean product sales (in INR million) for the balanced set of products, i.e. for products for which total sales (domestic production) is available for all the 24 months of data in our analyses. The mean number of balanced products in each state across the 12 months (408 observations for 34 states) are also provided. The product level 'Total Sales' is further divided into Intra-State and Inter-State Sales in Panel (b). Additionally, Panel (b) also shows the mean product value received from other states for the same balanced set of products. Panel (c) shows the plant level mean of pre-pandemic (2019) Inter-State Sales and Inputs fraction for the balanced set of plants on total sales and inputs respectively. It also shows the product level mean of pre-pandemic (2019) Inter-State Sales and Receivables fraction for the balanced set of products.
Source: Plant and Product level E-way bills data (January 2019-December 2020).

intra-state sales, and inter-state receivables. Here, inter-state sales and intra-state sales refer to outside and within home state sales of a product produced in a given state. Inter-state receivables refer to the value of a product received by a state from other states. Once again, a product is reported in a dataset as long as it falls within the top 1,000 products for a given state and sales type. We report summary statistics for a balanced set of products in a state, for which total sales data is available for each month (Panel (b) of Table 1).[15] We calculate total monthly sales of a product originating in a state as the sum of intra- and inter-state sales for that product in a given month and state. On average, each state reports 409.4 products, i.e., in total 13,919 product×state combinations.[16] We find that total sales in the product data fall from INR 669.6 million per month in 2019 to 613.1 million in 2020. The fall is larger for inter-state sales (8.6%) and receipts (8.6%) relative to intra-state sales (6%).

3 Trade Collapse: What Explains it?

In this section, we provide plant-level evidence for the trade collapse, followed by investigating the role of reshoring channel in explaining it. Figure 1 shows the trade collapse at all India-level after the lockdown in March 2020. We find similar evidence at the granular plant level, where we additionally control for plant level seasonality and unobserved heterogeneity. We use a difference-in-differences estimation strategy (details in Appendix B.1) to estimate the change in inter-to-intra sales (inputs) ratio at plant level for each month before and after the lockdown, relative to the baseline month of January 2020. These estimates are reported in Figure 3. Panel (a) shows that there is a fall in inter- to intra-state sales ratio by 15 percent in April 2020. The coefficient bounces back thereafter, but continues to remain negative (5%) and significant from August 2020 onward. Therefore, the inter- to intra-state sales ratio declines immediately post-lockdown and the decline persists even after the initial shock subsides. We find a similar pattern for inter- to intra-state inputs ratio which

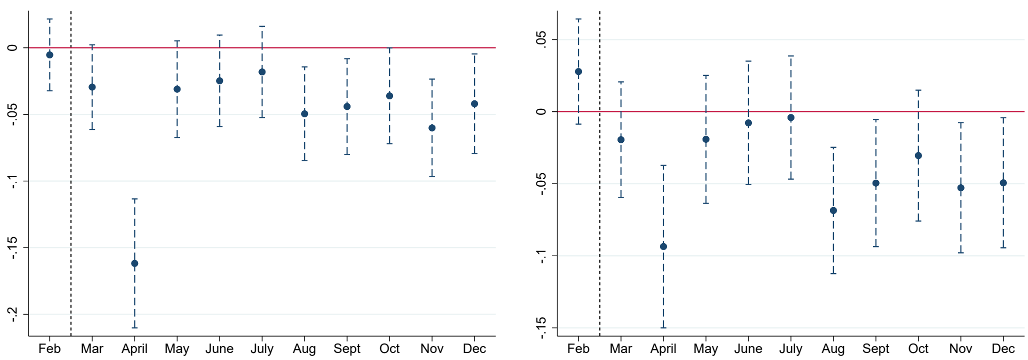
[15] The main results in the paper are based on these set of products. However, results are robust to inclusion of products that appear in our dataset for fewer months as well as those that strictly report intra-state and inter-state sales for each of the 24 months.

[16] Most products are mandated to register for an E-Way Bill. There are some exceptions related to food products, HSN Chapter 01-10, that do not require an E-Way Bill and are not present in our data. During the lockdown, food and medicine products were deemed essential and allowed to be produced and traded. As they suffered smaller disruption initially, we show robustness of our results by excluding them.

shows a persistent decline until the end of 2020 (Panel (b)).

Figure 3: Trade Collapse at Plant Level

(a) Inter- to Intra-state Sales ratio (b) Inter- to Intra-state Inputs ratio



Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_1^{\tau,c}$ in Equation B.1) for the impact on log of inter- to intra-state plant sales and inputs ratio respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Panel (a) includes a balanced set of plants for which both inter- and intra-state sales are observed every month. Similarly, Panel (b) includes a balanced set of plants for which both inter- and intra-state inputs are observed every month. All specifications include plant-month and year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India. More detailed exposition for this estimation is provided in Appendix Section B.1.

Next, we investigate the main determinants of the trade collapse. Ex-ante, it is not evident which factors lead to this phenomenon. For instance, it is plausible that plants with stronger pre-pandemic intra-state dependence increase their intra-state sales after the shock, or inter-state sales decline with no change in intra-state sales. Alternatively, plants with stronger pre-pandemic inter-state dependence may reshore their sales within home state to reduce any losses that may arise from future border restrictions. As discussed later, these plants have an incentive to reshore as their sales declined relatively more than those dependent on intra-state sales during the lockdown.

We present a model (similar to Gopinath and Neiman (2014)) with plant-level input sourcing and trade cost uncertainty in Appendix C to discuss these channels. A low but positive probability of border closure can increase uncertainty, leading to an increase in the expected price of inputs from outside states. In this simple setup, under reasonable parametric restrictions, we show that (a) an increase in inter-state trade cost leads to a decline in the share of inter-state inputs for a plant, and (b) plants more dependent on outside states for input sourcing shift to higher intra-state sourcing due to the cost increase. The trade collapse results demonstrate that the first implication holds. We now describe our empirical strategy to test the latter.

3.1 Empirical Strategy

We measure a plant's dependence on outside states (relative to home) for sales or inputs in the pre-pandemic period using the below definition:

$$f^c_{ir} = \frac{c^{inter}_{ir}}{c^{inter}_{ir} + c^{intra}_{ir}} \tag{1}$$

where f^c_{ir} is the fraction of inter-state over total sales (or inputs) in 2019 for plant i in state r and category $c \in \{Sales, Inputs\}$. For $c = sales$, a high value of f^{sales}_{ir} shows a higher dependence of plant i on inter-state sales. We calculate f^c_{ir} from data in 2019, so that inter-state dependence is a pre-pandemic measure. The summary statistics for f^c_{ir} are reported in Panel (c) of Table 1. For sales, the mean value of f^{sales}_{ir} is 0.53 while for inputs it is a bit higher at 0.64.

We examine the heterogeneous impact on plant outcomes after the lockdown based on their exposure to outside states (f^c_{ir}) using the following specification:

$$\begin{aligned} ln(z^c_{ijr,my}) = \gamma^c_0 \; &+ \sum_{\tau \in (m2020)} \gamma^{\tau,c}_1 (\mathbb{1}_m \times \mathbb{1}_{2020}) + \sum_{\tau \in (m2020)} \gamma^{\tau,c}_2 (\mathbb{1}_m \times \mathbb{1}_{2020} \times f^c_{ir}) \\ &+ \; \mathbb{1}_{2020} \times f^c_{ir} + \mathbb{1}_{2020} + \delta^c_{ir,m} + \delta^c_{j,my} + \mathbb{X}^c_{ir,my} + \varepsilon^c_{ijr,my} \end{aligned} \tag{2}$$

where $z^c_{ijr,my}$ is the outcome variable for plant i belonging to sector j in state r for category c in month m of year y. $\mathbb{1}_m$ is a dummy variable that takes a value equal to one if the observation belongs to month m, and zero otherwise. $\mathbb{1}_{2020}$ is a dummy that takes a value of one for year 2020, and zero otherwise. The set $m2020$ refers to the months in February–December 2020. We account for plant×month level unobserved heterogeneity through plant×month fixed-effects, $\delta^c_{ir,m}$, which also control for any plant specific seasonality in outcomes. These fixed effects ($\delta^c_{ir,m}$) preclude the need to control for $\mathbb{1}_m$ or $\mathbb{1}_m \times f^c_{ir}$ in the above specification. $\delta^c_{j,my}$ controls for sector×month×year fixed-effects. Inclusion of $\delta^c_{j,my}$ preclude us from estimating $\gamma^{\tau,c}_1$ as they get absorbed in the sector×month×year fixed-effects. We also include $\mathbb{X}^c_{ir,my}$ as a vector of time-varying controls at the plant-level. These controls are of the form $\sum_{\tau\in(m2020)} \phi^{\tau,c}(\mathbb{1}_m \times \mathbb{1}_{2020} \times X^c_{ir})$ and the relevant double interactions. In all specifications, when examining the impact of inter-state sales dependence on plant sales, we control for inter-state input dependence of the plant, i.e., $X^{sales}_{ir} = f^{input}_{ir}$. This controls for the input shock suffered by plants due to inter-state input dependence. Similarly, we control for inter-state sales dependence, $X^{input}_{ir} = f^{sales}_{ir}$, when estimating the effects on inputs.[17]

For detailed exposition of Equation 2, consider the case when $c = sales$ and inter-state sales is the outcome variable. The above estimation strategy is akin to estimating heterogeneous DID treatment effects where the DID effect is captured by $\gamma_1^{\tau,sales}$ that gives the average difference in inter-state sales between $\tau \in m2020$ i.e., for a given month m in 2020, and January 2020 relative to the difference between the same months in 2019 for all plants.[18] However, our main coefficient of interest is $\gamma_2^{\tau,sales}$ on the interaction term $\mathbb{1}_m \times \mathbb{1}_{2020} \times f^{sales}_{ir}$. This coefficient gives the impact of plants' inter-state sales dependence on their inter-state sales in τ. Specifically, it measures the differential change in inter-state sales in month m in year 2020 relative to January 2020, over and above the change in sales between month m in 2019 and January 2019, as a function of plants' inter-state sales dependence. A negative $\gamma_2^{\tau,sales}$ shows that plant inter-state sales fall more in τ if the plant has a higher inter-state dependence for sales before the pandemic. For reshoring to explain the trade collapse, $\gamma_2^{\tau,sales}$ coefficients would be negative for inter-state sales and positive for intra-state sales as the dependent variables.

Our identification strategy is based on the following assumptions. First, the plant outcomes should not affect the timing or the occurrence of the lockdown. As we discuss in Section 2.1, the imposition of the lockdown was sudden and exogenous. Second, the estimates should not be driven by seasonality. To address this, we control

[17] Theoretically, a greater dependence on inter-state inputs can reduce sales more post the lockdown, with the effect attenuated by inventory effects. Similarly, greater dependence on inter-state sales resulting in a larger reduction on the sales side can consequently decrease the demand for inputs post the lockdown..

[18] Here the first difference is the percent change in plant outcome between month m in year 2020 and January 2020 and that between month m in year 2019 and January 2019, and the second one is the difference between these two differences. The treatment is the lockdown in the country that began on March 25, 2020. Therefore, the treatment period is March–December 2020. In our estimation strategy, rather than taking a simple difference between treatment and control period (adjusting for seasonality), we directly estimate month-wise coefficients taking January as the base month. We do this because our main objective is to study the differential impact of the lockdown on the outcome variables over the months and not just the average effect before and after the lockdown.

for plant level seasonality, arising from the month-on-month changes in sales due to variation in plant characteristics like its industrial sector or destination of sales (through $\delta^c_{ir,m}$).[19] Third, we require that plants' dependence on outside states f^c_{ir}, should not influence their outcomes prior to the lockdown in March 2020. Since our specification measures month-by-month impact, we report the differential impact in February 2020, to rule out this concern. Additionally, we present pre-trends into a quarter before the lockdown using an estimation strategy that does not account for plant-month seasonality and hence allows us to plot longer pre-trends.

There can be a concern that the lockdown led to both supply and demand shocks for plants. To rule out the demand effects, we control for sector×month×year fixed-effects, $\delta^c_{j,my}$, that capture any time-varying changes at the sector level. It controls for any variation in plant outcomes that may arise if certain sectors are more dependent on inter-state trade. Therefore, our estimates isolate the differential impact on plants due to the supply shock. In fact, sector time fixed-effects also ensure that a differential change in sectoral prices does not drive our results.

3.2 Results: Reshoring

We estimate Equation 2 with log of inter- and intra-state monthly plant sales and inputs as the dependent variables. The coefficients ($\gamma_2^{\tau,c}$) from these estimations, that give the heterogeneous impact of inter-state dependence on the plant outcomes, are plotted in Figure 4. All estimations correspond to the most saturated specification i.e., the one which includes $\mathbb{X}^c_{ir,my}$ and $\delta^c_{j,my}$ as controls.[20]

Panel (a) shows an immediately greater decline (April 2020) in inter-state sales of plants that sell more outside their home state.[21] The coefficient in April gives a $0.4 \times 0.4 \times 100 = 16$ percent larger decline in inter-state sales for a one-standard-

[19] Seasonality can vary by durability of goods manufactured by a plant. It can also vary by states to which a plant sells output, since festive seasons vary across states in India given the diverse religious practices.

[20] Coefficient estimates for γ_1^τ along with those for γ_2^τ, without sector time fixed effects, are reported in Appendix Table A.1. Our results on γ_2^τ also hold without including any controls ($\mathbb{X}^c_{ir,my}$) and have been omitted for brevity, but available on request. In fact, we do not find any significant heterogeneous effect of inter-state Input Fraction (included as a control) on inter- or intra-state sales of a plant post the lockdown.

[21] The larger negative impact on inter-state sales during the lockdown in April 2020 for plants selling more outside their home state could be due to coordination issues. Plants with smaller inter-state sales fraction may have found it easier to transport smaller amounts or coordinate with a relatively smaller number of outside state buyers.

deviation increase in the fraction of inter-state sales dependence. Notably, inter-state sales remain relatively lower for these plants even in the later months as most coefficients remain negative and significant. We find a persistent $0.15 \times 0.4 \times 100 = 6$ percent lower value of inter-state sales for a one-standard-deviation increase in inter-state sales dependence. The trends are opposite for intra-state sales (Panel (b)). All the monthly coefficients are insignificant until June 2020 and suggest that outside state dependence does not differentially impact plants' intra-state sales immediately post the lockdown. However, the coefficients become positive and significant from July to December 2020, showing that the intra-state sales increase relatively more for plants that sell more outside their home state. The coefficient magnitude of around 0.2 gives a $0.2 \times 0.4 \times 100 = 8$ percent increase in intra-state sales for a one-standard-deviation increase in the fraction of inter-state sales dependence. Notably, we do not find any differential impact on the outcome variables by inter-state dependence in February 2020, before the lockdown, showing that these findings are not driven by pre-existing trends.

The above results for the home-ward shift in plant trade are based on value of goods. Given that our specification controls for differential trends in sectoral prices through time varying sector fixed-effects, our estimates account for any changes in prices. Nevertheless, we directly test for the impact on quantity. The E-Way Bills data do not provide quantity information but give the count of E-Way Bills generated by each plant. This count is extensive margin measure for quantity, as it provides a measure of the number of transactions each month. We report the impact of the plant's outside state dependence on its log count of inter-state and intra-state E-Way Sales Bills in Panels (c) and (d) of Figure 4, respectively. The monthly coefficients, plotted in Panel (c), show a relative decline in inter-state sales quantity with increase in inter-state sales dependence (similar to Panel (a)). We further find a differential increase in intra-state sales quantity in Panel (d) by inter-state dependence (similar to Panel (b)).

The results for plant inputs are reported in Figure 5. Inter-state input sourcing falls relatively more for plants that have higher inter-state dependence, since the interaction coefficients ($\gamma_2^{\tau,c}$) are negative and significant from June to December 2020 (Panel (a)). The average decline is equal to 4 percent for a one-standard-deviation increase in inter-state input fraction. We find no differential impact of inter-state input dependence on intra-state input sourcing until July 2020 (Panel (b)). However,

Figure 4: Reshoring in Plant Sales

Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state sales and intra-state sales respectively (sales refers to value of sales, unless otherwise mentioned), by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The log count of E-Way Sale Bills is used as the dependent variable as a proxy for quantity in the regressions in Panels (c) and (d). The figures in Panels (c) and (d) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state sales E-Way Bills and intra-state sales E-Way Bills respectively, by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. All specifications include plant$\times$month and sector$\times$month$\times$year fixed effects. We additionally control for heterogeneous impacts of plant-level inter-state Inputs fraction (2019) for every month in 2020. The regressions include a set of plants for which total sales information is available for every month. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure 5: Reshoring in Plant Inputs

(a) Inter-state Inputs (b) Intra-state Inputs

(c) Inter-state Inputs Quantity (d) Intra-state Inputs Quantity

Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively (inputs refers to value of inputs, unless otherwise mentioned), by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The log count of E-Way Input Bills is used as the dependent variable as a proxy for quantity in the regressions in Panels (c) and (d). The figures in Panels (c) and (d) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state inputs E-Way Bills and intra-state inputs E-Way Bills respectively, by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. All specifications include plant×month and sector×month×year fixed effects. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019) for every month in 2020. The regressions include a set of plants for which total inputs information is available for every month. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

there is a relative increase in intra-state input sourcing from August to December 2020 by plants with a higher inter-state input dependence. The intra-state inputs increase by $0.25 \times 0.23 \times 100 = 6$ percent for a one-standard-deviation increase in input dependence. Once again, we do not find any significant impact on outcome variables during February 2020. Furthermore, Panels (c) and (d) show that these results are driven by changes in quantity traded. There is a persistent decline in inter-state input quantity (Panel (c)) and a persistent increase in intra-state input quantity (Panel (d)) for plants with higher inter-state input dependence.[22]

The above results provide evidence for reshoring led trade collapse. We find an increase in intra-state trade with a simultaneous decline in inter-state trade, for plants' having higher inter-state dependence. In terms of timing, there is an immediate and large relative decline in inter-state sales and less than full relative recovery until December 2020 for plants depending on outside state sales. These plants could not substitute to selling within the home state immediately after the lockdown. However, once they start to sell more intra-state in July 2020, they continue to do so until the end of the year, months after border restrictions were completely eased. These results indicate that there is a lag (few months) between the initial shock and reshoring by plants. It might also explain why Fujiy et al. (2021) find no substitutability in inputs as they consider plant response in the quarter immediately after the lockdown.

We further test if reshoring is sufficient to overcome the loss in inter-state trade for plants with high outside state dependence. We run similar regressions as in Equation 2, with the log of total sales (inputs) as our dependent variables. We find that the impact on total sales (inputs) continues to be negative towards the later months of 2020 (Appendix Table A.2). Therefore, reshoring only aids in partial recovery for plants with high inter-state dependence. We also find that the reduction in total sales during the lockdown period was higher for plants previously more exposed to inter-state trade. It again indicates a stronger incentive for these plants to reshore in order to minimize future losses due to border disruptions.

[22]The estimated Equation 2 also allows us to evaluate the impact of inter-state input dependence on plant sales and vice versa. The results are reported in Figure A.3. We find no impact of inter-state input dependence on sales (Panel (a) and (b)). However, a high inter-state sales dependence has a negative impact on input sourcing, both intra- and inter-state. It suggests that sales dependence determine both input sourcing and final sales destination decision.

3.3 Plant's Prior Financial Conditions

Our results until now show that reshoring by plants can explain the trade collapse. However, it is possible that other plant attributes are equally important. One such attribute is plants' financial condition before the shock. In the international trade context, Amiti and Weinstein (2011) and Chor and Manova (2012) show that a decline in trade credit, affecting financially weaker firms, was one of the main factors behind the trade collapse after the GFC. Notably, trade credit cycles are likely to play a smaller role for domestic trade. Nonetheless, a sudden decline in cash flow and credit crunch during the initial phase of the lockdown could have had a larger negative impact on production and sales of firms with a weak financial position. If such firms are also more vulnerable to disruptions in inter-state trade, they may reduce their dependence on it.

To test this, we merge our data with Prowess data (2019) to obtain information on firm-level financial variables.[23] Our approach is similar to Behrens et al. (2013), and we use pre-pandemic cash-to-assets and leverage ratio in 2019 interacted with $\mathbb{1}_m \times \mathbb{1}_{2020}$ (and all double interactions therein) as additional explanatory variables in Equation 2.

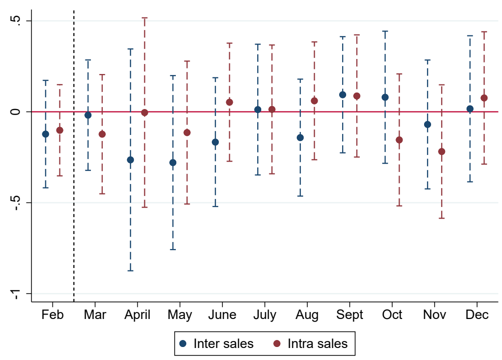
Figure 6, Panels (a) and (b), plot the coefficients for the effect of cash-to-assets ratio ($\mathbb{1}_m \times \mathbb{1}_{2020} \times$ cash-to-assets ratio) and leverage ratio ($\mathbb{1}_m \times \mathbb{1}_{2020} \times$ leverage ratio) on sales, respectively. Each panel shows the results from two regressions with inter-state and intra-state sales as dependent variables. We find that all coefficients are insignificant. Similarly, in Panels (c) and (d), we do not find any differential effect of any financial ratio on sourcing of inputs from either inter- or intra-state. Thus, plants' prior financial condition does not explain the trade collapse. In all these regressions, the coefficients on inter-state dependence (γ_2^τ) continue to be in line with the results in Section 3.2.[24]

[23] https://prowessdx.cmie.com/ provides data for over 40,000 listed and unlisted Indian firms. Hence, these regressions are estimated on a smaller set of plants which can be matched across the two datasets. We are able to get financial details for 36 percent of the plants in our data from Prowess.

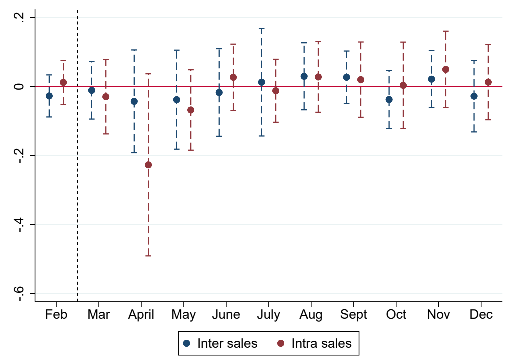
[24] We also test the effect of financial condition for plants more dependent on outside states on reshoring. We include $\mathbb{1}_m \times \mathbb{1}_{2020} \times f_{ir}^c \times$ financial variable as an explanatory variable in Equation 2 and find no differential impact on reshoring by these financial ratios.

Figure 6: Effect of Plants' Financial Condition On Trade

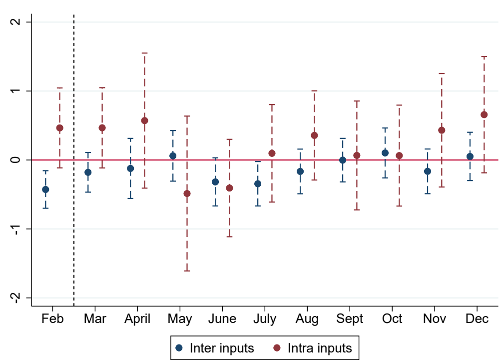
(a) Sales: By cash to assets ratio



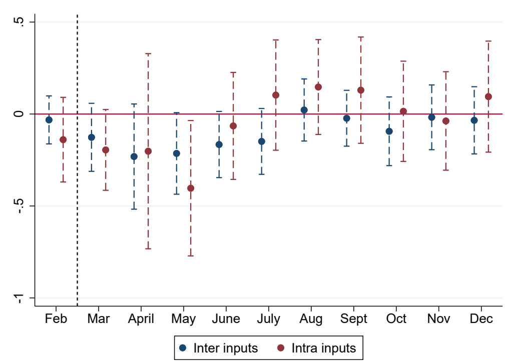
(b) Sales: By leverage ratio



(c) Inputs: By cash to assets ratio



(d) Inputs: By leverage ratio



Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-state sales and intra-state sales, by plant-level cash to assets ratio and leverage ratio, respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The figures in Panels (c) and (d) plot the monthly coefficients for the heterogeneous impact on log of inter-state inputs and intra-state inputs, by plant-level cash to assets ratio and leverage ratio, respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019), inter-state Inputs Fraction (2019), heterogeneous impacts of total within-country sales of the plant in 2019 (size), indicator variables for plants belonging to multi-plant firms and those lying in border districts, for every month in 2020. The regressions in Panels (a)-(b) and (c)-(d) include a set of plants in a state for which total sales and inputs are available for every month, respectively. All specifications include plant×month and sector×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

3.4 Robustness

Longer Pre-trends: As discussed earlier, our DID specification allows us to look at pre-trends only in February 2020 due to data availability constraints. However, a strategy without controls for plant-level seasonality, can give us pre-trends before February 2020.[25] To check this, we estimate a specification, with February 2020 as the base month, and look at changes in plant outcomes varying by plant-level inter-state dependence. We report coefficients until the last quarter of 2019. Appendix Figure A.4 plots the monthly coefficients of the heterogeneous impact of inter-state dependence obtained from this specification. There are no significant pre-trends, while post-lockdown coefficients continue to match our baseline results.

Unbalanced Plant Sample: Our main results are based on a balanced set of plants, which exist in the data for the entire duration. Alternatively, we test if our results hold for a larger sample of plants by including all plants that appear for a minimum of six months in 2019. Figure A.5 shows that our main results continue to hold for this sample of mid-sized plants too.

Variation in Restrictions across Districts: While all economic activities returned to pre-lockdown levels across most states after August 2020, some localities within a state could still enforce restrictions to contain the COVID-19 spread. There was also variation in stringency of restrictions across districts between mid-April to May (Beyer et al., 2021; Fujiy et al., 2021). Therefore, we include district$\times$month$\times$year fixed-effects to control for time-varying heterogeneity in stringency on mobility restrictions at the lowest administrative level observed in our plant data. Figure A.6 shows that our results continue to hold even in this stringent specification.

Export and Import Status: For our main analysis, we use data only on domestic sales and sourcing of plants since approximately 80% (70%) of the plants did not export (import) anything in 2019. Even among the ones who engaged in international trade, more than half exported or imported less than 10% of the sales or inputs value in 2019. Therefore, the exposure of an average plant to international trade is minimal. Nevertheless, we check if our results are driven by plants exposed to international

[25] In this specification we control for overall plant-level unobserved heterogeneity (δ_{ir}) instead of $\delta_{ir,m}$. Seasonality is controlled at the sector level in this specification.

trade. To do this, we re-estimate our plant-level regressions for the sub-set of plants not engaged in exports and imports in 2019. Our results remain the same (Figure A.7).

Other Robustness at Plant Level: Our results are robust to using an indicator variable to capture whether a plants' outside state dependence is above the median level (Figure A.8). In another specification, we estimate the heterogeneous impacts due to plants' parent-firm structure (part of a multi-plant firm or not), plants' prior financial condition and plant size (total sales in 2019). None of the results change (Figure A.9). This allays any concerns that outside state dependence is correlated with other plant characteristics and those factors drive the results.

Product Level: We use the product data at state level and find that products having higher pre-pandemic inter-state sales dependence witness a relative decline in inter-state sales and a relative increase in intra-state sales post-lockdown (Appendix Figure B.3). These findings confirm reshoring at product level. We discuss the detailed strategy and results in Appendix Section B.2.

4 Determinants of Reshoring

The above results show that plants more dependent on outside states for sales and inputs are the ones that switch to within state trade. Below we test for channels that explain this switch.

4.1 State Administrative Boundaries

We first test if the reshoring is differentially affected by the distance of a plant from the state border. This test allows us to differentiate between the impact of distance vs uncertainty behind the observed reshoring. It is possible that the reshoring results mainly reflect distance effect, i.e., all plants prefer to buy and sell near their own geographic location after the shock, and administrative state boundaries do not matter. If true, plants located away from the state border (inland plants) and having high prior inter-state sales exposure would increase their intra-state sales differentially more as they prefer to sell near their location after the shock. At the same time, border plants with similar inter-state dependence would witness a lower reduction in inter-state sales as neighboring states are closer to them. If the distance effect dominates, we would see a lower increase in intra-state sales (inputs) and a lower decline in inter-state sales (inputs) for border plants, vis-a-vis the inland ones. Alternatively, a low but positive probability of future border closures can increase uncertainty, leading to an increase in the expected trade costs and price of goods from outside states. Since the uncertainty about crossing the administrative state border is similar for both inland and border plants, their intensity of reshoring would be similar.

For this test, we define an indicator variable, $Border_{ir}$, that takes a value of one if plant i in r is in a district lying on the state border, else zero. We estimate the effect of $\mathbb{1}_m \times \mathbb{1}_{2020} \times f^c_{ir} \times Border_{ir}$ as an additional explanatory variable in Equation 2.[26] We estimate the impact on inter-state and intra-state sales and inputs as the dependent variables and plot the coefficients for sales and inputs in Panel (a) and (b) of Figure 7, respectively. In both the panels, most coefficients on the interaction terms $\mathbb{1}_m \times \mathbb{1}_{2020} \times f^{sales}_{ir} \times Border_{ir}$ are insignificant, showing that reshoring by border plants is not significantly different from the inland ones. Further, none of the coefficients on $\mathbb{1}_m \times \mathbb{1}_{2020} \times Border_{ir}$ are significant (omitted for brevity). Therefore, uncertainty about administrative state boundary closure seems more relevant than distance for plant reshoring.

4.2 Scope for Home Expansion (SHE)

The outside state dependence, f^c_{ir}, is a plant level supply side measure and an insufficient demand in the home state may limit the extent of reshoring. Using product level data, we define a novel measure, *Scope for Home Expansion* (SHE), that incorporates both demand and supply side constraints. We first define a product's dependence on outside states for sales (analogous to the plant measure):

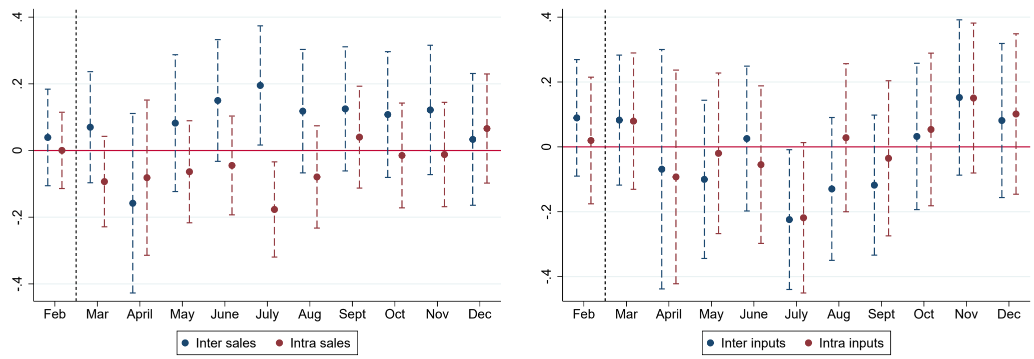
$$f_{kr,sales} = \frac{\text{Sales}^{inter}_{kr}}{\text{Sales}^{inter}_{kr} + \text{Sales}^{intra}_{kr}} = \frac{\text{Sales}^{inter}_{kr}}{\text{Total Production}_{kr}} \tag{3}$$

where $f_{kr,sales}$ is the fraction of inter-state sales over home-state production in 2019, for product k produced in state r. Here, $\text{Sales}^{inter}_{kr}$ refers to the inter-state sales and

[26]We control for all relevant triple and double interactions to account for the direct effect of inter-state dependence and plants' location on the border in this specification: $\mathbb{1}_m \times \mathbb{1}_{2020} \times f^c_{ir}$, $\mathbb{1}_m \times \mathbb{1}_{2020} \times Border_{ir}$., $\mathbb{1}_{2020} \times f^c_{ir}$ and $\mathbb{1}_{2020} \times Border^c_{ir}$.

Figure 7: State Administrative Border Effect on Plant Reshoring

(a) Sales: By Inter-state Sales Fraction × Border (b) Inputs: By Inter-state Inputs Fraction × Border



Notes: Panel (a) plots the monthly coefficients for the heterogeneous impact on log of inter- state sales and intra-state sales by plant-level Inter-State Sales Fraction (2019) by whether a plant is located on the border of a state, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Panel (b) plots the monthly coefficients for the heterogeneous impact on log of inter- state inputs and intra-state inputs by plant-level inter-state Inputs Fraction (2019) by whether a plant is located on the border of a state, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions in Panels (a) and (b) include a set of plants in a state for which total sales and inputs are available for every month, respectively. We control for the heterogeneous border effect of plant-level inter-state Inputs (Sales) Fraction (2019) when examining the effect on sales (inputs). All specifications include plant×month and sector×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

$\text{Sales}_{kr}^{intra}$ is the intra-state sales for the product in r. A high $f_{kr,sales}$ shows a high dependence of state r on outside states to sell k.

The $f_{kr,sales}$ is a supply side measure and does not capture demand constraints for reshoring. For instance, consider Tamil Nadu, a state in India, that sells a large quantity of coffee to other states. At the same time, it also buys a considerable quantity of coffee from other states, displaying the *love for variety* effect. Tamil Nadu's inter-state sales along with consumption of coffee from outside states allow for the potential substitutability of outside coffee with coffee produced within Tamil Nadu. The excess demand for product k in state r which is fulfilled through receivables (or imports from other states) is given by:

$$f_{kr,receivables} = \frac{\text{Receivables}_{kr}^{inter}}{\text{Receivables}_{kr}^{inter} + \text{Sales}_{kr}^{intra}} = \frac{\text{Receivables}_{kr}^{inter}}{\text{Total Sales}_{kr}} \tag{4}$$

where $f_{kr,receivables}$ is the fraction of inter-state receivables over home-state sales in 2019. A high $f_{kr,receivables}$ shows a high dependence of state r on outside states to source k. We capture the constraints presented in the above example through the

Scope for Home Expansion (SHE) measure defined at the product-state level as:

$$SHE_{kr} = \min\left[f_{kr,sales} \ , \ f_{kr,receivables}\right]. \tag{5}$$

If state r does not sell any k outside its home state before the pandemic, then the first fraction in the minima function is zero and r cannot fulfill the demand for k through home production. In this case, SHE_{kr} is zero. Similarly, if state r does not buy k from other states before the pandemic, then r cannot divert k towards home consumption. The second fraction in the minima function is now zero. Only when both these fractions are large, SHE_{kr} is large, and the outside state sales of product k produced in state r can be substituted by selling within the home state.[27]

A list of products (at 2-digit HSN) with the highest and the lowest *SHE* is provided in Appendix Table A.4. Apparel, fabrics and shoes (HSN 50, 52, 61, 62, 64) have high *SHE* on average. While mineral and chemical based products (HSN 80, 78, 36, 31, 37) and furskins (HSN 43) have the least *SHE*. Processed food items (HSN 22, 19, 15) also have low *SHE*, reflecting state-level supply catering to local tastes (Atkin, 2013).

[27] This measure of *SHE* is more appropriate for our analyses than using Grubel-Lloyd index, an intra-industry substitution measure. For the i-th product, Grubel-Lloyd index is given by $GL_i = 1 - \frac{|X_i - M_i|}{X_i + M_i}$ where X and M represents export and import. However, our choice of using SHE_{kr} instead of the Grubel-Lloyd index stems from two reasons. First, our objective is to estimate the impact on intra-state sales, and not just the change in inter-state trade. The presence of intra-state sales in the denominator of SHE_{kr}, therefore, captures the potential for change in intra-state sales. Under Grubel-Lloyd index, this dimension is absent. Second, Grubel-Lloyd index does not respond to total production capturing inter- and intra-state sales whereas the proposed measure SHE_{kr} does. For example, an export-import pair with values $\{5, \ 5\}$ would have different impacts with respect to the total production value being 10 or 100. The case with total production of 10 would provide plants stronger incentive to switch to intra-state sales to mitigate against future uncertainty. While Grubel-Lloyd index does not capture this, SHE_{kr} incorporates this level effect. Using a similar argument, Grubel-Lloyd index would be equal for export-import pairs with values $\{5, \ 5\}$ and $\{100, \ 100\}$. However, even with the same intra-state sales value, say 10, the latter pair would provide greater potential for the plant to shift towards the home state. Our proposed measure captures this possibility too. Consequently, the Grubel-Lloyd index does not determine the shift from inter to intra-state trade in our analyses. These results are omitted for brevity but available on request.

4.2.1 Effect of *SHE* on Reshoring

We use a DID specification to measure the heterogeneous impact of SHE on product outcomes:

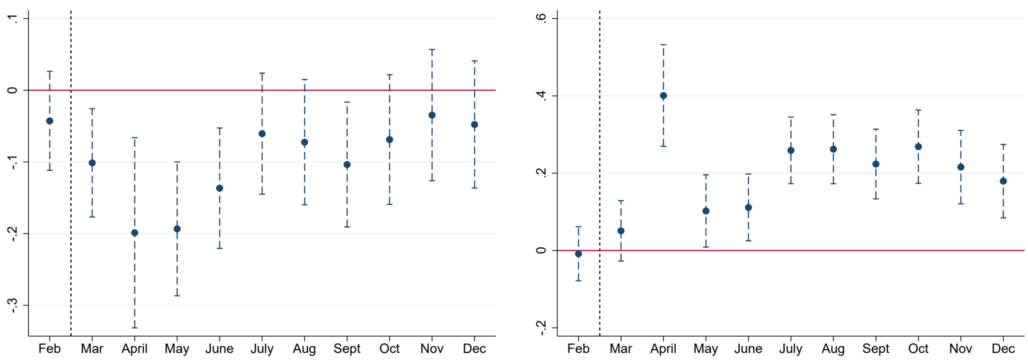
$$ln(z_{kr,my}) = \pi_0 + \sum_{\tau \in (m2020)} \pi_1^{\tau}(\mathbb{1}_m \times \mathbb{1}_{2020}) + \sum_{\tau \in (m2020)} \pi_2^{\tau}(\mathbb{1}_m \times \mathbb{1}_{2020} \times SHE_{kr})$$
$$+ \mathbb{1}_{2020} \times g_{kr} + \mathbb{1}_{2020} + \delta_{kr,m} + \delta_{k,my} + \mathbb{X}_{kr,my} + \varepsilon_{kr,my} \quad (6)$$

where $z_{kr,my} \in$ {inter-state sales, intra-state sales} is the outcome variable for product k produced in state r, in month m and year y. Here, $\delta_{kr,m}$ is product×state specific month fixed-effects and accounts for product-state level monthly seasonality. Note that the double interaction term $(\mathbb{1}_m \times SHE_{kr})$ is subsumed in $\delta_{kr,m}$. $\delta_{k,my}$ are the product-specific time fixed-effects to capture the overall variation in outcome variable for product k with time. These fixed effects control for variation in product demand over time at four-digit HSN code level (product×month×year fixed-effects) and therefore allow us to measure the differential impact due to SHE_{kr} of a product in a state, net of any demand effect. The inclusion of $\delta_{k,my}$, which captures the change in overall product sales over time, precludes us from estimating π_1^{τ} since all the variation is absorbed in product×month×year fixed-effects. Standard errors are clustered at the product-state level. The main coefficient of interest is π_2^{τ}, which captures the impact of SHE_{kr}, on product level outcomes in period τ. For *SHE* to explain reshoring, π_2^{τ} would be negative for inter-state sales and positive for intra-state sales.

We estimate Equation 6 and plot the π_2^{τ} coefficients in Figure 8, Panels (a) and (b), for inter- and intra-state sales respectively. We find that higher SHE leads to a relatively larger decline in inter-state sales throughout the period post-lockdown but the effect declines over time. The largest relative decline in inter-state product sales is in April and May 2020 when one standard-deviation increase in SHE leads to $0.2 \times 0.26 \times 100 = 5$ percent decline in inter-state sales. The coefficients remain negative during July–December 2020 but are insignificant during November–December 2020. On the other hand, high SHE leads to a relatively large increase in intra-state sales immediately post-lockdown (Panel (b)). The largest positive impact is during April 2020 (by $0.4 \times 0.26 \times 100 = 10\%$ for a one-standard-deviation increase in SHE). Thereafter, the impact remains positive and significant, though the magnitude declines. Even during August–December 2020, when there were no border restrictions, intra-

Figure 8: Reshoring in Product Sales: By Scope for Home Expansion

(a) Inter-state Sales (b) Intra-state Sales



Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2^τ in Equation 2) for the heterogeneous impact on log of inter-state and intra-state sales of a product originating in a state by product-state level Scope for Home Expansion respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The product-state level Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of products in a state for which total sales information is available for every month. All specifications include product×state×month and product×month×year fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

state product sales are higher by 6.5 percent for every standard-deviation increase in SHE. These results are not driven by either differential changes in demand across products over time or pre-existing trends in February 2020. Lastly, these results are on account of change in quantity as shown in Appendix Figure A.10.

These results demonstrate that intra-state sales increase immediately for products that are easy to substitute with home-state production during the lockdown (April 2020). This result is consistent with the closure of inter-state borders in the initial lockdown phase. It is, therefore, natural that within-state production, sold inter-state earlier, was diverted to satisfy demand within the home state when the need for local substitutes was the most critical. The large positive and significant impact on intra-state product sales of SHE in April 2020 therefore provides us the key product attribute behind the reshoring results. The same set of products that witness higher intra-state sales in April 2020 also continue to see higher sales within the home state until the end of the year. At the same time, high SHE has an opposite impact on inter-state sales. The outside home state sales decrease for these products immediately after the lockdown and the effect persists until December 2020.

Robustness of *SHE* Results: The above results for the impact of SHE on reshoring post-lockdown hold across a range of robustness checks. First, we estimate longer pre-trends (Appendix Figure A.11) and find no significant trends before the lockdown. Second, we use a larger sample of products that appear for a minimum of six months in 2019 (Appendix Figure A.12). Third, we control for state×month×year fixed-effects to control for time-varying heterogeneity in stringency measures at the state level and find that our results remain robust (Appendix Figure A.13). Lastly, we show that our main results are not driven by essential products like food and medical supplies that faced fewer movement restrictions during the lockdown (Figure A.14) and are also robust to using an indicator variable to capture whether a product's *SHE* is above the median level (Appendix Figure A.15).

4.2.2 Ruling Out Alternate Channels at Product Level

We look at product differentiation as classified in Rauch (1999) as an alternate product attribute that can explain reshoring. It is possible that products with high *SHE* are those that are non-differentiated and it is the latter attribute that determines *SHE* as well as reshoring. We should highlight here that the product differentiation measure is the same for a given HS 4-digit product across all states. Since we include product(HS 4-digit)×month×year fixed-effects in all regressions in Section 4.2.1, our results account for any variation arising due to product differentiation. Nevertheless, we estimate the direct impact of product differentiation on reshoring.

We estimate a similar specification as in Equation 6 by using product(HS 2-digit)×month×year fixed-effects to allow for estimation of the impact due to product differentiation. We use an indicator variable that equals one for differentiated products ($Diff_k$), else zero, and interact it with $\mathbb{1}_m \times \mathbb{1}_{2020}$ as an additional variable in Equation 6.[28] The results of this estimation are reported in Figure A.16. We find some immediate negative impact on inter- and intra-sales of differentiated products in April 2020. However, the effect dissipates immediately after. There are two plausible reasons why we do not see reshoring for less differentiated products. First, product differentiation measure from Rauch (1999) is at the product-level and hence, invariant across the

[28] We use the correspondence between SITC and HS 4-digit classification to merge Rauch (1999) product classification with our data.

states. Consequently, it does not capture product-state heterogeneity, unlike the *SHE*. Second, the complete breakdown of inter-state trade during the initial lockdown was an aggregate shock. In such a scenario, it is possible that all differentiated and non-differentiated products have a strong likelihood of getting reshored as long as they have a high *SHE*.[29]

However, product differentiation may still matter for reshoring within high *SHE* products. For instance, it could be less difficult to reshore non-differentiated products for a given *SHE*. To test this, we interact product differentiation indicator variable ($Diff_k$) with $\mathbb{1}_m \times \mathbb{1}_{2020} \times SHE_{kr}$ and estimate its impact on inter- and intra-state sales. The coefficients on $\mathbb{1}_m \times \mathbb{1}_{2020} \times SHE_{kr} \times Diff_k$ are plotted in Appendix Figure A.17 and are mostly insignificant. On the other hand coefficients on $\mathbb{1}_m \times \mathbb{1}_{2020} \times SHE_{kr}$ are significant and in the same directions as the results discussed in Section 4.2.1. Hence, product differentiation does not matter for reshoring.

4.3 Discussion

There are three key takeaways from our analyses. First, for plants and products more dependent on inter-state trade, reshoring is persistent until December 2020. The coefficient estimates from August–December 2020 are almost similar in magnitude and do not decay over time. Second, reshoring is similar for plants situated on the state border vs. those located inland. It shows that administrative state boundaries are more relevant for reshoring than distance. This result is not surprising as the most stringent movement restrictions during the first lockdown were imposed at the state borders, and reshoring serves as insurance against uncertainty regarding border closures in the future.[30] Furthermore, other plant-level attributes like financial condition prior to the lockdown do not explain reshoring. Crucially, all these results hold after controlling for

[29] Martin et al. (2022) use China shock, as it was the first country to undergo lockdown in 2020, to study the impact on French firms that use non-differentiated inputs. In their case, at least for the initial months when trading partners other than China were not under lockdown, French firms could substitute non-differentiated products from alternate countries, conditional on the existence of a pre-pandemic trade relationship.

[30] Another reason for the insignificance of the distance effect could be on account of a marginal change in fuel prices during this time. We know that Indian railways cut freight cost during this period (Source: The Hindu Business Line) and diesel prices did not see any sharp increase during August 2020–December 2020 (Source: Business Today). There was an increase in retail diesel price in India immediately post-lockdown from March 2020 to June 2020 (INR 70 per litre to 80 per litre), as government tax on fuel went up. However, from July onward the imposed taxes were reduced, thereby lowering the price until December 2020 (around INR 75 per litre).

time-varying changes in sectoral demand, and therefore, reshoring is not on account of demand shifts after the lockdown.

Lastly, we propose and test a new measure, *Scope for Home Expansion*, as the key product attribute that determines reshoring. It captures both the demand and supply side factors, at product×state level, necessary for capturing reshoring. *SHE* results also show that the substitutability of outside vs. home inputs alone is an insufficient measure, and one needs to account for home production to determine reshoring. In comparison to *SHE*, other product attributes like product differentiation, that do not capture both factors, do not explain the observed reshoring.

5 Reshoring: Contribution to Sales Growth

We now measure the quantitative importance of the reshoring channel by estimating the impact of reshoring on aggregate product sales. For this exercise, we divide products into three categories based on the above/below median value of inter-state sales dependence and scope for home expansion. Products with above-median SHE_{kr} are grouped together (29% share based on value in 2019). Out of the remaining, those with above-median f_{kr} form the second group (18% share). Lastly, products with below-median SHE_{kr} and below-median f_{kr} are pooled together in the baseline product group for our regression. The baseline group is the one that is unlikely to undergo reshoring. Further, we group months instead of estimating monthly coefficients and report the impact on the last quarter, October–December 2020, that captures the persistence in impact on product sales.

We focus on three counterfactual scenarios to quantify the effects of reshoring on aggregate sales recovery and report them in Table 2. The row named "Coefficient" reports the estimated difference in growth rate for the two types of products relative to the baseline group during October–December 2020, in columns (1) and (2).[31] We find a 1.2 percent relative growth in sales for products with above-median inter-state sales dependence and below-median SHE_{kr} (column (1)), while it is 2.6 percent for products with above-median SHE_{kr} (column (2)), compared to the baseline group.

In counterfactual Scenario I (column (3)), we calculate the overall impact of

[31] This is obtained by estimating Equation 6 where the dependent variable is log of total product sales, and instead of $f_{kr,sales}$ or SHE_{kr}, the above-median indicator variables for the two product attributes are interacted with $\mathbb{1}_m \times \mathbb{1}_{2020}$. Here, the months in the last quarter October–December indicate a single indicator variable in $\mathbb{1}_m$.

Table 2: Counterfactual Analyses: Impact on Sales Recovery due to Reshoring (October–December 2020)

	Below-Median SHE_{kr} & Above-Median $f_{kr,sales}$	Above-Median SHE_{kr}	Counterfactual Scenarios		
			I	II	III
	(1)	(2)	(3)	(4)	(5)
Coefficient	0.012	0.026			
Aggregate Sales Share (%)	18	29	47	29	29
Sales Growth Difference Actual-Scenario (% points)			0.97	0.75	0.41

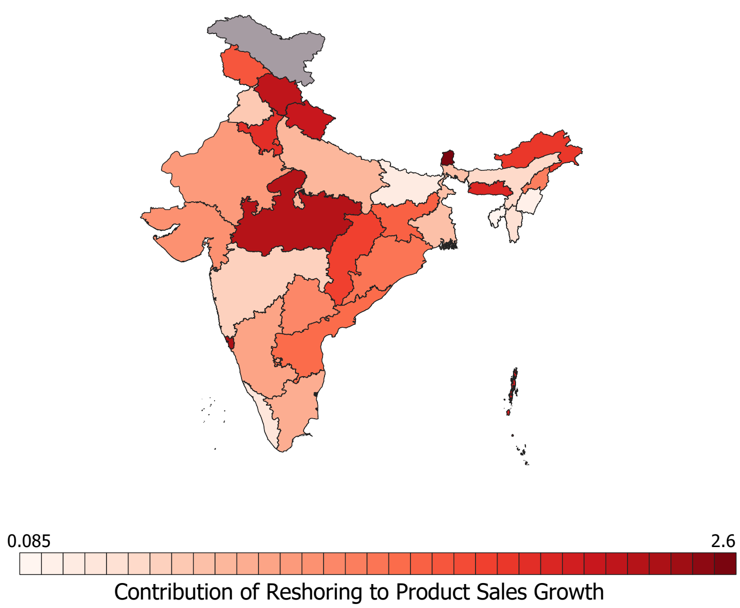
Notes: The coefficient value in columns (1) and (2) correspond to the regression with total product sales (state-product level) as the dependent variable. The independent variables include the interaction of two dummy variables (product categories based on above-median inter-state sales dependence and below-median SHE_{kr}, and above-median SHE_{kr}) with different time periods. The reported coefficients are for the interaction of these dummy variables with the October–December 2020 quarter. The Aggregate Sales Share (%) is the share of a given category of products in aggregate product sales in India in 2019. Scenario I is the full reshoring case with sales growth equal to zero for both types of products. Scenario II is the case with reshoring only for above-median SHE_{kr} products. Here, in the absence of reshoring, the sales would be zero instead of 2.6 percent. Scenario III captures the effect due to scope for home expansion alone. We now assume the sales growth to decline from 2.6 percent (column (2)) to 1.2 percent (column (1)), i.e., similar to the products with above-median $f_{kr,sales}$ and below-median SHE_{kr}.

reshoring on growth due to the non-baseline products (total share 18+29 = 47%). In the absence of reshoring, there would be no difference in their growth relative to the baseline group. Therefore, the growth difference between the actual and Scenario I would be $(0.012 \times 18 + 0.026 \times 29 =)$ 0.97 percentage points and captures the overall impact of reshoring.

Scenario II corresponds to the case with no reshoring only for the above-median SHE_{kr} products (column (4)). In this case, sales growth goes from 2.6 percent (actual) to zero (Scenario II) for 29 percent of the products. It results in a $(0.026 \times 29 =)$ 0.75 percentage points difference in the actual aggregate sales growth and sales growth under Scenario II. Therefore, in terms of explaining the overall impact of reshoring as captured in counterfactual Scenario I, $(100 \times 0.75/0.97 =)$ 77 percent comes from the above-median SHE_{kr} products. Finally, Scenario III (column (5)) gives the impact on above-median SHE_{kr} products over and above the impact on products in the first group (below-median SHE_{kr} and above-median $f_{kr,sales}$). This additional impact is equivalent to 1.4 percentage points change in growth (2.6 percent growth in column (2)

- 1.2 percent growth in column (1)). It translates into $(0.014 \times 29 =)$ 0.41 percentage points difference in actual aggregate sales growth and sales growth under Scenario III. It accounts for $(100 \times 0.41/0.97 =)$ 42 percent of the overall impact of reshoring as seen in Scenario I. The decomposition through Scenario II and III suggests that the contribution of products with the above-median SHE_{kr} to reshoring is higher than those with above-median f_{kr} and below-median SHE_{kr}.

Figure 9: Impact of Reshoring on Total Product Sales: Across State Heterogeneity



Notes: The map plots the increase in total sales (percentage points) under Scenario I, due to reshoring, for each state. The data is unavailable for grey-shaded states.

Overall, the reshoring channel leads to 0.97 percentage points increase in aggregate sales (under Scenario I). How much does this increase contribute to aggregate sales growth during this period? The aggregate product sales grew by 12.8 percentage points during October-December 2020. Thus, the contribution of reshoring to aggregate sales growth is equal to $(100 \times 0.97/12.8 =)$ 7.6 percent, confirming that the reshoring channel plays a crucial role in the recovery phase.[32] In general, a decline in inter-state trade after a shock can lead to loss in both producer and consumer welfare. The above

[32] The 12.8 percent value is obtained as the nominal growth in aggregate sales between the last quarter of 2020 and January 2020, over and above the change during the same time period in 2019.

results suggest that the reshoring channel would partially arrest such loss in welfare.

Finally, we evaluate the variation in recovery across states based on the reshoring channel. Given that states differ based on the product mix that they produce and consume, we expect substantial heterogeneity in their scope for home expansion and hence sales recovery. To gauge this heterogeneity, we perform the counterfactual exercise for each state in the absence of reshoring. We find the share of products (by value) in each of three product categories in each state and calculate the impact under counterfactual Scenario I. The gains from reshoring are reported in Figure 9.[33] We find that all states gain through reshoring, however, there is substantial heterogeneity in the magnitude. While some states see a minimal change of 0.08 percentage points, others gain as much as 2.6 percentage points in aggregate sales. Since the heterogeneity in reshoring potential determines the output recovery across states, it can be used as a factor for determining fiscal transfers after such shocks.

6 Conclusion

This paper is the first to document a within-country trade collapse after a temporary trade disruption. Using monthly plant- and product-level data on sales and inputs from 35 trading states in India, we find that reshoring by plants explains the observed trade collapse. Further, we find that the reshoring is more likely for products with high *Scope for Home Expansion*, a new measure we define in the paper. Such products not only increase their intra-state sales but also witness relatively higher growth in total sales towards the end of 2020, compensating for the decline in their inter-state sales. Overall, the reshoring channel accounts for 7.6 percent of the sales growth in October–December 2020.

Our analyses account for changes in demand, district-level variation in movement stringency and other plant (e.g. financial conditions), and product characteristics (e.g. product differentiation). The domestic trade context allows us to rule out other channels, such as protectionism and exchange rate movements. These findings can have implications for adjustment by firms to international trade disruptions. Since countries differ in their production-import-export baskets, our proposed measure *SHE* can potentially explain the heterogeneous recovery based on the flexibility of firms to

[33] Appendix Table A.5 shows the gains in total sales in each state under each of the three scenarios along with average value of *SHE* in each state (column (4)).

switch trading partners after trade disruptions. This question remains open for future research.

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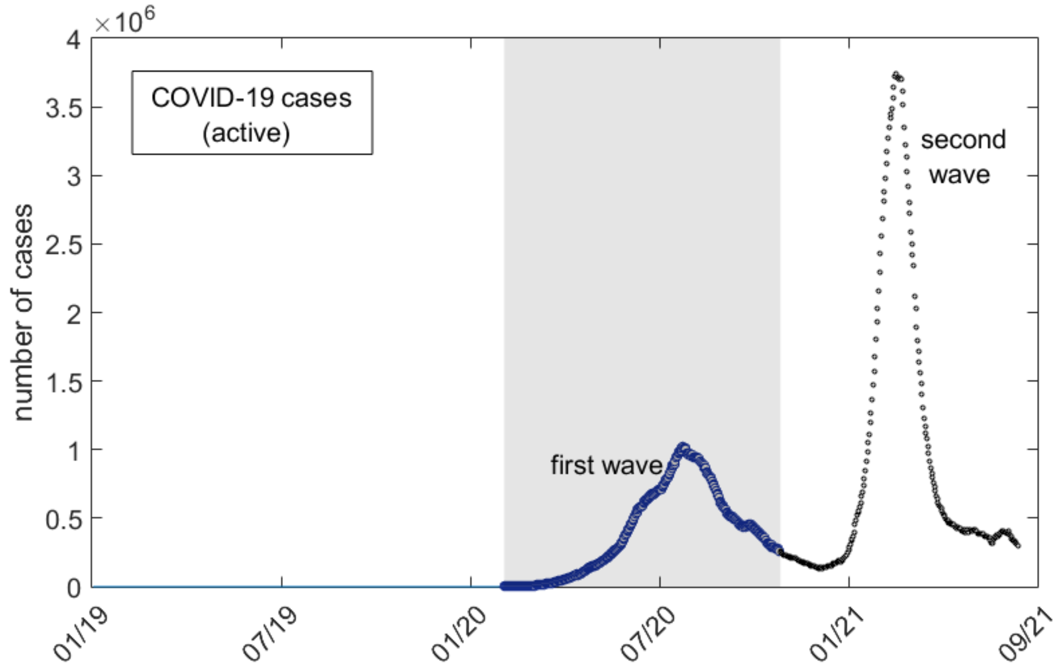
ONLINE APPENDIX

A Appendix: Figures and Tables

Figure A.1: Across State Border Closure post the National Lockdown in India

Source: Business Standard

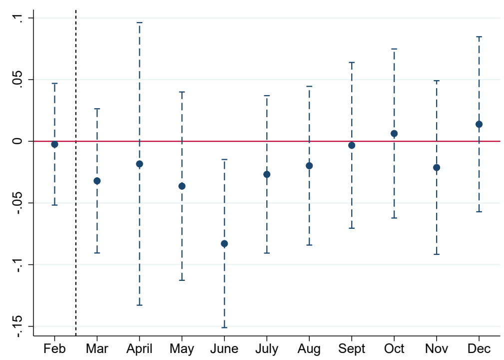
Figure A.2: Evolution of Active COVID-19 Cases in India



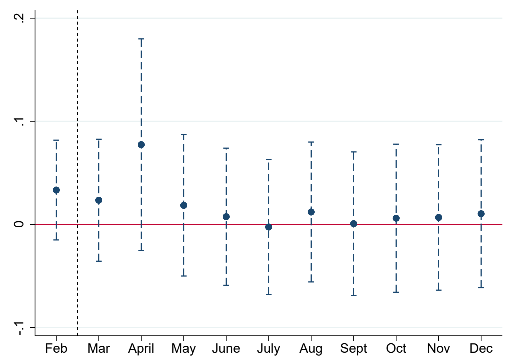
Notes: The figure plots the evolution of active COVID-19 cases in India, in monthly frequency from January 2019 till December 2021. The shaded area represents the period from the beginning of lockdown in India till December, 2020.

Figure A.3: Effect of Control Variables on Plant Sales and Input Sourcing

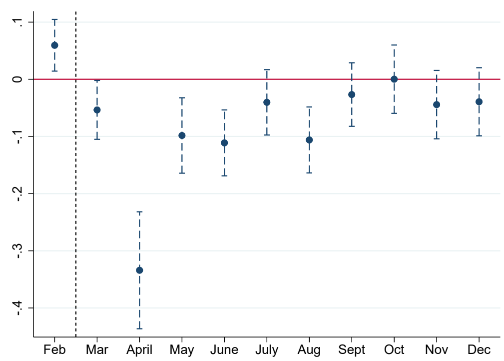
(a) Inter-State Sales: By Inputs Fraction



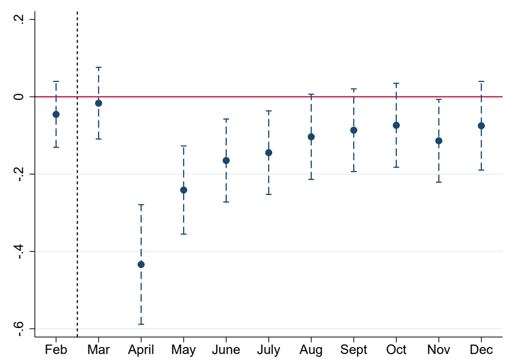
(b) Intra-State Sales: By Inputs Fraction



(c) Inter-State Inputs: By Sales Fraction



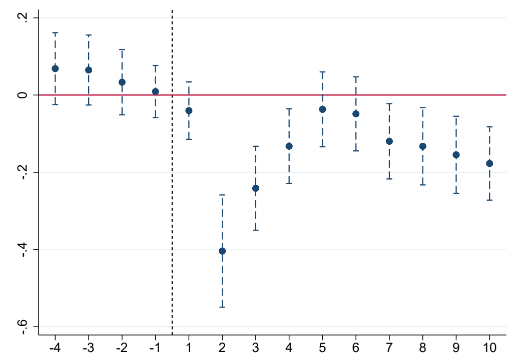
(d) Intra-State Inputs: By Sales Fraction



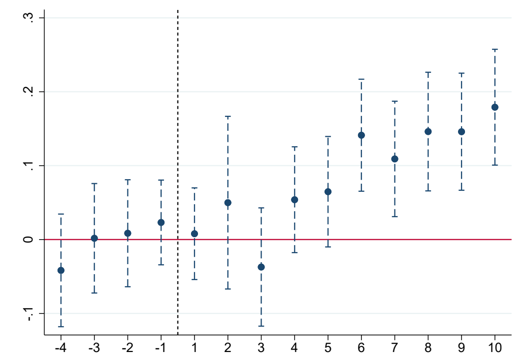
Notes: The figures in Panels (a) and (b) plot the monthly coefficients on $\mathbb{X}^{c}_{ir,my}$ (Equation 2) for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019) for every month in 2020. The regressions include a set of plants for which total sales information is available for every month. The figures in Panels (c) and (d) plot the monthly coefficients on $\mathbb{X}^{c}_{ir,my}$ (Equation 2) for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively, by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. All specifications include plant×month and sector×month×year fixed effects. We additionally control for heterogeneous impacts of plant-level inter-state Inputs fraction (2019) for every month in 2020. The regressions include a set of plants for which total inputs information is available for every month. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.4: Reshoring (Plants): Pre-trends

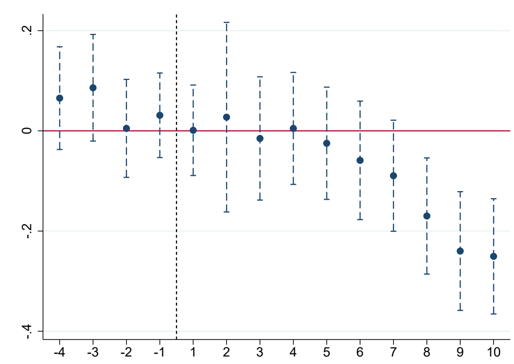
(a) Inter-State Sales: By Sales Fraction



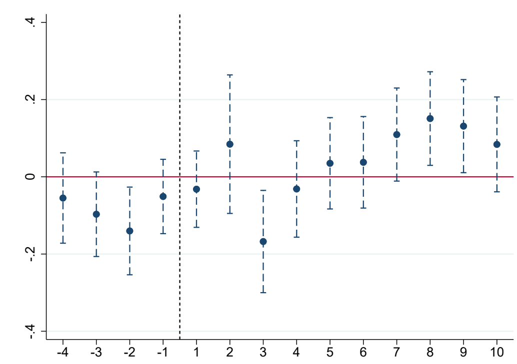
(b) Intra-State Sales: By Sales Fraction



(c) Inter-State Inputs: By Inputs Fraction



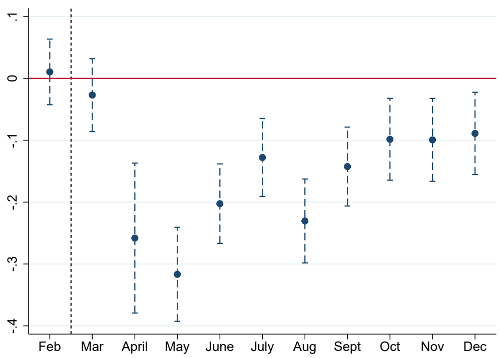
(d) Intra-State Inputs: By Inputs Fraction



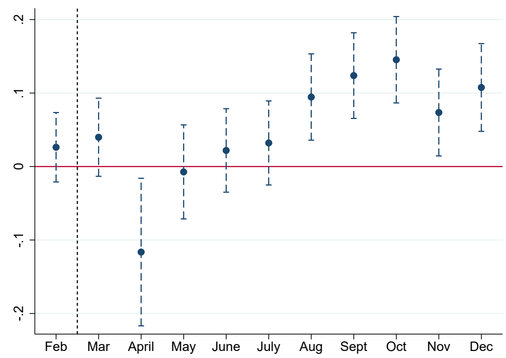
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by plant-level Inter-State Sales Fraction (2019), for four months before February 2020 (-4=October 2019, -3=November 2019, -2=December 2019, -1=January 2020) and every month after February 2020 (1=March 2020, 2=April 2020 and so on till 10=December 2020), with February 2020 as the base month. We additionally control for heterogeneous impacts of plant-level inter-state Inputs Fraction (2019) for each of the month-year combinations. The regressions include a balanced set of plants for which total sales information is available for every month. The figures in Panels (c) and (d) plot the monthly coefficients for the heterogeneous impact on log of inter-state Inputs and intra-state Inputs respectively, by plant-level inter-state Inputs Fraction (2019), for the last quarter in 2019 and every month in 2020, with February 2020 as the base month. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019) for each of the month-year combinations. The regressions include the set of plants for which total inputs information is available for every month. All specifications include plant-state×sector×month and sector×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.5: Reshoring (Plants): Robustness (Unbalanced Plants)

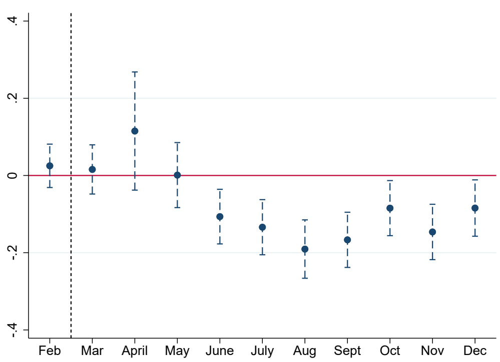
(a) Inter-State Sales: By Sales Fraction



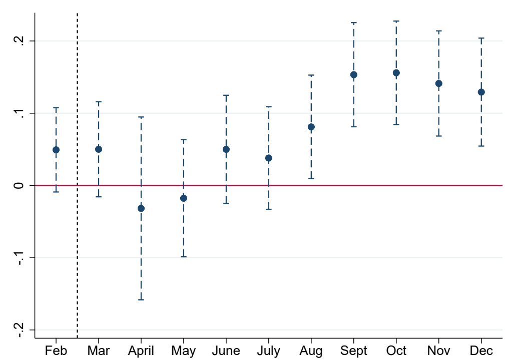
(b) Intra-State Sales: By Sales Fraction



(c) Inter-State Inputs: By Inputs Fraction



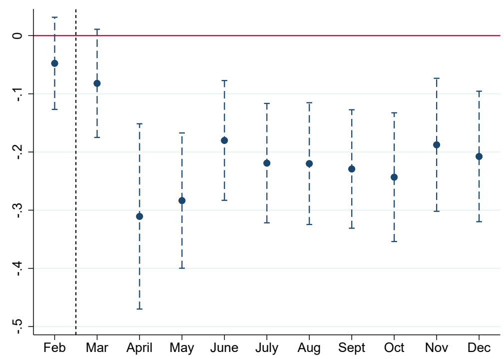
(d) Intra-State Inputs: By Inputs Fraction



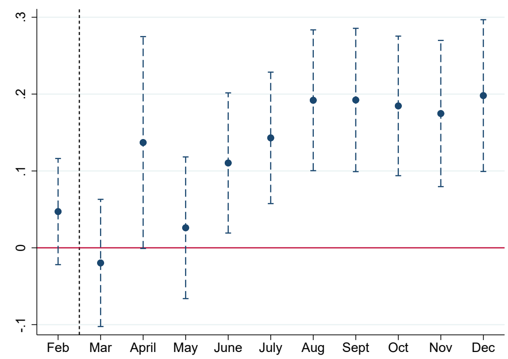
Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level inter-state Inputs fraction (2019) for every month in 2020. The regressions include a set of plants for which total sales information is available for more than six months in 2019. The figures in Panels (c) and (d) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively, by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019) for every month in 2020. The regressions include a set of plants for which total inputs information is available for more than six months in 2019. All specifications include plant×month and sector×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.6: Reshoring (Plants): Robustness (Variation in Stringency across Districts)

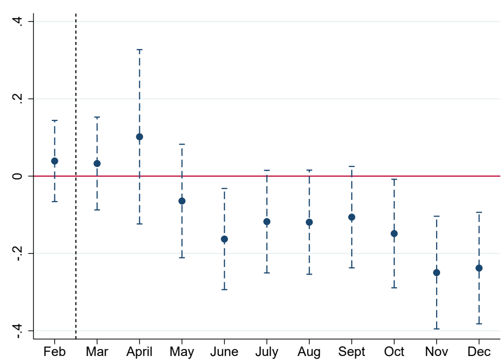
(a) Inter-State Sales: By Sales Fraction



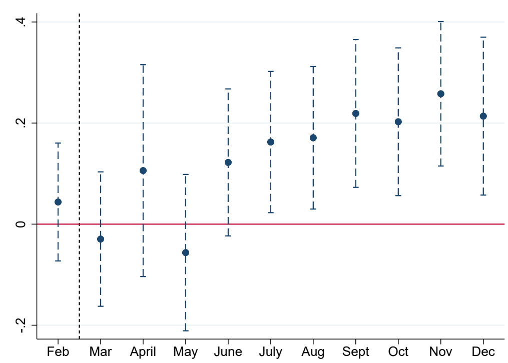
(b) Intra-State Sales: By Sales Fraction



(c) Inter-State Inputs: By Inputs Fraction



(d) Intra-State Inputs: By Inputs Fraction



Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level inter-state Inputs fraction (2019) for every month in 2020. The regressions include a set of plants for which total sales information is available for every month. The figures in Panels (c) and (d) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively, by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019) for every month in 2020. The regressions include a set of plants for which total inputs information is available for every month. All specifications include plant×month, sector×month×year and district×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.7: Reshoring (Plants): Robustness (Dropping exporters and importers)

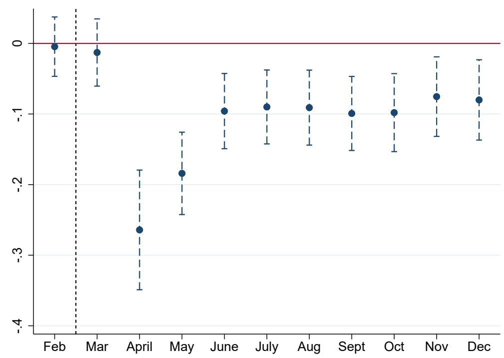
(a) Inter-State Sales: By Sales Fraction (b) Intra-State Sales: By Sales Fraction

(c) Inter-State Inputs: By Inputs Fraction (d) Intra-State Inputs: By Inputs Fraction

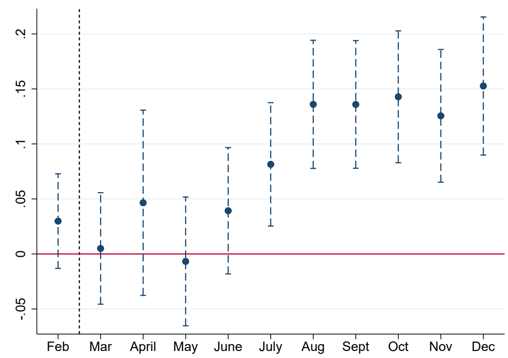
Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level inter-state Inputs fraction (2019) for every month in 2020. The regressions include a set of plants for which total sales information is available for every month. The figures in Panels (c) and (d) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively, by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-State Sales Fraction (2019) for every month in 2020. The regressions include a set of plants for which total inputs information is available for every month. Plants which exported any of their sales in 2019 are dropped from the analyses in Panels (a) and (b). Plants which imported any of their inputs in 2019 are dropped from the analyses in Panels (c) and (d). The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.8: Reshoring (Plants): Robustness (Above Median Fraction)

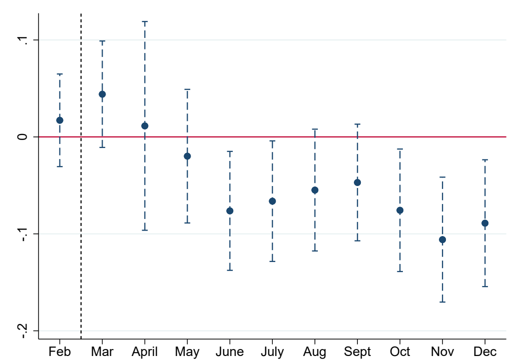
(a) Inter-State Sales: By Sales Fraction



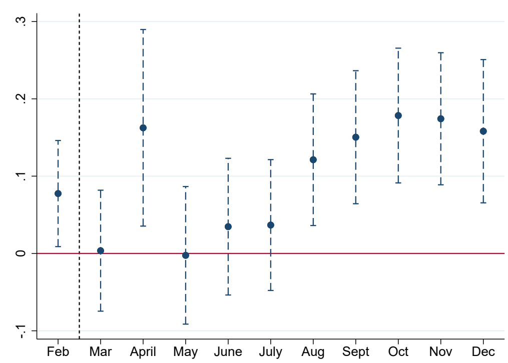
(b) Intra-State Sales: By Sales Fraction



(c) Inter-State Inputs: By Inputs Fraction



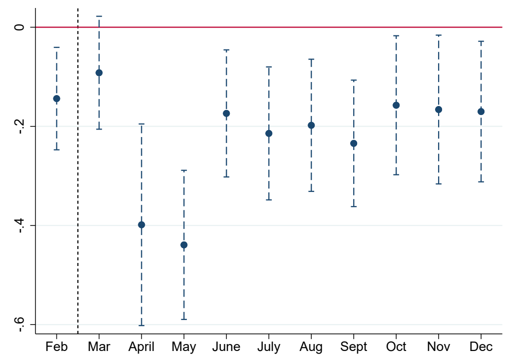
(d) Intra-State Inputs: By Inputs Fraction



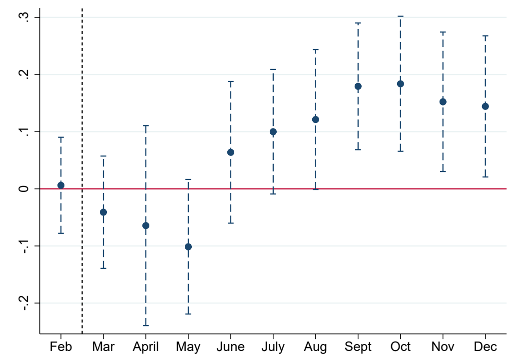
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by an indicator variable, that takes a value of one for above median measure of plant-level Inter-State Sales Fraction (2019) and zero otherwise, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level indicator variable for above median inter-state Inputs Fraction (2019) for every month in 2020. The regressions include a set of plants for which total sales information is available for every month. The figures in Panels (c) and (d) plot the monthly coefficients for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively, by an indicator variable, that takes a value of one for above median measure of plant-level inter-state Inputs Fraction (2019) and zero otherwise, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level indicator variable for above median level Inter-State Sales Fraction (2019) for every month in 2020. The regressions include a set of plants for which total inputs information is available for every month. All specifications include plant×month and sector×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.9: Reshoring (Plants): Robustness (Additional Plant and Firm Level Controls)

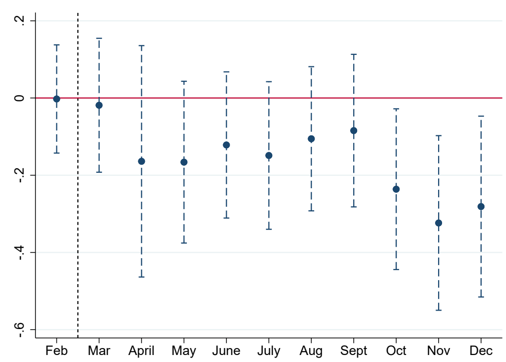
(a) Inter-State Sales: By Sales Fraction



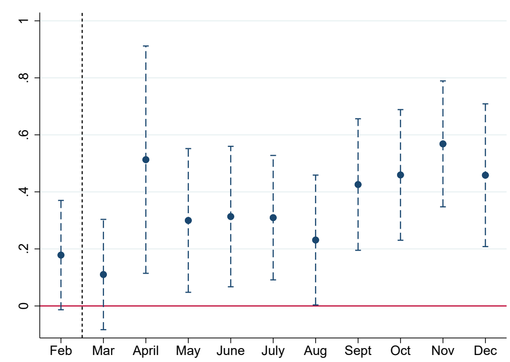
(b) Intra-State Sales: By Sales Fraction



(c) Inter-State Inputs: By Inputs Fraction



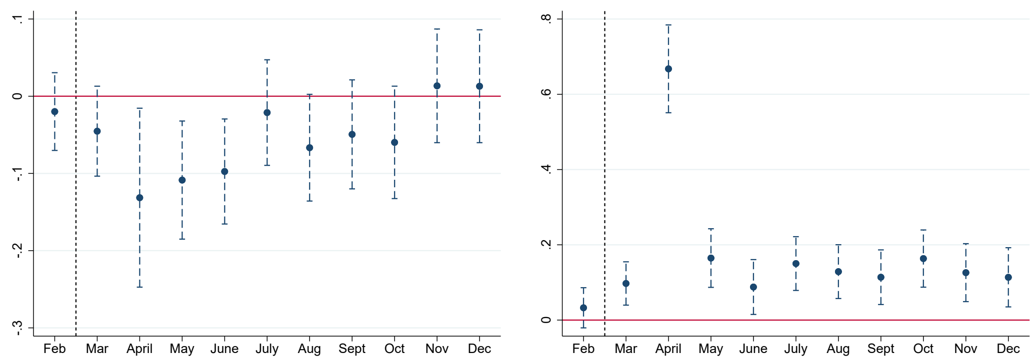
(d) Intra-State Inputs: By Inputs Fraction



Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by plant-level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a set of plants for which total sales information is available for every month. The figures in Panels (c) and (d) plot the monthly coefficients ($\gamma_2^{\tau,c}$ in Equation 2) for the heterogeneous impact on log of inter-state inputs and intra-state inputs respectively, by plant-level inter-state Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a set of plants for which total inputs information is available for every month. We control for heterogeneous impacts of plant-level inter-state Inputs fraction (2019) for every month in 2020 (Panels (a) and (b)) and plant-level Inter-State Sales Fraction (2019) for every month in 2020 (Panels (c) and (d)). All specifications additionally control for heterogeneous impacts of indicator variables for plants belonging to multi-plant firms and those lying in border districts, total within-country sales of the plant in 2019 (size), firm-level cash-assets ratio and leverage for every month in 2020. All specifications include plant×month and sector×month×year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.10: Reshoring in Quantity (Products) due to *SHE*

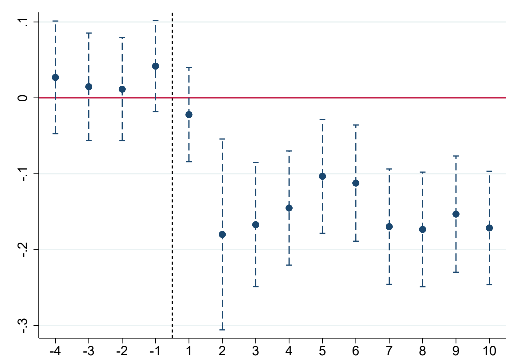
(a) Inter-State: By Scope for Home Expansion (b) Intra-State: By Scope for Home Expansion



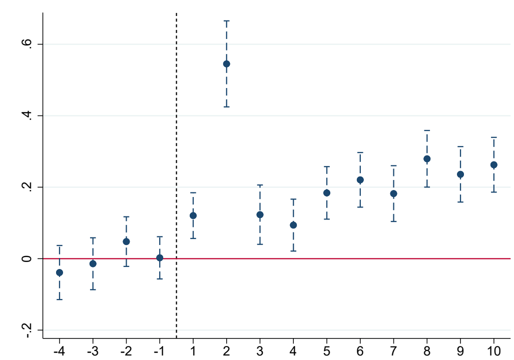
Notes: The count of E-Way Bills is used as a proxy for quantity in these regressions. The figures in Panels (a) and (b) plot the monthly coefficients (π_2^{τ} in Equation 6) for the heterogeneous impact on log of inter-state and intra-state E-Way sale bills of a product originating in a state by product-state level Scope for Home Expansion (2019) respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The product-state level intra-state Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of products in a state for which total sales information is available for every month. All specifications include product×state×month and product×month×year fixed-effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.11: Reshoring (Products): Pre-trends

(a) Inter-State Sales: By Scope for Home Expansion



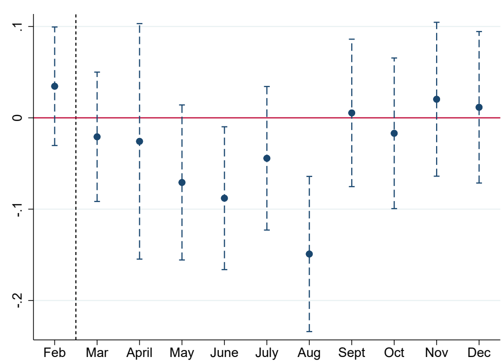
(b) Intra-State Sales: By Scope for Home Expansion



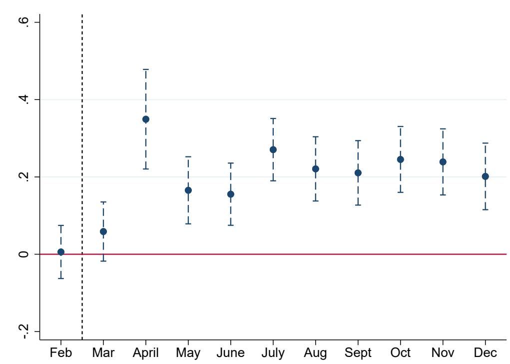
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-state sales and intra-state sales respectively, by product-state level Scope for Home Expansion (2019), for four months before February 2020 (-4=October 2019, -3=November 2019, -2=December 2019, -1=January 2020) and every month after February 2020 (1=March 2020, 2=April 2020 and so on till 10=December 2020), with February 2020 as the base month. The product-state level intra-state Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of products for which total sales information is available for every month. All specifications include state×product(HSN 4-digit), state×product(HSN 2-digit)×month and product×month×year fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.12: Reshoring (Products): Robustness (Unbalanced Products)

(a) Inter-State Sales: By Scope for Home Expansion



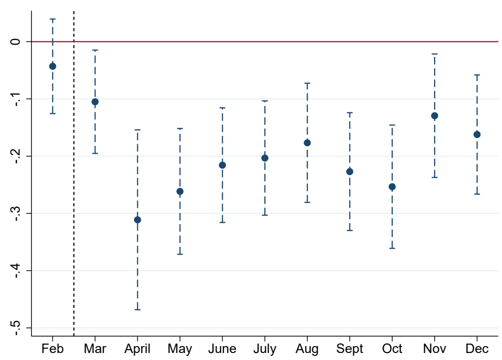
(b) Intra-State Sales: By Scope for Home Expansion



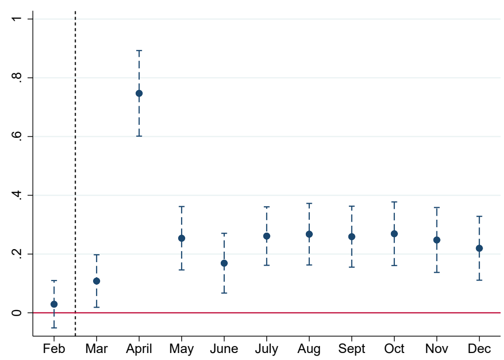
Notes: Panels (a) and (b) plot the monthly coefficients (π_2^τ in Equation 6) for the heterogeneous impact on log of inter-state and intra-state sales of a product from a state respectively, by the product-state level Scope for Home Expansion (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The product-state level intra-state Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of products for which total sales information is available for more than six months in 2019. All specifications include product-state-month and product-month-year fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.13: Reshoring (Products): Robustness (Variation in Stringency Across States)

(a) Inter-State Sales: By Scope for Home Expansion



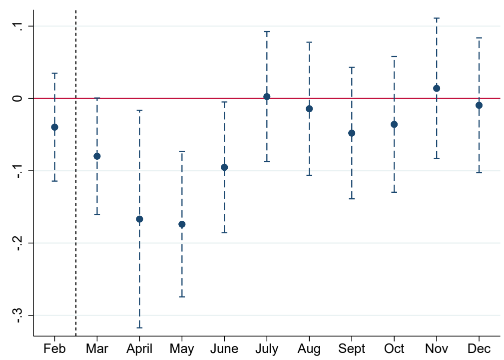
(b) Intra-State Sales: By Scope for Home Expansion



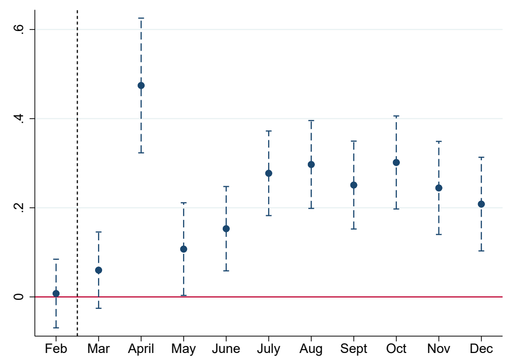
Notes: Panels (a) and (b) plot the monthly coefficients (π_2^τ in Equation 6) for the heterogeneous impact on log of inter-state and intra-state sales of a product from a state respectively, by the product-state level Scope for Home Expansion (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The product-state level intra-state Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of products in a state for which total sales information is available for every month. All specifications include product×state×month, product×month×year and state×month×year fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.14: Reshoring (Products): Robustness (Non-Essential Products)

(a) Inter-State Sales: By Scope for Home Expansion



(b) Intra-State Sales: By Scope for Home Expansion

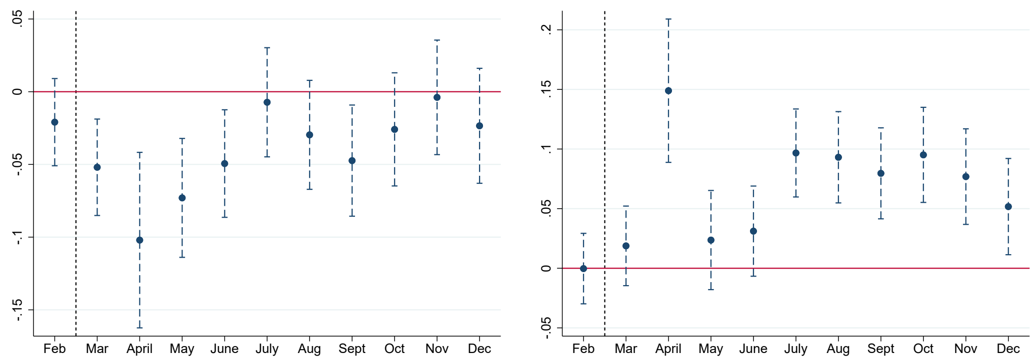


Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2^τ in Equation 6) for the heterogeneous impact on log of inter-state and intra-state E-Way sale bills of a product originating in a state by product-state level Scope for Home Expansion (2019) respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The product-state level intra-state Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of on-essential (non-food, non-medical) products in a state for which total sales information is available for every month. All specifications include product×state×month and product×month×year fixed-effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.15: Reshoring (Products): Robustness (Above Median Product Attributes)

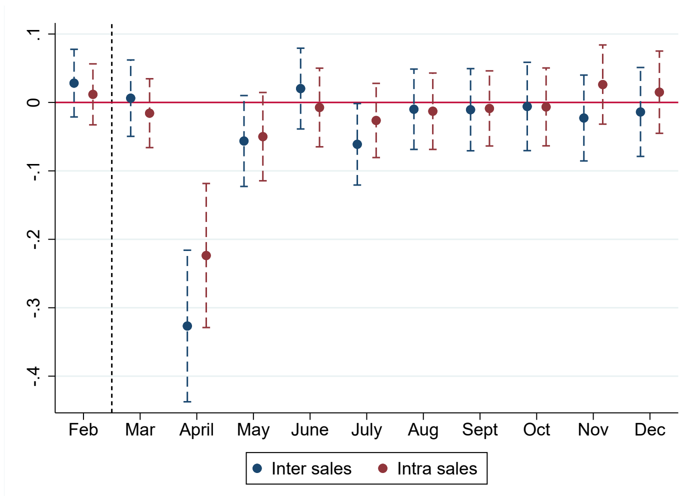
(a) Inter-State Sales: Above Median Scope for Home Expansion

(b) Intra-State Sales: Above Median Scope for Home Expansion



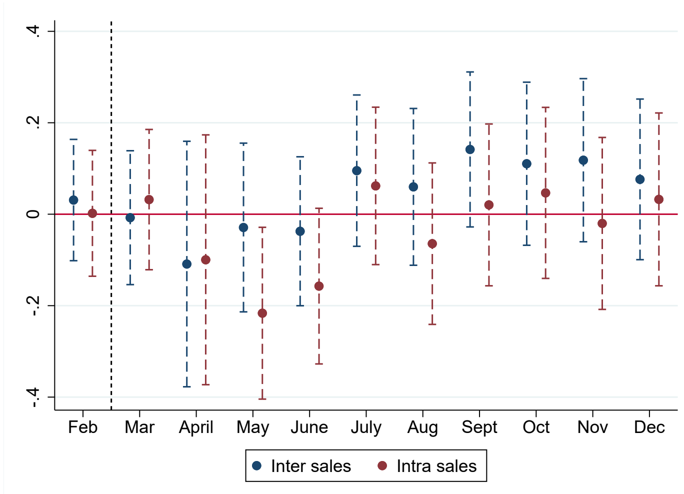
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-state and intra-state sales of a product originating in a state by an indicator variable at product-state level which takes a value of one for above median Scope for Home Expansion (2019) and zero otherwise, respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The product-state level intra-state Scope for Home Expansion (2019) is defined as the minimum of Inter-State Sales Fraction (2019) and inter-state Receivables Fraction (2019). The regressions include a set of products in a state for which total sales information is available for every month. All specifications include product×state×month and product×month×year fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.16: Effect of Product Differentiation on Reshoring



Notes: The figure plots the monthly coefficients for the heterogeneous impact on log of inter-state and intra-state sales of a product originating in a state by whether a product is classified as a differentiated one by Rauch (1999) at the 4-digit HSN level, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a set of products in a state for which total sales information is available for every month. All specifications control for the heterogeneous impact on the outcome variables by product-state level Scope for Home Expansion; include product×state×month at 4-digit level and product×month×year at 2-digit level fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure A.17: Effect of Product Differentiation on Reshoring: Additional Evidence



Notes: The figure plot the monthly coefficients for the heterogeneous impact on log of inter-state and intra-state sales of a product originating in a state by Scope for Home Expansion by whether a product is classified as a differentiated one by Rauch (1999) at the 4-digit HSN level, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a set of products in a state for which total sales information is available for every month. All specifications control for the heterogeneous impact on the outcome variables by product-state level Scope for Home Expansion; by whether a product is classified as a differentiated one; include product×state×month at 4-digit level and product×month×year at 2-digit level fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Table A.1: Reshoring (Sales and Inputs, Plants): Without Sector × Month × Year Fixed Effects

Dependent variable:	log(Inter Sales)		log(Intra Sales)		log(Inter Inputs)		log(Intra Inputs)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\gamma_1^{\tau,c}$	$\gamma_2^{\tau,c}$	$\gamma_1^{\tau,c}$	$\gamma_2^{\tau,c}$	$\gamma_1^{\tau,c}$	$\gamma_2^{\tau,c}$	$\gamma_1^{\tau,c}$	$\gamma_2^{\tau,c}$
Feb 2020	0.01	–0.01	–0.02	0.06**	–0.03	0.05	–0.00	0.11***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.02)	(0.04)
Mar 2020	–0.39***	0.01	–0.37***	–0.00	–0.41***	0.11***	–0.32***	0.04
	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	(0.04)	(0.02)	(0.04)
Apr 2020	–1.13***	–0.34***	–1.28***	0.06	–1.09***	0.24***	–0.85***	0.18***
	(0.06)	(0.06)	(0.04)	(0.05)	(0.08)	(0.09)	(0.03)	(0.07)
May 2020	–0.19***	–0.21***	–0.32***	–0.02	–0.35***	0.07	–0.20***	–0.03
	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)	(0.02)	(0.05)
June 2020	0.08**	–0.12***	–0.07***	0.04	0.06	–0.09*	–0.02	0.13***
	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.05)	(0.02)	(0.05)
July 2020	0.07**	–0.14***	–0.09***	0.10***	0.03	–0.08*	–0.03*	0.10**
	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.05)	(0.02)	(0.05)
Aug 2020	0.11***	–0.15***	–0.06***	0.19***	0.09**	–0.11**	–0.04*	0.21***
	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.05)	(0.02)	(0.05)
Sep 2020	0.22***	–0.17***	0.03	0.21***	0.18***	–0.11**	0.04**	0.24***
	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.05)	(0.02)	(0.05)
Oct 2020	0.24***	–0.11***	0.07***	0.24***	0.23***	–0.13***	0.09***	0.25***
	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)	(0.02)	(0.05)
Nov 2020	0.15***	–0.19***	–0.02	0.21***	0.24***	–0.24***	0.00	0.26***
	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)	(0.02)	(0.05)
Dec 2020	0.25***	–0.17***	0.08***	0.24***	0.28***	–0.17***	0.08***	0.23***
	(0.04)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)	(0.02)	(0.05)
Plant-Month FE	✓		✓		✓		✓	
Additional Controls ($\mathbb{X}^c_{ir,my}$)	✓		✓		✓		✓	
N	142084		145488		130274		87908	

Notes: Columns (1)-(2), (3)-(4), (5)-(6) and (7)-(8) show results from the estimated Equation (2). Columns with heading $\gamma_1^{\tau,c}$ show the overall impact on the dependent variable in each month in the year 2020 with January 2020 as the base, relative to change between the same months in 2019. Columns (2) and (4) with heading $\gamma_2^{\tau,c}$ show the heterogeneous impact on the dependent variable, by plant level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Columns (6) and (8) with heading $\gamma_2^{\tau,c}$ show the heterogeneous impact on the dependent variable, by plant level Inter-State Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Columns (1)-(4) and (5)-(8) include a set of plants for which total sales and total inputs information is available for every month, respectively. Additional controls: Columns (1)-(4) include interaction of each month in 2020 with plant Inter-State Inputs Fraction (2019); Columns (5)-(8) include interaction of each month in 2020 with plant Inter-State Sales Fraction (2019). The number of observations (N) are the effective observations used in estimation after including all the fixed effects. Clustered standard errors (at plant level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Impact on Plant Sales and Inputs: By Inter-State Dependence

Dependent variable:	log(Sales)			log(Inputs)		
	(1)	(2)	(3)	(4)	(5)	(6)
Reg. Dependence=	Inter-State Sales Fraction ×			Inter-State Inputs Fraction ×		
Feb 2020	0.01	0.00	–0.00	–0.01	0.02	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Mar 2020	–0.03**	–0.03**	–0.05**	–0.05***	0.01	–0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Apr 2020	–0.20***	–0.26***	–0.38***	–0.27***	–0.02	–0.17***
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)
May 2020	–0.13***	–0.14***	–0.17***	–0.14***	–0.10***	–0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
June 2020	–0.05***	–0.05***	–0.06***	–0.07***	–0.04**	–0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
July 2020	0.01	0.00	–0.00	–0.06***	–0.03	–0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Aug 2020	–0.04**	–0.04**	–0.05**	–0.04**	–0.01	–0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Sep 2020	–0.02	–0.03	–0.05**	–0.01	–0.01	–0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Oct 2020	0.03*	0.03	0.01	–0.01	–0.00	–0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Nov 2020	–0.07***	–0.07***	–0.06**	–0.06***	–0.05**	–0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Dec 2020	–0.04**	–0.04**	–0.03	0.01	–0.00	–0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Plant-Month FE	✓	✓	✓	✓	✓	✓
Additional Controls ($\mathbb{X}^c_{ir,my}$)		✓	✓		✓	✓
Sector-Month-Year FE			✓			✓
N	222048	205944	164736	216696	163344	122712

Notes: The dependent variable in column (1)-(3) is the log of total sales for a plant. The coefficients in columns (1)-(3) show the heterogeneous impact on total sales, by plant level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a balanced set of plants for which total sales information is available for every month. The dependent variable in column (4)-(6) is the log of total inputs for a plant. The coefficients in columns (4)-(6) show the heterogeneous impact on total inputs by plant level Inter-State Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a balanced set of plants for which total inputs information is available for every month. Additional controls: interaction of each month in 2020 with plant Inter-State Input Fraction (2019) in columns (2)-(3), interaction of each month in 2020 with plant Inter-State Sales Fraction (2019) in columns (5)-(6). The number of observations (N) are the effective observations used in estimation after including all the fixed effects. Clustered standard errors (at plant level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Reshoring (Sales, Product level): Without Product × Month × Year Fixed Effects

Dependent variable:	log(Inter Sales)		log(Intra Sales)		log(Inter Sales)		log(Intra Sales)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heterogeneity Fraction=	Inter-State Sales Fraction				Scope for Home Expansion			
	π_1^τ	π_2^τ	π_1^τ	π_2^τ	π_1^τ	π_2^τ	π_1^τ	π_2^τ
Feb 2020	0.05**	−0.05	−0.00	0.00	0.06***	−0.03	0.04***	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
Mar 2020	−0.40***	−0.11***	−0.48***	0.00	−0.38***	−0.08**	−0.45***	0.02
	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)
Apr 2020	−2.65***	−0.93***	−3.09***	0.10	−2.25***	−0.17**	−2.50***	0.49***
	(0.06)	(0.08)	(0.06)	(0.07)	(0.04)	(0.08)	(0.04)	(0.08)
May 2020	−0.65***	−0.38***	−0.83***	−0.18***	−0.60***	−0.26***	−0.67***	−0.07
	(0.03)	(0.05)	(0.03)	(0.04)	(0.02)	(0.05)	(0.02)	(0.05)
June 2020	−0.12***	−0.24***	−0.30***	−0.03	−0.09***	−0.17***	−0.20***	0.07*
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
July 2020	−0.09***	−0.16***	−0.28***	0.12***	−0.08***	−0.12***	−0.22***	0.19***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.04)
Aug 2020	−0.02	−0.23***	−0.22***	0.12***	0.00	−0.16***	−0.16***	0.17***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Sep 2020	0.13***	−0.19***	−0.06**	0.09**	0.13***	−0.14***	−0.01	0.15***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Oct 2020	0.20***	−0.16**	−0.01	0.17***	0.22***	−0.09**	0.05**	0.21***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Nov 2020	0.07**	−0.13***	−0.09***	0.10***	0.06***	−0.12***	−0.05***	0.14***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Dec 2020	0.19***	−0.15***	0.02	0.09**	0.19***	−0.12***	0.07***	0.11***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Product-Region-Month FE	✓		✓		✓		✓	
Additional Controls ($\mathbb{X}_{kr,my}$)	✓		✓					
N	315280		315882		315280		315882	

Notes: Columns (1)-(2), (3)-(4), (5)-(6) and (7)-(8) show results from the estimated Equation (6). Columns with heading π_1^τ show the overall impact on the dependent variable in each month in the year 2020 with January 2020 as the base, relative to change between the same months in 2019. Columns (2) and (4) with heading π_2^τ show the heterogeneous impact on the dependent variable, by product level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Columns (6) and (8) with heading π_2^τ show the heterogeneous impact on the dependent variable, by product level Scope for Home Expansion (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We include a set of products in a region for which total sales information is available for every month. Additional controls: Columns (1)-(4) include interaction of each month in 2020 with product Inter-State Receivables Fraction (2019). The number of observations (N) are the effective observations used in estimation after including all the fixed effects. Clustered standard errors (at product-region level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Average Scope for Home Expansion across Products (HSN 2-digit)

HSN Code (1)	Product Description (2)	SHE_{kr} (3)
	Bottom Ten Products: Scope for Home Expansion	
43	Furskins and Artificial Fur	0.13
22	Beverages, spirits, and vinegar	0.31
45	Natural Cork, Shuttlecock Cork	0.32
37	Photographic & Cinematographic Films	0.35
31	Fertilisers	0.35
36	Propellants, Explosives, Fuses, Fireworks	0.36
78	Unwrought Lead – Rods, Sheets & Profiles	0.36
19	Preparations of cereals, flour, starch or milk;	0.37
15	Prepared Edible fats; Animal or Vegetable waxes	0.37
80	Unwrought Tin – Rods, Sheets & Profiles	0.38
	Top Ten Products: Scope for Home Expansion	
90	Optical, photographic, medical or surgical instruments	0.60
52	Cotton materials, Synthetics & Woven fabrics	0.61
46	Plaiting Materials, Basketwork	0.61
86	Vehicles, Aircraft, Vessels and transport equipment	0.62
29	Organic Chemicals	0.62
13	Gums, Resins, Vegetable SAP & Extracts	0.63
50	Textiles and Textile Articles	0.65
64	Shoes & Footwear Products	0.65
61	Articles of Apparel & Clothing, knitted or crocheted	0.66
62	Articles of Apparel & Clothing, not knitted or crocheted	0.67

Notes: The table provides the list of bottom and top ten products by Scope for Home Expansion (SHE_{kr}) at HSN 2-digit level. The above numbers are the mean of Scope for Home Expansion values derived at (HSN 4-digit) product×region level.

Table A.5: Gains in Sales from Reshoring and Scope for Home expansion: Heterogeneity across States

State	(1) CF Scenario I	(2) CF Scenario II	(3) CF Scenario III	(4) Average SHE_{kr}
Sikkim	2.578	2.577	1.419	0.972
Dadra and Nagarhaveli	2.556	2.530	1.393	0.749
Chandigarh	2.493	2.490	1.371	0.765
Puducherry	2.438	2.357	1.298	0.768
Goa	2.011	1.770	0.974	0.624
Madhya Pradesh	1.953	1.875	1.032	0.612
Himachal Pradesh	1.689	1.318	0.726	0.538
Uttarakhand	1.659	1.437	0.791	0.516
Andaman and Nicobar	1.640	1.640	0.903	0.627
Meghalaya	1.631	0.907	0.500	0.353
Haryana	1.617	1.550	0.853	0.536
Arunachal Pradesh	1.430	1.430	0.788	0.474
Chhattisgarh	1.306	0.793	0.437	0.358
Delhi	1.295	1.236	0.681	0.464
Jammu and Kashmir	1.267	1.127	0.620	0.444
Jharkhand	1.228	0.703	0.387	0.355
Andhra Pradesh	1.105	0.878	0.484	0.397
Odisha	1.038	0.480	0.264	0.285
Nagaland	1.015	1.015	0.559	0.541
Telangana	1.006	0.821	0.452	0.395
Gujarat	0.861	0.611	0.336	0.331
Rajasthan	0.804	0.586	0.323	0.345
Karnataka	0.803	0.645	0.355	0.387
Tamil Nadu	0.800	0.522	0.288	0.361
Uttar Pradesh	0.778	0.558	0.307	0.361
West Bengal	0.766	0.635	0.349	0.314
Punjab	0.747	0.582	0.320	0.320
Maharashtra	0.747	0.504	0.278	0.365
Assam	0.611	0.480	0.264	0.365
Mizoram	0.508	0.508	0.280	0.194
Kerala	0.334	0.232	0.128	0.175
Bihar	0.314	0.250	0.138	0.191
Manipur	0.182	0.100	0.102	0.070
Tripura	0.085	0.047	0.056	0.032

Notes: The coefficient value in columns (1) and (2) in Table 2 are used for counterfactual estimation for each state with Aggregate Sales Share (%) varying across states for the different categories of products. Scenario I is the full reshoring case with sales growth equal to zero for both types of products. Scenario II is the case with reshoring only for above-median SHE_{kr} products. Scenario III captures the effect due to scope for home expansion alone. Column (4) shows the product sales weighted average value of SHE_{kr} for a state in 2019. Greater the value of σ, larger is the gains from home expansion in a state.

B Appendix: Additional Results

B.1 Additional Evidence for Trade Collapse

We describe our empirical strategy to identify trade collapse at plant level and discuss the results below.

B.1.1 Empirical Strategy

As described earlier, the sudden lockdown in March 2020 led to an immediate disruption in inter-state trade and economic activity. We measure the impact of this disruption on inter- vs intra-state sales (inputs) of a plant using an event-study design around the lockdown and plant-level monthly data from January 2019 to December 2020. We estimate the below specification:

$$ln(z^c_{ijr,my}) = \alpha^c_0 \quad + \sum_{\tau \in (m2020)} \alpha^{\tau,c}_1 (\mathbb{1}_m \times \mathbb{1}_{2020}) + \mathbb{1}_{2020} + \delta^c_{ir,m} + \varepsilon^c_{ijr,my} \qquad \text{(B.1)}$$

where $z^c_{ijr,my}$ is the outcome variable for plant i belonging to sector j in state r in month m and year y for category $c \in \{Sales, Inputs\}$. Our plant level outcome variables include total sales (inputs) and inter- to intra-state sales (inputs) ratio.[1] $\mathbb{1}_m$ is a dummy variable that takes a value equal to one if the observation belongs to month m, and zero otherwise. $\mathbb{1}_{2020}$ is a dummy that takes a value of one for year 2020, and zero otherwise. The set $m2020$ refers to the months in February–December 2020. We account for plant-level seasonality in outcomes through plant×month fixed effects, $\delta^c_{ir,m}$. Our coefficient of interest $\alpha^{\tau,c}_1$ on $(\mathbb{1}_m \times \mathbb{1}_{2020})$ captures the month-wise impact on plant outcomes for month m in year 2020, relative to the baseline month of January 2020, over and above any change between the same months in 2019. Standard errors are clustered at plant level.

This estimation strategy is akin to a difference-in-differences (DID) strategy where the first difference is the percent change in plant outcome between month m in year 2020 and January 2020 and that between month m in year 2019 and January 2019, and the second one is the difference between these two differences.[2] The treatment is

[1] The nature of the data precludes us from observing the products sold by a plant, unlike in Behrens et al. (2013) and Bricongne et al. (2012). Therefore, our empirical strategy to estimate trade collapse at plant-level cannot account for the nature of the product directly.

[2] To elaborate, $\alpha^{\tau,c}_1$ = (Percent change in plant outcome between month m in 2020 and January

the lockdown in the country that began on March 25, 2020 and the treatment period is March–December 2020.

B.1.2 Results: Inter-State Trade Collapse

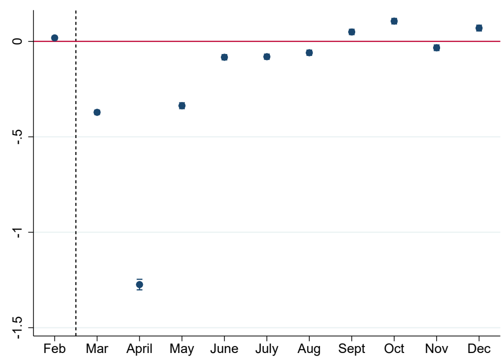
We begin by documenting the decline in overall economic activity after the lockdown and its gradual recovery. Figure B.1, Panel (a) plots the estimated monthly impact in 2020 on log of total plant sales, while Panel (b) plots it on log of total plant inputs (given by $\alpha_1^{\tau,c}$ in Equation B.1). The percentage change is given by $exp(\alpha_1) - 1$. We find a 30 percent fall in total sales in March 2020 (the lockdown occurred on March 25, 2020) followed by a 70 percent fall in April 2020 from that in January 2020, relative to the change between the same months in 2019 (i.e., over and above any seasonal effects). The total sales partially recovered in May 2020 as the restrictions eased but continued to suffer until August 2020 (lower by 6%). From September 2020 onward we see a recovery in total sales to the pre-lockdown levels (in line with the official quarterly GDP statistics). We see a similar pattern for inputs (Panel (b)) with the most drastic fall in April 2020 (63%) and recovery from September 2020 onward. In both the figures, we see no significant effect in February 2020, when there was no lockdown in the country.

Next, we test for trade collapse. We plot the coefficients ($\alpha_1^{\tau,c}$) with log of inter- to intra-state sales ratio and inputs ratio as the dependent variables in Figure B.1, Panel (c) and (d), respectively. We find a collapse in inter-state trade for a period much beyond the initial lockdown. There is a fall in inter- to intra-state sales ratio by 15 percent in April 2020. The coefficient bounces back initially, but then continues to remain negative (5%) and significant from August 2020 onward. Clearly, these results show that the inter- to intra-state sales ratio declines immediately post-lockdown and the decline persists even after the initial shock subsides. We find a similar pattern for the inter- to intra-state inputs ratio in Panel (d). We check the robustness of the trade collapse results to an alternate estimation strategy in Appendix Section B.1.3, which controls for changes in sectoral demand over time and find that these results continue to hold.

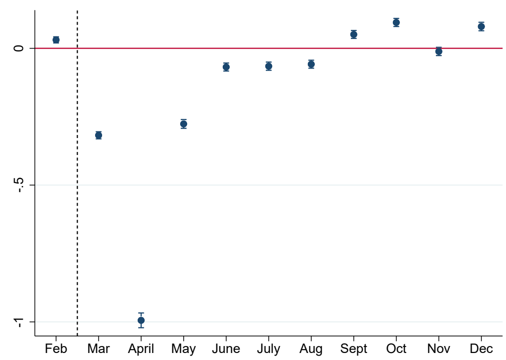
2020) - (Percent change in plant outcome between month m in 2019 and January 2019).

Figure B.1: Economic Impact of Lockdown on Plants: Inter-State Trade Collapse

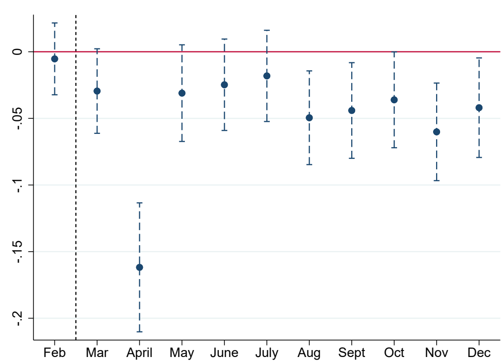
(a) Total Sales



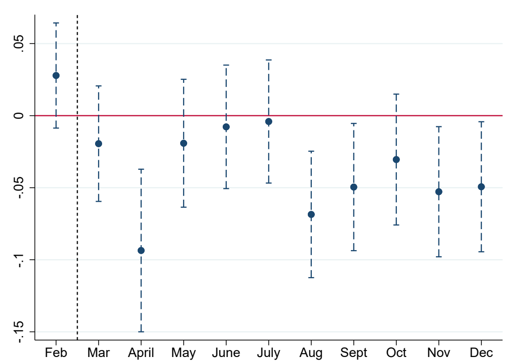
(b) Total Inputs



(c) Inter- to Intra-State Sales ratio



(d) Inter- to Intra-State Inputs ratio



Notes: The figures in Panels (a) and (b) plot the monthly coefficients ($\alpha_1^{\tau,c}$ in Equation B.1) for the impact on log of total plant sales and inputs respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The figures in Panels (c) and (d) plot the monthly coefficients ($\alpha_1^{\tau,c}$ in Equation B.1) for the impact on log of inter- to intra-state plant sales and inputs ratio respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Panel (a) includes a balanced set of plants for which total sales information is available for every month in our data. Panel (b) includes a balanced set of plants for which total inputs information is available for every month in our data. Panel (c) includes a balanced set of plants for which both inter- and intra-state sales are observed every month. Similarly, Panel (d) includes a balanced set of plants for which both inter- and intra-state inputs are observed every month. All specifications include plant-month and year fixed effects. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

B.1.3 Alternate Test for Trade Collapse

As an alternative strategy, we also measure trade collapse using a slightly modified specification given by:

$$ln(z^c_{ijtr,my}) = \beta^c_0 + \sum_{\tau\in(m2020)} \beta^{\tau,c}_1(\mathbb{1}_m \times \mathbb{1}_{2020}) + \sum_{\tau\in(m2020)} \beta^{\tau,c}_2(\mathbb{1}_m \times \mathbb{1}_{2020} \times \mathbb{1}(Inter_t))$$
$$+ \mathbb{1}_{2020} \times \mathbb{1}(Inter_t) + \mathbb{1}_{2020} + \delta^c_{itr,m} + \delta^c_{j,my} + \varepsilon^c_{ijtr,my} \quad \text{(B.2)}$$

where $z^c_{ijtr,my}$ is the outcome of $c \in \{sales, inputs\}$ differentiated by state type $t \in \{inter - state, intra - state\}$ for plant i belonging to sector j in state r in month m and year y. The variable $\mathbb{1}(Inter_t)$ takes a value of one if type t belongs to inter-state, else it is zero. Compared to Equation B.1, here we have an additional interaction term $\mathbb{1}_m \times \mathbb{1}_{2020} \times \mathbb{1}(Inter_t)$ that captures the differential impact on inter-state sales (or inputs) after the lockdown. Once again, January 2020 serves as the baseline month. The coefficient $\beta^{\tau,c}_1$ captures the average impact on sales in time period τ i.e., month m in 2020 over January 2020, relative to the same months in 2019, while $\beta^{\tau,c}_2$ captures the heterogeneous impact on the inter-state sales (or inputs). For instance, in the regression with sales as outcome variable, if inter-state sales fall more in a month, then $\beta^{\tau,sales}_2$ will be negative.

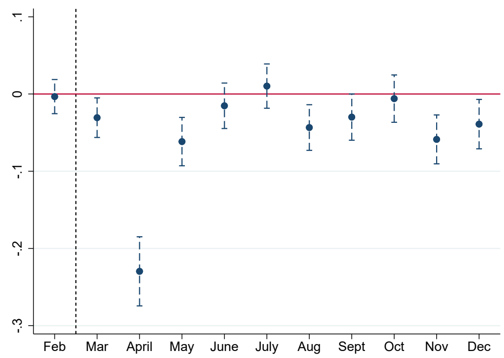
We also include plant×type×month fixed-effects, $\delta^c_{itr,m}$, which account for plant-type level unobserved heterogeneity and plant-type monthly seasonality in outcomes, the two important confounding factors for identifying the trade collapse. In addition, we include controls for sector×month×year fixed effects denoted by $\delta^c_{j,my}$ to control for differential change in demand across plants in different sectors post-lockdown. Thus, our identification uses within-plant variation in a given month-year across its intra-state and inter-state sales (inputs). Lastly, if the impact is driven by the lockdown then we should observe no differential pre-trends between intra- and inter-state sales (inputs) in February and the corresponding $\beta^{Feb2020}_2$ should be insignificant.

We plot the coefficients $\beta^{\tau,c}_2$ that capture the differential impact of lockdown on inter-state sales and inputs relative to the intra-state outcomes in Panels (a) and (b) of Figure B.2, respectively. Panel (a) shows that the initial fall (April 2020) in inter-state sales is 21 percent larger. The difference reduces but remains negative and significant for the rest of the year except a few months. We see a similar impact on inputs in Panel (b). The initial fall in inter-state inputs is larger by 21 percent in

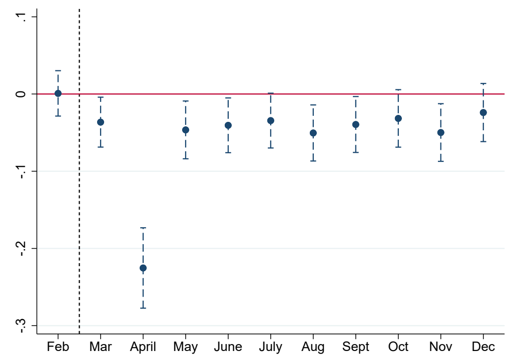
April 2020 and continues to remain subdued by 5 percent for the rest of the year.

Figure B.2: Domestic Trade Collapse: Alternate Specification

(a) Sales



(b) Inputs



Notes: The figures plot the coefficients $\beta_2^{\tau,c}$ from the estimated Equation B.2. Panel (a) plots the monthly coefficients for the impact on log of inter-state plant sales versus intra-state plant sales, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Panel (b) plots the monthly coefficients for the impact on log of inter-state plant inputs versus intra-state plant inputs, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a balanced set of plants for which total sales (Panel (a)) and total inputs (Panel (b)) information is available for every month. All specifications include plant×type×month fixed effects and sector×type×month×year fixed effects, where type is inter- or intra-state value at the plant level. The standard errors are clustered at plant level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

B.2 Reshoring: Products with High Outside State Dependence

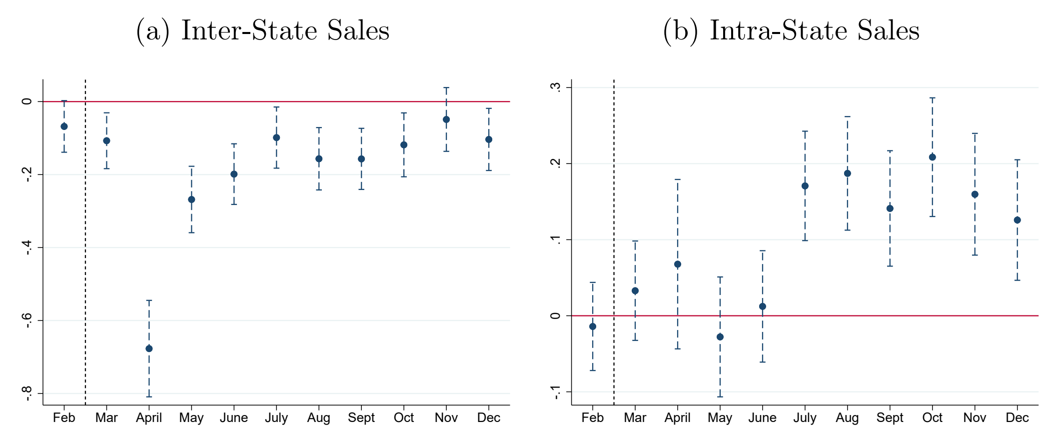
We also estimate the heterogeneous impact of inter-state sales dependence on product outcomes to show the robustness of plant level results on reshoring. We estimate Equation 6 with inter-state sales and intra-state sales as the dependent variables and $f_{kr,sales}$ as the explanatory variable instead of SHE_{kr}. We then plot the estimates for π_2^{τ} coefficients in Panels (a) and (b) of Figure B.3, respectively.

There is a sharp fall in inter-state sales at the start of the pandemic during April 2020 for products with a higher inter-state sales dependence. The decline persists until December 2020 as most of the coefficients continue to be negative and significant, though the magnitude becomes smaller over time. The average point estimate of -0.15 translates into a 4 percent decline in the inter-state sales for a one-standard-deviation increase in inter-state sales fraction. We find no impact on the intra-state sales initially (March–June 2020). However, we see an increase in intra-state sales from July–December 2020 (coefficients are positive and significant) for products that have higher initial inter-state dependence. Quantitatively, the coefficients are around 0.15 and translate into a $0.15 \times 0.27 \times 100 = 4$ percent increase in the intra-state sales for a one-standard-deviation increase in inter-state sales fraction. Thus, decline in inter-state sales is offset by an increase in the intra-state sales in the recovery phase, for products that had a greater reliance on outside states for sales.[3] In addition, we find that the above change in sales value is driven by the change in quantity (results available on request).

The above product level results mimic the reshoring documented using plant data, both in timing and persistence. While the relative collapse in inter-state product sales was immediate, the intra-state product sales increased a few months later for products more dependent on outside states for sales, possibly reflecting the time taken to shift sales from inter- to intra-state. Notably, all the regressions at product level control for product×month×year fixed-effects. Therefore, our results are not driven by products whose demand is also likely to fall more after the lockdown, like durable goods (Levchenko et al., 2010).

[3]More detailed estimates, i.e., for both π_1 along with that for π_2 (when product time fixed effects are excluded), are reported in Appendix Table A.3. All the results presented in this section go through for this specification as well.

Figure B.3: Reshoring in Product Sales: By Inter-State Sales Fraction



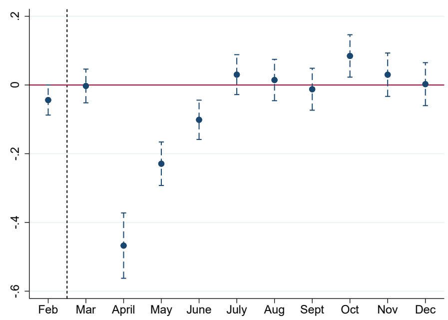
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2^τ in Equation 6) for the heterogeneous impact on log of inter-state and intra-state sales of a product originating in a state by product-state level Inter-State Sales Fraction (2019) respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. All panels additionally control for the heterogeneous impacts of product-state level inter-state Receivables Fraction (2019) for every month in 2020. The regressions include a set of products in a state for which total sales information is available for every month. All specifications include product×state×month and product×month×year fixed effects. The standard errors are clustered at product×state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

B.3 Impact on Total Product Sales

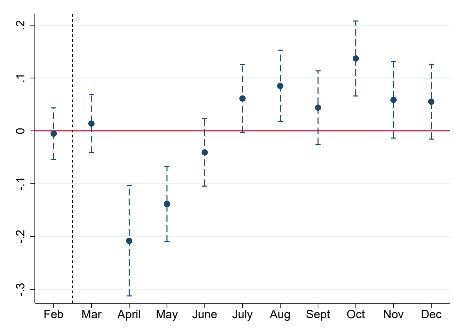
We plot the impact on total product sales by inter-state sales dependence and *SHE* in Figure B.4, Panels (a) and (b) respectively, by estimating Equation 6 with total product sales as the dependent variable. Comparing the two panels we find that the total sales fall relatively more in April 2020 for products having higher inter-state dependence and *SHE*. This is because the relative fall in inter-state sales is higher than the relative gain in intra-state sales for these products immediately post-lockdown. However, the relative decline in total sales is lower in Panel (b) (point estimate is -0.2) than in Panel (a) (point estimate is -0.5). Therefore, the total sales of products with high SHE_{kr} suffer less immediately after the lockdown. This is primarily on account of higher intra-state sales that help improve total sales for high SHE_{kr} products (Panel (b) in Figure 8). In fact, Figure B.4, Panel (b) shows that products with higher SHE_{kr} witness a relatively higher increase in total sales in the later months of 2020. The point estimates give $0.1 \times 0.26 \times 100 = 2.6$ percent increase in total sales for one-standard-deviation increase in SHE_{kr} until the end of 2020. Similar increase is absent for products that only have high inter-state dependence (Panel (a)). It again demonstrates the relevance of *SHE* measure in aiding reshoring.

Figure B.4: Impact on Total Product Sales

(a) By Inter-State Sales Fraction



(b) By Scope for Home Expansion



Notes: The figure in Panel (a) plots the monthly coefficients (π_2^τ in Equation 6) for the heterogeneous impact on log of total sales of a product originating in a state by product-state level Inter-State Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regression additionally controls for the heterogeneous impacts of product-state level inter-state Receivables Fraction (2019). The figure in Panel (b) plots the monthly coefficients (π_2^τ in Equation 6) for the heterogeneous impact on log of total sales of a product originating in a state by product-state level Scope for Home Expansion measure (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. The regressions include a balanced set of products in a state for which total sales information is available for every month. All specifications include product×state×month and product×month×year fixed effects. The standard errors are clustered at product-state level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

C Appendix: Model

We consider a model of firm input choice from intra-state and inter-state product varieties as in Gopinath and Neiman (2014). The firm uses all intra-state varieties and chooses an optimal number of inter-state varieties, as for the latter they have to pay fixed costs to import. Consider a home-state firm i which manufactures a unique good i and uses the following production technology:

$$Y_i = A_i L_{p,i}^{1-\mu} X_i^{\mu} \tag{C.1}$$

where A_i is the productivity of firm i, $L_{p,i}$ is the labor used for production and X_i is the intermediate input. $1-\mu$ and μ gives the share of labor and intermediate inputs in the production cost. X_i consists of intra-state inputs Z_i and inter-state inputs M_i, combined together through a CES aggregator:

$$X_i = \left[Z_i^{\rho} + M_i^{\rho}\right]^{\frac{1}{\rho}}. \tag{C.2}$$

$1/(1-\rho)$ is the elasticity of substitution between intra-state and inter-state varieties. Both Z_i and M_i are based on CES aggregation of intra-state and inter-state varieties, respectively:

$$Z_i = \left[\int_j z_{ij}^{\theta} dj\right]^{\frac{1}{\theta}} \quad , \quad M_i = \left[\int_{k\in\Omega_i} m_{ik}^{\theta} dk\right]^{\frac{1}{\theta}}. \tag{C.3}$$

We assume elasticity of substitution to be same and equal to $1/(1-\theta)$ over the bundles. z_{ij} is the set of intra-state inputs j and m_{ik} is the set of inter-state inputs k. Firm i only imports a set Ω_i of the available inter-state varieties. Adding varieties to the inter-state input bundle is costly and a function of fixed costs given by:

$$F(|\Omega_i|) = f|\Omega_i|^{\lambda} \tag{C.4}$$

where $f > 0, \lambda > 0$. The fixed costs are increasing in number of inter-state varieties imported and paid in terms of labor units, $L_{f,i}$.

Finally, output from each firm i is used for final good production as well as intermediate input by other firms:

$$Y_i = g_i + z_i = g_i + \int_j z_{ji} dj. \tag{C.5}$$

The aggregate final good $G = \left[\int_j g_i^{\theta} di\right]^{\frac{1}{\theta}}$ is the CES aggregator over all goods produced domestically.

All firms in the economy are monopolistically competitive and take the input prices as given to solve their production problem. Firm i takes wages w, set of intra-state prices p_j, and inter-state prices as given. It chooses labor $L_{p,i}$, the intra-state nputs z_{ij}, the number of inter-state inputs Ω_i and their amount m_{ik}. The price of inter-state inputs is p_m and is the same for all varieties, which also makes m_i same across all k.[4] p_m is inclusive of the per-unit iceberg trade cost as well as price increase that accommodates uncertainty in arrival of good. If the uncertainty goes up, p_m goes up. For instance, in the baseline case assume zero uncertainty and trade costs. In this case one has to ship one unit of inter-state input to receive one unit. In case uncertainty increases, it requires shipment of more than one units to receive one unit for production. The unit cost function of the firm is given by:

$$C_i = \frac{1}{\mu^{\mu}(1-\mu)^{(1-\mu)}} \frac{w^{1-\mu} P_{X_i}^{\mu}}{A_i}. \tag{C.6}$$

Here P_{X_i} is the price index of the intermediates for firm i:

$$P_{X_i} = \left[P_Z^{\frac{\rho}{\rho-1}} + P_{M_i}^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}}. \tag{C.7}$$

The home-state and inter-state input price indices are given by:

$$P_Z = \left[\int_j p_i^{\frac{\theta}{\theta-1}} di\right]^{\frac{\theta-1}{\theta}} \quad , \quad P_{M_i} = \left[\int_k p_m^{\frac{\theta}{\theta-1}} dk\right]^{\frac{\theta-1}{\theta}} = p_m |\Omega_i|^{\frac{\theta-1}{\theta}}. \tag{C.8}$$

The home-state price index P_Z is the same across all firms, while the inter-state price index varies depending on the number of inter-state varieties $|\Omega_i|$ used by i. The firm i charges a price given by C_i/θ. Finally firm i chooses the optimal number of varieties Ω_i to maximize its profits. We can further solve the model to obtain the following propositions.

Proposition 1: *If* $\frac{\partial\, lnP_Z}{\partial\, lnp_m} < 1$ *and* $\frac{\partial\, ln\Omega_i}{\partial\, lnp_m} < 0$, *an increase in uncertainty captured by an increase in inter-state input price* p_m, *increases the share of domestic inputs in*

[4] One can also solve for a general case.

total inputs for firm i.

This proposition follows from evaluating the elasticity of γ_i w.r.t. p_m:

$$\frac{\partial\ ln\gamma_i}{\partial\ lnp_m} = \frac{\rho(1-\gamma_i)}{1-\rho}\left[1 - \frac{\partial\ lnP_Z}{\partial\ lnp_m} + \frac{\theta-1}{\theta}\frac{\partial\ ln\Omega_i}{\partial\ lnp_m}\right] > 0. \tag{C.9}$$

Intuitively, the share γ_i would fall after an increase in p_m under two sufficient conditions. First, the home-state price index should not rise quickly due to an increase in p_m, or $\frac{\partial\ lnP_Z}{\partial\ lnp_m} < 1$. Second, the number of inter-state varieties Ω_i should fall with an increase in p_m, i.e., $\frac{\partial\ ln\Omega_i}{\partial\ lnp_m} < 0$. Next, we look at differential impact on firms based on γ_i.

Proposition 2: *Under $\frac{\partial\ lnP_Z}{\partial\ lnp_m} < 1$, $\frac{\partial\ ln\Omega_i}{\partial\ lnp_m} < 0$, and $\partial(\frac{\partial\ ln\Omega_i}{\partial\ lnp_m})/\partial\gamma_i > 0$, the shift to inter-state inputs is larger for firms with a higher dependence on inter-state intermediate inputs after an increase in uncertainty captured by an increase in p_m.*

Taking a derivative of Equation C.9 w.r.t. γ_i gives the above sufficient condition (see Gopinath and Neiman (2014) for details).