Society for Economics Research in India
Working Paper Series

AGGREGATE SHOCKS, DOMESTIC TRADE COLLAPSE AND
REGIONAL REALIGNMENT

Anindya S. Chakrabarti
(Indian Institute of Management, Ahmedabad)
Kanika Mahajan
(Ashoka University, Haryana)
Shekhar Tomar
(Indian School of Business, Hyderabad)

Working Paper No. 20
http://seri-india.org/research

September 2021

Aggregate Shocks, Domestic Trade Collapse and Regional Realignment*

Anindya S. Chakrabarti† Kanika Mahajan‡ Shekhar Tomar§
IIMA *Ashoka University* *ISB*

September 24, 2021

Abstract

How does trade within a country respond to aggregate shocks? Using novel administrative data, we show that COVID-19 induced shutdown in March 2020 led to a collapse in domestic trade across regions in India. Well after the movement restrictions were lifted, trade continues to suffer while GDP recovers as plants shift from inter- to intra-region sales and input-sourcing. Plants more dependent on inter-region sales (inputs) lead this regional realignment. Additionally, products with a higher pre-pandemic scope to expand into the home market witness greater realignment, accounting for 7.6 percent of the sales growth in the last quarter of 2020.

JEL Codes: F14, E32, L23, L6
Keywords: Trade Collapse, Regional Realignment, Scope for Home Expansion.

---

*We thank Shilpa Aggarwal, Shoumitro Chatterjee, Jonathan Eaton, Bhanu Gupta, Jean Imbs, Kala Krishna, Bharat Ramaswami, Krishnamurthy Subramanian, and Stephen Yeaple for helpful comments and discussions. We also thank seminar participants at Ashoka, Penn State, University of Virginia and Society for Economic Research in India (SERI, 2021) for their feedback. Satyabhushan Chintamaneni and Sai Krishna Dammalapati provided excellent research support. Shekhar Tomar acknowledges the research support from EY-IEMS grant. All remaining errors are ours.

†Indian Institute of Management Ahmedabad, Gujarat, India. Email: anindyac@iima.ac.in
‡Ashoka University, Haryana, India. Email: kanika.mahajan@ashoka.edu.in
§Indian School of Business, Hyderabad, India. Email: stomar.dse@gmail.com

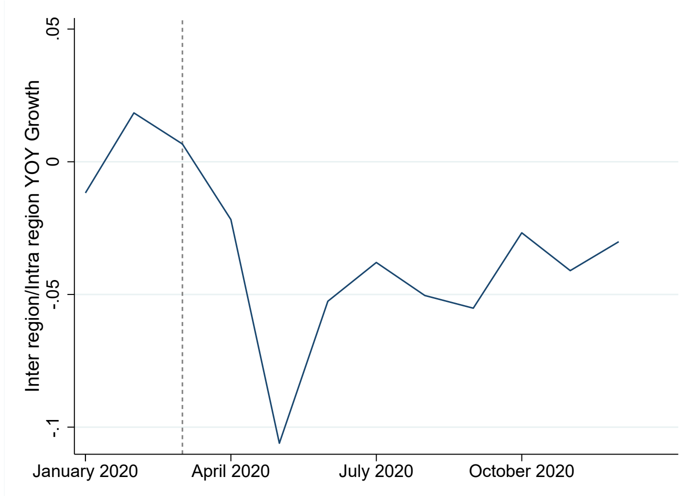
1 Introduction

Large aggregate economic shocks often induce a significant decline in total output and trade followed by gradual recovery, albeit with potentially different trends for the two variables. After the 2008 Global Financial Crisis (GFC), international trade not only contracted more but also recovered more slowly than the global GDP (Bems *et al.*, 2013), a phenomenon referred to as *trade collapse* in the literature. Since the GFC, a rich body of research has emerged to explain the underlying reasons behind trade collapse, ranging from trade credit (Amiti & Weinstein, 2011; Chor & Manova, 2012), protectionist policies (Baldwin & Evenett, 2009), demand heterogeneity (Levchenko *et al.*, 2010) to decline in durables investment efficiency (Eaton *et al.*, 2016). After the recent COVID-19 shock, international trade once again fell more, 5.3 percent, relative to the world GDP, 3.8 percent, in 2020 (WTO, 2021).

Notwithstanding the evidence on international trade collapse, there is no research on the impact of aggregate shocks on domestic (or within-country) trade. This is despite a large body of recent work documenting significant intra-national trade costs across administrative boundaries within a country (Donaldson, 2018; Atkin & Donaldson, 2015). We fill this gap by studying the impact of a large aggregate shock, the COVID-19 pandemic, and the ensuing economic shutdown (lockdown) on domestic trade within India. Analyzing domestic trade collapse within India is also a uniquely useful setting to test for regional realignment i.e., switch from inter- to intra-region sales and input-sourcing as a new channel for explaining trade collapse. Here, inter-region trade refers to trade across the administrative regions i.e., the states and the union territories of India. There were 35 regions within India as of January 2019. Our setting allows us to effectively rule out other mechanisms such as tariff change as well as control for shift in demand that can possibly confound the international trade analyses, while maintaining a large number of trading partners.

We first document a sharp and prominent *domestic trade collapse* right after the pandemic-induced lockdown in India. The first national lockdown started on March 25, 2020, and was extended multiple times until May 2020. The sudden lockdown curtailed movement of goods as regional borders were closed and freight services reduced in the initial phase (Appendix Figure C.1). In line with this, Figure 1 shows a drastic fall of more than 10 percent in inter- to intra-region sales growth immediately after the lockdown. The ratio remains 3–5 percent lower relative to the pre-lockdown

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



Notes: The figure plots the evolution of inter- to intra-region sales ratio growth (year-on-year) in India. The inter-region (intra-region) sales is the sum of inter-region (intra-region) sales of all regions. A region is a state or a union territory in India (35 in total). 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.

level even towards the end of 2020, signifying that inter-region sales recovery has been slower than intra-region sales. These results continue to hold at plant-level even after controlling for unobserved heterogeneity and seasonality in plant sales. Given the stringent measures, the immediate impact on inter-region sales and inputs until May 2020 can be explained by administrative restrictions on transportation. However, it does not explain the slow recovery in inter-region vis-à-vis intra-region sales in the latter half of 2020, when the restrictions were lifted.

Theoretically, we can explain the trade collapse via multiple channels at the plant-level. First, plants engaged in relatively higher level of inter-region trade before the shock shift to intra-region trade. We call this the regional realignment channel. Given the uncertainty ensuing from the shock, it is likely that these plants would reorient their trade towards the home region to diversify and insure against any future disruptions.[1] Second, plants selling more in the home region before the shock can further increase their intra-region trade by utilizing their pre-existing intra-region

[1] Novy & Taylor (2020) propose uncertainty as a reason for firms buying less imported inputs after the GFC. However, they do not test whether the imported inputs are substituted by domestic ones.

connections, while those selling inter-region fail to recover after the shock. However, capacity constraints of these intra-region dependent plants can prevent such gains, as ramping up production within one quarter is less feasible.[2] Lastly, trade collapse could also occur if all plants witness an equally smaller decline in their intra-region sales relative to inter-region sales after the shock. Our empirical results support the regional realignment channel.

We use two novel administrative datasets that come from the E-way Bills information collected by the Goods and Services Tax Network (GSTN) of India. As per law, every establishment in India is required to generate an E-way Bill for shipments above INR 50,000 (around USD 700) in value. We observe the data at plant×region and product×region level with monthly frequency for 2019–2020 for the top thousand plants and products in every region by sales and inputs. 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. Importantly, for both plants and products data we observe the value of inter- vs. intra-region sales.

We first test if the change in plant level inter- to intra-region sales (inputs) ratio post the lockdown varies by their pre-pandemic dependence on inter-region sales (inputs). We measure a plant's inter-regional sales (inputs) dependence as the fraction of its inter-region sales (inputs) to total sales (inputs) in 2019, i.e., before the pandemic. The estimates show that inter- to intra-region sales (inputs) ratio declines more for plants having higher inter-region sales (inputs) dependence.

We then decompose the ratio and estimate the effects separately for inter- and intra-region sales (inputs). We find a decline in inter-region sales (inputs) by 6 percent (4%) and a simultaneous increase in intra-region sales (inputs) by 8 percent (6%) for a one-standard-deviation increase in plant-level inter-regional sales (inputs) dependence until December 2020. We find similar results for the count of shipments (proxy measure for quantity) instead of trade value as our dependent variable. Therefore, the trade collapse is a result of a decline in trade volume rather than prices as also seen after the GFC (Bems *et al.*, 2013).

These results show that the persistence in trade collapse is driven by plants with

[2] A higher level of production for the manufacturing plants would require more labor and capital. During the pandemic, employing more labor or capital would be difficult. At the same time, higher economic policy uncertainty may lead to lower investments (Baker *et al.*, 2016).

higher inter-regional dependence as they shift their sales (inputs) from inter- to intra-region. This shift enables total sales recovery, though not fully, as total sales continue to remain 1.5–2 percent lower until the end of the year for these plants. We test the robustness of the regional realignment channel at product level and continue to find support for it.

Given these results, we ask which products are more likely to undergo realignment? We show that *scope for home expansion*, a measure we construct from two pre-pandemic product-region attributes determines the extent of realignment —the product originating in a region should have high inter-region sales in the pre-pandemic period and the same region should also import sufficient value of this product from other regions. These two attributes together guarantee that excess production (sold inter-region before the lockdown) can be diverted toward local consumption (intra-region sales) in that region after the lockdown. We find that products with a higher scope for home expansion not only realign their sales more but also witness higher growth in total sales until the end of the year. Based on our estimates, this channel explains 7.6 percent of the aggregate sales growth (year-on-year) in India in October–December 2020. We find substantial heterogeneity in product-mix across regions, leading to divergence in their average scope for home expansion and sales recovery.

We now describe our identification strategy. We use an event study design around the first national lockdown in India post the COVID-19 outbreak. As we discuss later, the lockdown was unanticipated. For the plant-level trade collapse, we estimate the change in sales and inputs for a given plant every month before and after the lockdown with January 2020 as our baseline month, correcting for seasonality in outcomes in 2019 (by using plant$\times$month fixed-effects). This is akin to a difference-in-differences (DID) strategy, where the change in outcomes in 2020 over and above the change in outcomes in 2019, between the same months, is estimated. To test the regional realignment hypothesis, we estimate the heterogeneity in the impact on inter- and intra-region sales by a plant's pre-pandemic dependence on outside regions for sales or inputs. We use a similar strategy for product level analyses. We compare the difference in product outcomes (inter- and intra-region sales) between a given month after the lockdown and January 2020, relative to the change in outcomes between the same months in 2019, for products with high vs. low scope for home expansion in a region.

We include a range of fixed-effects to get consistent estimates for the effect of pre-pandemic inter-region dependence on plant outcomes. We include plant×month fixed-effects to rule out plant-specific seasonality. We also include sector×month×year fixed-effects to rule out differential change in demand across plants in different sectors (National Industry Classification (NIC) five-digit level). When using product data we include product×region×month fixed-effects to control for product specific seasonality in a region and product×month×year fixed-effects to rule out product-specific (HSN four-digit) changes in demand over time. These fixed effects also rule out the possibility that changes in product prices drive our results. We also directly test and rule out the existence of any pre-trends, before the lockdown was imposed. Lastly, we use a balanced set of plants and products, for which total sales (inputs) information is available for each month in our analyses. Therefore, our results are not driven by entry-exit of plants and products in the top thousand list for a given region in a month.[3]

We conduct a battery of robustness checks to test the sensitivity of our results. The realignment results go through even after we control for plants' financial situation (Behrens *et al.*, 2013) or other plant-level characteristics like plant size and location; use district×month×year fixed-effects to control for variation in movement restrictions at district level over time; include a larger set of plants/products.[4]

Related Literature: Our paper makes three contributions to the literature. We are the first to causally link trade collapse to regional realignment and directly extend the literature studying the origin of trade collapse. For instance, Amiti & Weinstein (2011) and Chor & Manova (2012) provide evidence in favor of decline in trade credit as a reason for trade collapse after 2008. Levchenko *et al.* (2010), Behrens *et al.* (2013), and Bricongne *et al.* (2012), among others, cite differential change in demand across sectors as the primary reason. Baldwin & Evenett (2009) and Evenett (2020) discuss how increase in protectionism after large shocks can lead to trade collapse. Antràs (2020) and Bonadio *et al.* (2020) warn of re-nationalization of supply chains after the COVID-19 pandemic; however, causal evidence on such realignment is non-existent. The previous work could not test regional realignment channel because, unlike imports/exports, home country sales data are less likely to be available on an

[3]We cannot test the extensive margin effects, as we do not know if plants exit from the market. See Section 2.2 for details.

[4]A district is a smaller administrative unit within a State (region) in India. The 35 regions of India were divided into 723 districts in 2019.

intra-annual frequency at the firm level (Bricongne *et al.*, 2012).

In addition, we show that not all products can undergo regional realignment. A high scope for home expansion, as defined in our paper, is necessary for a product to undergo realignment after an aggregate shock. In the international trade context, this measure could explain heterogeneous outcomes across countries after a global economic shock. The average scope for home expansion would differ across countries based on their import-export product basket leading to differential realignment.[5]

Second, our paper is the first to show trade collapse within a country after an aggregate shock. It shows that trade collapse is not restricted to international trade. In fact, a within-country setting provides cleaner identification for the regional realignment channel as many of the confounding factors present in the international trade context are absent. For instance, protectionism is ruled out since we are dealing with intra-national trade. Similarly, the trade credit cycles are relatively shorter for domestic economy, making reliance on trade credit less critical in our context. Importantly, we are also able to rule out differential changes in demand in our empirical specification. More broadly, our work is related to the emerging literature on domestic trade. Some of the recent research in the domestic trade literature includes work on estimating intra-national trade costs, studying optimal transport network, or local frictions to international trade (Asturias *et al.*, 2019; Coşar & Fajgelbaum, 2016; Ramondo *et al.*, 2016; Sotelo, 2020; Van Leemput, 2021). Atkin & Khandelwal (2020) provide a summary of studies detailing domestic trade frictions.

Third, our paper shows how regional realignment can help dampen the impact of a shock on the aggregate output. A large body of recent work has documented how supply chains can propagate and amplify shocks. Barrot & Sauvagnat (2016) and Carvalho *et al.* (2021) empirically show how disruption to supply chains propagate upstream and downstream after a firm in the network is hit by a sector- or region-specific shock. In our case, closure of regional borders provides temporary freezing of inter-region trade for all plants; that is, inputs and sales to plants outside one's home region were cut off. However, plants with greater inter-regional dependence shift to intra-region sales and input sourcing within a few months of this shock.[6] This

[5]The scope for home expansion measure is different from Grubel-Lloyd index, an intra-industry substitution measure used in the existing literature. We discuss the differences with Grubel-Lloyd index in Section 5.

[6]The flexibility in organizing supply chains can be also seen 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

realignment, in turn, helps in the recovery of the aggregate output. In the absence of such adjustment, the negative impact of the shock on aggregate output would have been larger.

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 the results for trade collapse in Section 3, and for regional realignment using plant and product data in Sections 4 and 5, respectively. Section 7 provides the impact on the aggregate sales due to the realignment channel. Section 6 presents robustness checks, and Section 8 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 that led to the regional trade collapse in the country. 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 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 a span of 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 (Mahajan & Tomar, 2021) during the first lockdown.

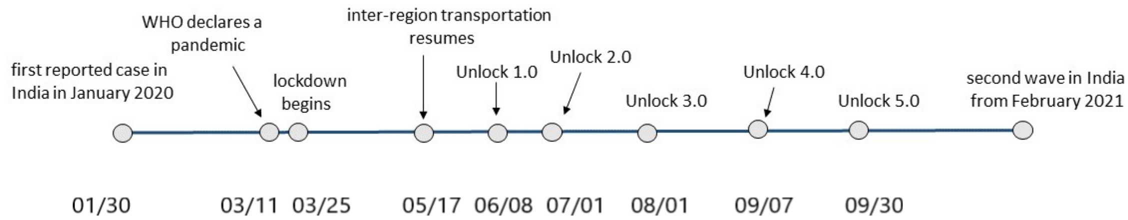
The impact was more severe for inter-region trade, as restrictions on movement led to choking of inter-state borders with trucks (Appendix Figure C.1). Freight movement is dominated by road transport in India, accounting for 75% of the share in 2019.[7] The complete lockdown was extended multiple times until May 31, 2020. Resumption of economic activity or "Unlockdowns," spread across five phases, was

---

and firm performance. Korovkin & Makarin (2020) use simulation to calculate how new network formation across firms compensates for the network destruction after the Ukraine-Russia crisis. In broader context, Acemoglu *et al.* (2012), Baqaee & Farhi (2020), and Carvalho (2014) provide theoretical framework for studying the role of network linkages in generating aggregate fluctuations.

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

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. A series of Unlockdown measures (1.0 to 5.0) took place, gradually relaxing the restrictions on various forms of economic and social activities. 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.

only initiated from June 8, 2020, with a gradual easing of mobility restrictions on people and goods.[8] The restrictions on inter-state transportation were fully lifted by August 1, 2020, while those on other public activities were completely removed by September 30, 2020. India witnessed a secular decline in the number of infections until December 2020. Overall, the first wave of infections was much smaller than expected, making the lockdown a bigger factor behind the loss in output in 2020 rather than the health shock. The second more infectious wave hit the country in February 2021, leading to resumption of lockdowns and significant disruption in economic activity thereafter (Appendix Figure C.2).

The above timeline is also reflected in the overall economic activity in India. The economy suffered a severe decline after the lockdown as the GDP contracted by 23.9 percent (April–June, 2020) and by 7.5 percent (July–September, 2020) in comparison to 4.2 percent growth in the previous year (April 2019–March 2020). Finally, economic

[8]See: Hindustan Times and Business Standard. The restrictions on 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.

recovery picked up in the October–December 2020 quarter, with a GDP growth of 0.4 percent.

2.2 Data

We use data on Electronic-way (E-way) Bills collected by the Goods and Services Tax Network (GSTN) in India for our analyses. 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 we consider 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 two unique administrative datasets provided by the GSTN.

Plant Data: It has plant-level monthly sales and input information from January 2019 to December 2020.[9] On the sales side there are two datasets that record sales by the destination type (inter-region vs. intra-region). One records inter-region plant sales for the top 1,000 plants by inter-region sales in a given region and month. Similarly, the second one records intra-region plant sales for the top 1,000 plants by intra-region sales in a given region and month. Each plant has a unique identifier at the region level. It can be tracked over time and across the two datasets, as long as it falls within the top 1,000 plants. It is possible that some plants may not be observed in both the datasets in a given month.[10]

These data cover a significant portion of manufacturing sales in India and adequately capture regional economic activity. The top 1,000 plants contribute on average 59 percent to the total regional sales, while the top 200 plants contribute 42 percent. Given that there are more than 1,000 plants in most regions for each destination type, the set of reported plants changes each month.[11] However, a large fraction of plants

[9] 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.

[10] For instance, a plant may lie in the top 1,000 for inter-region sales in a month but have low intra-region sales and never lie in the top 1,000 plants by intra-region sales in that region. In this case, we only observe its inter-region sales.

[11] In 2019, around 80 percent of regions reported 1,000 plants across all combinations. See

are reported every month, as they continue to be a part of the set of top 1,000 plants for the entire duration.

The two input sourcing datasets are similar and provide information on intra- and inter-region input sourcing for top 1,000 plants in each input sourcing destination type. Once again, the unique plant identifier allows us to track a plant across the sales and the inputs data. One crucial difference between the total 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.[12]

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-region 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 subset 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 exit of plants from the set of top 1,000 plants and cover a significant part of the regional activity as we include the largest plants from each region.[13] The first four rows of Table 1, Panel (a), show the summary statistics for the sales data—number of plants per region (row (1)), average total monthly sales (row (2)) and average monthly sales by type (row (3) and row (4))—for this set of plants. On average there are 272.1 plants from each region, i.e., a total of 9,252 plants from 34 regions. 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-region sales. The former

Chakrabarti & Tomar (2021) for more details on the coverage of E-way Bills data.

[12]The ratio of sales in intermediates to the sales in consumer products within India, is quite similar to the corresponding ratio in global trade (UNCTAD, 2020).

[13]To elaborate, if a plant reports any of the two type of sales (inputs) in a given month, i.e., intra- or inter region, then it is defined as reporting total sales (inputs). Therefore, if a plant reports either inter-region or intra-region sales (input) for all 24 months, it is a part of the final sales (inputs) data used for analyses. This restriction minimizes concerns that our results on total sales are driven by entry and exit of plants. The main results in the paper are based on this set of plants in 34 regions of India (one region has no plants satisfying this criteria, resulting in a reduction of regions from 35 to 34 in our analyses). However, results are robust to inclusion of plants that appear in our dataset for fewer months as well as those that strictly report intra-region and inter-region sales (inputs) for each of the 24 months.

falls by 7.86 percent and the latter by 3.35 percent. These statistics immediately highlight a larger negative impact of the lockdown on inter-region 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 region, i.e., in total 9,029 plants (row (5)). 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-region (6.4%) than intra-region inputs (4%).

The above administrative data do not provide information on the nature of the products sold by each plant. Therefore, 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. After matching with MCA data this reduces to 47 percent of total plant sales, hence we continue to capture a large fraction of plant sales even after loss in some plants due to merging with MCA database.[14]

Product Data: The E-way Bills data also provide product level (at HSN four-digit level) data for every region and month. It records information for the top 1,000 products in each region across three datasets based on the sales type—inter-region sales, intra-region sales, and inter-region receivables. Here, *Inter-Region Sales* and *Intra-Region Sales* refer to outside and within-region sales of a product produced in a given region. *Inter-Region Receivables* refers to the value of a product received by a region from other regions (outside its geographical boundary) within the country. Once again, a product is reported in a dataset as long as it falls within the top 1,000 products for a given region and sales type. We use the monthly data from January 2019 to December 2020 for the product-level analyses. As earlier, we report summary statistics for a balanced set of products in a region, for which total sales data is available for each month in our data (Panel (b) of Table 1).[15] We calculate total

[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.

[15]To elaborate, if a product reports any of the two type of sales i.e., intra- or inter region, in a

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-Region Sales	81092	309	1238.5	81983	285.4	1368.5
(4) Intra-Region 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-Region Inputs	81883	200.8	597.3	83113	187.2	913.1
(8) Intra-Region 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-Region Sales	162252	360.6	1612.4	160179	329.7	1640.5
(4) Intra-Region Sales	161793	329.6	1259.4	160322	309.3	1253.1
(5) Inter-Region Receivables	164161	343.4	1079.9	162318	313.9	1161.0

Panel (c): Inter-Regional Dependence (2019)						
	Obs.	Mean	Median	S.D.	Min	Max
(1) Plants: Inter-Region Sales Fraction	9252	0.53	0.59	0.40	0.00	1.00
(2) Plants: Inter-Region Inputs Fraction	9029	0.64	0.84	0.40	0.00	1.00
(3) Products: Inter-Region Sales Fraction	13912	0.53	0.55	0.27	0.00	1.00
(4) Products: Inter-Region 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 region across the 12 months (408 observations for 34 regions) for each category (Sales and Inputs) are also provided. The 'Total Sales (Inputs)' is further divided into Intra-Region and Inter-Region 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 region across the 12 months (408 observations for 34 regions) are also provided. The product level 'Total Sales' is further divided into Intra-Region and Inter-Region Sales in Panel (b). Additionally, Panel (b) also shows the mean product value received from other regions for the same balanced set of products. Panel (c) shows the plant level mean of pre-pandemic (2019) Inter-Region 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-Region Sales and Receivables fraction for the balanced set of products.
Source: Plant and Product level E-way bills data (January 2019-December 2020).

monthly sales of a product originating in a region as the sum of intra- and inter-region sales for that product in a given month and region. On average, each region reports 409.4 products, i.e., in total 13,919 product×region 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, due to the impact of the pandemic. The fall is larger for the mean value of the inter-region sales (8.6%) and receipts (8.6%) relative to the intra-region sales (6%), once again suggesting domestic trade collapse.

3 Measuring Trade Collapse

In this section, we first describe the empirical strategy to identify the trade collapse, followed by results.

3.1 Empirical Strategy

As described earlier, the sudden lockdown in March 2020 led to an immediate disruption in economic activity. We measure the impact of this disruption using an event-study design around the lockdown using plant-level monthly data from January 2019 to December 2020. The impact on monthly sales and inputs is estimated using the below specification:

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

where $z^c_{ijr,my}$ is the outcome variable for plant i belonging to sector j in region 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-region sales (inputs) ratio.[17]

given month, then it is defined as reporting total sales. 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-region and inter-region 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 to excluding them.

[17]The nature of the data precludes us from observing the products sold by a plant, unlike in the cases of Behrens *et al.* (2013) and Bricongne *et al.* (2012). Therefore, our empirical strategy to

$\mathbb{1}_m$ 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$\times$month fixed effects, $\delta_{ir,m}$. Our coefficient of interest α_1^{τ} 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. Finally, 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 difference is the difference between these two differences.[18] Here, 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. We expect no impact on plant outcomes in February 2020, it being a control month.

For the identification, we require the lockdown imposition to be exogenous and present evidence in support of this in Section 2.1. We also control for plant level seasonality (through $\delta^c_{ir,m}$) so that our estimates do not reflect any monthly fluctuations in plant outcomes. Our estimation strategy, therefore, effectively nets out changes in plant outcomes during the same months in 2019 from the observed changes in 2020.[19]

3.2 Results: Inter-region Trade Collapse

We begin by documenting the decline in overall economic activity after the lockdown and its gradual recovery. As discussed earlier, we carry out all further analyses on a balanced set of plants in the sales (inputs) data for whom we observe total sales

estimate trade collapse at plant-level cannot account for the nature of the product directly.

[18] To elaborate, α_1^{τ} = (Percent change in plant outcome between month m in 2020 and January 2020) - (Percent change in plant outcome between month m in 2019 and January 2019).

[19] Inclusion of $\delta^c_{ir,m}$ subsumes the need to control for $\mathbb{1}_m$ in the specification.

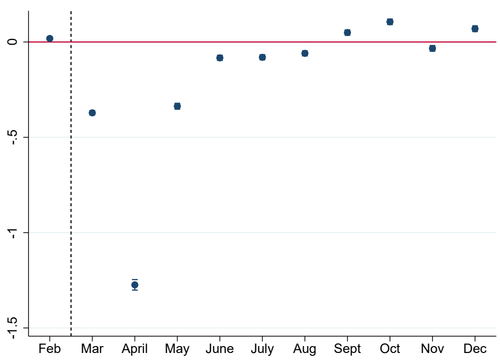
(inputs) in each of the 24 months in the data. Figure 3, Panel (a) plots the estimated monthly impact in 2020 on log of total plant sales, while Panel (b) plots it on log of total plant inputs (given by α_1^τ in Equation 1). The percentage fall is given by $exp(\alpha_1) - 1$. We find a 30 percent fall 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 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 the trade collapse. We plot the coefficients (α_1^τ) when the log of inter- to intra-region sales ratio and inputs ratio are the dependent variables in Figure 3, Panel (c) and (d), respectively. Here, we find a collapse in inter-region trade for a period much beyond the initial lockdown. There is a fall in inter- to intra-region 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. Therefore, we can conclude that the inter- to intra-region 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-region inputs ratio which also shows a persistent decline in Panel (d). We check the robustness of the trade collapse results to an alternate estimation strategy in Appendix B, which controls for changes in sectoral demand over time and find that these results continue to hold.

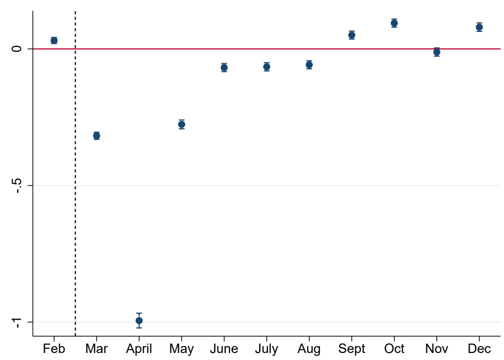
The above estimates document a persistent fall in inter-region trade relative to the intra-region trade as a response to the initial shock caused by the lockdown. Since movement restrictions across regional borders were completely eased after August 2020, the next question is what led to low inter-region trade in the later months of 2020? We answer it in the following sections.

Figure 3: Economic Impact of Lockdown on Plants: Regional Trade Collapse

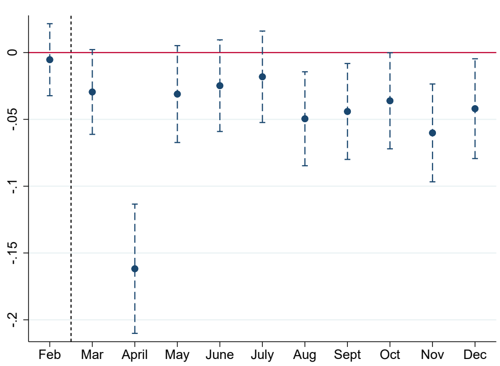
(a) Total Sales



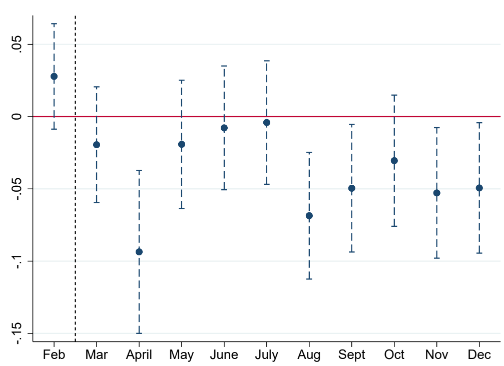
(b) Total Inputs



(c) Inter- to Intra-region Sales ratio



(d) Inter- to Intra-region Inputs ratio



Notes: The figures in Panels (a) and (b) plot the monthly coefficients (α_1^τ in Equation 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 (α_1^τ in Equation 1) for the impact on log of inter- to intra-region 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. 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-region sales are observed every month. Similarly, Panel (d) includes a balanced set of plants for which both inter- and intra-region 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.

4 Regional Dependence and Realignment

In this section, we ask which plants realign their sales (inputs) towards home region during the recovery phase. Ex-ante, this question has no obvious answers. It is plausible that plants with stronger pre-pandemic intra-region dependence are the ones leading the increase in intra-region sales in the recovery phase or that inter-region sales decline with no change in intra-region sales for all plants alike. Mahajan & Tomar (2021) show how local food supply chains were more resilient to border restrictions in India during the initial phase of the pandemic. Alternatively, it is also plausible that plants with stronger pre-pandemic inter-region dependence shifted toward intra-region trade to diversify sales and sourcing partners and cut down potential losses arising from future border restrictions, i.e. the regional realignment channel.[20]

We present a model (similar to Gopinath & Neiman (2014)) with plant-level input sourcing and trade cost uncertainty in Appendix A to present 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 regions.[21] In this simple setup, we can show two things under reasonable parametric restrictions. (a) An increase in inter-region trade cost can lead to a decline in share of inter-region inputs for a plant, and (b) plants more dependent on outside regions for input sourcing would shift to higher intra-region sourcing due to the cost increase. Section 3 already demonstrates that the first implication holds true. Next, we test the second prediction. Since two-thirds of sales in our data consists of intermediate goods, sales would display a similar persistence in realignment towards intra-region as input sourcing. We now describe our empirical strategy to test this hypothesis.

[20] Another possibility for these plants is to trade more with their existing connections from the home region.

[21] We do not explicitly test if increase in transportation costs has any influence on our results. However, we know that Indian railways cut freight cost during this period (Source: The Hindu Business Line) and diesel prices do 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 in 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 up to December 2020 (to around INR 75 per litre).

4.1 Empirical Strategy

We first measure a plant's dependence on outside regions (relative to home region) for sales or inputs in the pre-pandemic period. For a plant i in region r and category c, we define:

$$f_{ir}^{c} = \frac{c_{ir}^{inter}}{c_{ir}^{inter} + c_{ir}^{intra}} \tag{2}$$

where f_{ir}^{c} is the fraction of inter-region sales (inputs) over total sales (inputs) in 2019 for a plant. For $c = sales$, a high value of f_{ir}^{sales} shows a higher dependence of plant i on inter-region sales. Similarly, for $c = input$, f_{ir}^{input} measures dependence of plant i on inter-region inputs. We calculate f_{ir}^{c} from data in 2019, so that inter-region dependence is a pre-pandemic measure for each plant. The summary statistics for f_{ir}^{c} are reported in Panel (c) of Table 1. For sales, the mean value of f_{ir}^{sales} is 0.53 while for inputs it is a bit higher at 0.64.

Using f_{ir}^{c} as a measure of plants' inter-regional dependence, we examine its impact on plant outcomes after the lockdown. We estimate the following specification:

$$\begin{aligned} ln(z_{ijr,my}^{c}) = \gamma_0^{c} \;\; &+ \sum_{\tau \in (m2020)} \gamma_1^{\tau,c}(\mathbb{1}_m \times \mathbb{1}_{2020}) + \sum_{\tau \in (m2020)} \gamma_2^{\tau,c}(\mathbb{1}_m \times \mathbb{1}_{2020} \times f_{ir}^{c}) \\ &+ \;\; \mathbb{1}_{2020} \times f_{ir}^{c} + \mathbb{1}_{2020} + \delta_{ir,m}^{c} + \delta_{j,my}^{c} + \mathbb{X}_{ir,my}^{c} + \varepsilon_{ijr,my}^{c} \end{aligned} \tag{3}$$

where $z_{ijr,my}^{c}$ is the outcome variable for plant i belonging to sector j in region r for category c in month m and year y. We account for plant×month level unobserved heterogeneity through plant×month fixed-effects, $\delta_{ir,m}^{c}$, which also control for any plant specific seasonality in outcomes.[22] $\delta_{j,my}^{c}$ controls for sector×month×year fixed-effects. We also include $\mathbb{X}_{ir,my}^{c}$ as a vector of time-varying controls at the plant-level. These controls are of the form $\sum_{\tau \in (m2020)} \phi^{\tau,c}(\mathbb{1}_m \times \mathbb{1}_{2020} \times X_{ir}^{c})$ and the relevant double interactions. In all specifications, when examining the impact of inter-regional sales (inputs) dependence on plant sales (inputs) post-lockdown, we control for inter-regional input (sales) dependence of the plant, i.e., $X_{ir}^{sales} = f_{ir}^{input}$ and $X_{ir}^{input} = f_{ir}^{sales}$. Thus, we control for input shock suffered by a plant due to inter-regional input dependence when examining the effect of inter-regional sales dependence on sales post the lockdown and vice versa.[23]

[22] These fixed effects ($\delta_{ir,m}^{c}$) preclude the need to control for $\mathbb{1}_m$ or $\mathbb{1}_m \times f_{ir}^{c}$ in the above specification.

[23] Theoretically, a greater dependence on inter-region inputs can reduce sales more post the

For detailed exposition of the main coefficient of interest, consider the case when $c = sales$ with the inter-region sales as our 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-region sales between month m in 2020 and January 2020 for all plants, relative to the same difference in 2019. However, our main coefficient of interest is $\gamma_2^{\tau,sales}$ on the interaction term $\mathbb{1}_m \times \mathbb{1}_{2020} \times f_{ir}^{sales}$. For a given month in 2020 (τ), this coefficient shows the impact of initial inter-regional sales dependence on plant inter-region sales in τ. More specifically, it measures the differential change in plant inter-region 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-regional sales dependence. Therefore, a negative $\gamma_2^{\tau,sales}$ shows that plant inter-region sales fall more in a given month if the plant has a higher inter-regional dependence for sales before the pandemic.

Our identification strategy is based on the following assumptions. First, the plant outcomes should not affect the timing or the occurrence of the lockdown. We discuss the sudden and exogenous imposition of the lockdown in Section 2.1. Second, the estimates should not be driven by seasonality. To address this, we control 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 $\delta_{ir,m}^c$).[24] Third, we require that plants' dependence on outside regions f_{ir}^c, does 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 longer term pre-trends into a quarter before the lockdown using a single difference estimation strategy that does not control for plant-level seasonality.

We note that plants' inter-regional dependence may vary with industrial sector of the plant. Our estimates in this case would reflect a differential shift in demand across sectors after the lockdown. To account for this possibility, we control for sector×month×year fixed-effects, $\delta_{j,my}^c$, that capture any time-varying changes at the

lockdown, with the effect attenuated by inventory effects. Similarly, greater dependence on inter-region sales resulting in a larger reduction on the sales side can consequently decrease the demand for inputs post the lockdown. We also check the robustness of our results to addition of more plant-level controls (Behrens *et al.*, 2013) in Section 6.

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

sector level, including any demand shifts faced by a plant. This allows us to isolate the impact due to a plant's inter-regional dependence. In fact, sector time fixed-effects also ensure that a differential change in sectoral prices does not drive our results. However, inclusion of $\delta^c_{j,my}$ preclude us from estimating $\gamma_1^{\tau,c}$ as they get absorbed in the sector×month×year fixed-effects. As we discuss later, our results on realignment continue to hold even if we exclude these time-varying sectoral fixed-effects.

4.2 Results: Plant Realignment

In this part, we test whether plants with higher inter-regional dependence differently realign themselves toward intra-region sales and inputs and hence contribute to the inter-region trade collapse after the lockdown. We estimate Equation 3 with the log of inter- and intra-region monthly plant sales and inputs as our dependent variables. The coefficients (γ_2^τ) from these estimations, that give the heterogeneous impact of inter-regional 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.[25]

Figure 4, Panel (a) shows an immediately greater fall (April 2020) in inter-region sales of plants that initially sell more outside their home region.[26] The coefficient in April gives a $0.4 \times 0.4 \times 100 = 16$ percent larger decline in inter-region sales for a one-standard-deviation increase in the fraction of inter-regional sales dependence. Notably, inter-region 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-region sales for a one-standard-deviation increase in inter-regional sales dependence. The trends reverse in the case of intra-region sales (Panel (b)). We find no differential impact on intra-region sales due to differences in initial dependence on inter-region sales in the pre-lockdown and during the early lockdown phase. All the monthly coefficients are insignificant until June

[25] Coefficient estimates for γ_1^τ along with those for γ_2^τ, without sector time fixed effects, are reported in Appendix Table C.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-Region Input Fraction (included as a control) on inter or intra region sales of a plant post the national lockdown, as discussed later.

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

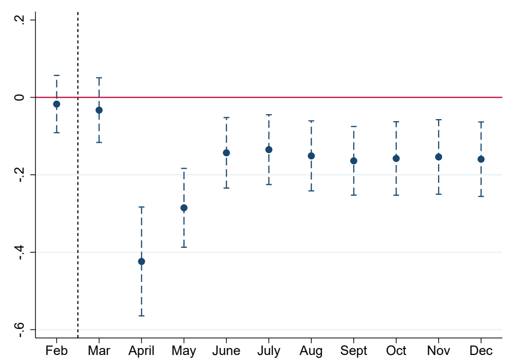
2020 and suggest that outside region dependence does not differentially impact plants' intra-region sales immediately post the lockdown. However, the coefficients become positive and significant from July to December 2020, showing that the intra-region sales increase relatively more for plants that sell more outside their home region. The coefficients are around 0.2, which gives a $0.2 \times 0.4 \times 100 = 8$ percent increase in intra-region sales for a one-standard-deviation increase in the fraction of inter-regional sales dependence. Notably, we do not find any differential impact on the outcome variables by regional dependence in February 2020, before the lockdown, showing that are findings are not driven by pre-existing trends. Our DID specification with plant specific monthly seasonality and time period of data availability do not allow for estimating longer pre-trends. However, we provide longer pre-trends with alternate specifications in Section 6.

The above results for the home-ward shift in plant sales are based on total value. Given that our specification controls for differential trends in sectoral prices through time varying sector fixed-effects, our estimates capture changes in quantity traded. 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. We use this count as a proxy for quantity, as it provides a measure of the number of transactions each month. We report the impact of the plant's outside region dependence on its log count of inter-region and intra-region E-way Sales bills in Panels (c) and (d), Figure 4, respectively. The monthly coefficients in these regressions are negative (similar to Panel (a)) and show a relative decline in inter-region sales quantity with increase in inter-regional sales dependence. These results align with the findings in the GFC context (Levchenko *et al.*, 2010; Gopinath *et al.*, 2012), where the fall in quantity, rather than prices, explains the international trade collapse. However, we further find a differential increase in intra-region sales quantity (Panel (d)), thereby showing that trade collapse is driven by the realignment in quantity of trade from inter-region to intra-region led by plants with higher inter-regional dependence.

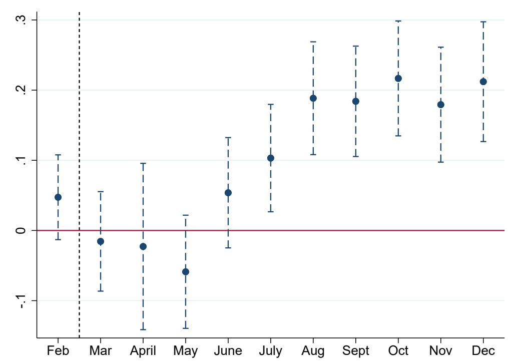
In summary, there is an immediate and large relative decline in inter-region sales and less than full relative recovery until December 2020 for plants depending on outside region sales. These plants could not substitute to selling within the home region immediately after the lockdown (perhaps driven by scope for home expansion constraints, as we discuss later). However, once they sell more intra-region in July 2020, they continue to do so until the end of the year. These two results taken

Figure 4: Realignment in Plant Sales: By Inter-Region Sales Fraction

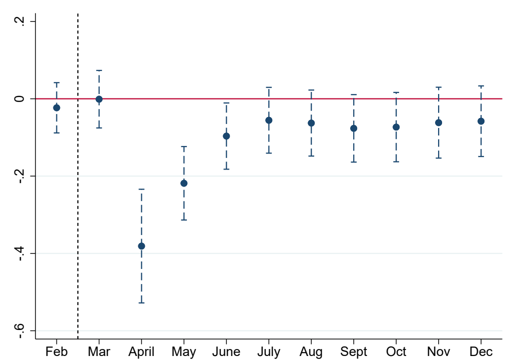
(a) Inter-Region Sales



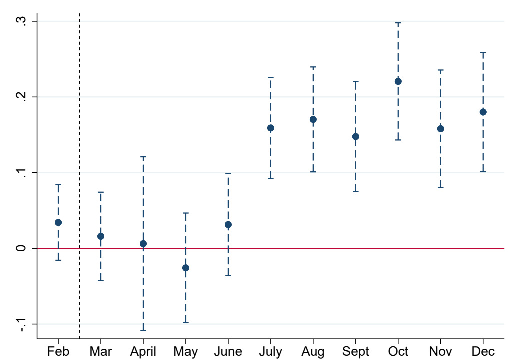
(b) Intra-Region Sales



(c) Inter-Region Sales Quantity



(d) Intra-Region Sales Quantity



Notes: The figures in Panels (a) and (b) plot the monthly coefficients (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region sales and intra-region sales respectively (sales refers to value of sales, unless otherwise mentioned), by plant-level Inter-Region 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 (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region sales E-Way Bills and intra-region sales E-Way Bills respectively, by plant-level Inter-Region 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-Region 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.

together provide evidence for an inward shift in regional trade and show that the plants with high inter-regional sales dependence lead this shift. It also explains why trade collapse is more persistent than the decline in aggregate GDP. On the one hand, the aggregate GDP suffers due to lower inter-region sales. However, it recovers faster than inter-region trade as intra-region sales go up. This creates a divergence between total economic activity and inter-region trade. These results also highlight that plants are flexible in realigning their sales, in the absence of which the aggregate economy would have seen a much higher decline in output.

We find similar realignment on the input side (Figure 5). Inter-region input sourcing falls relatively more for plants that have higher initial inter-regional dependence, since the interaction coefficients (γ_2^{τ}) 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-region input fraction. We find no differential impact of inter-region input dependence on intra-region input sourcing until July 2020 (Panel (b)). However, the intra-region input sourcing relatively increases from August to December 2020 for plants with a higher inter-regional input dependence. The intra-region 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. This rules out differential pre-trends in inter- and intra-region sales or inputs for plants based on their inter-regional dependence. Furthermore, Panels (c) and (d) show that these results are driven by changes in quantity traded. There is a persistent decline in inter-region input quantity (Panel (c)) and a persistent increase in intra-region input quantity (Panel (d)) for plants with higher inter-regional input dependence.

We also test if this realignment is sufficient to overcome the loss in inter-state trade for plants with high outside region dependence. We run similar regressions as in Equation 3, 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 C.2). Therefore, realignment only aids in partial recovery for plants with high inter-region dependence.

Impact of Other Variables: The estimated Equation 3 also allows us to evaluate the impact of inter-regional input dependence on plant sales and vice versa. The results are reported in Figure C.3. We find no impact of inter-regional input dependence on sales (Panel (a) and (b)). However, a high inter-regional sales dependence has a negative impact on input sourcing, both intra- and inter-region. It suggests that sales dependence determine both input sourcing and final sales destination decision.

We also test if inward movement in trade by plants is affected by the distance of the plant from the region border. The lockdown led to closure of regional borders in India, however, if there were disruptions to trade within a region the plants farther from the border could be affected more in terms of a relatively larger decline in inter-region sales. We find no differential impact on sales or inputs based on plant's location from the regional border.[27] This shows that it is the border that acts as a barrier and not the distance per se from the regional border. These results are available on request.

5 Realignment across Products

In this section, we use product data to find the key product attributes that drive the realignment in sales.

5.1 Which Product Attributes Matter?

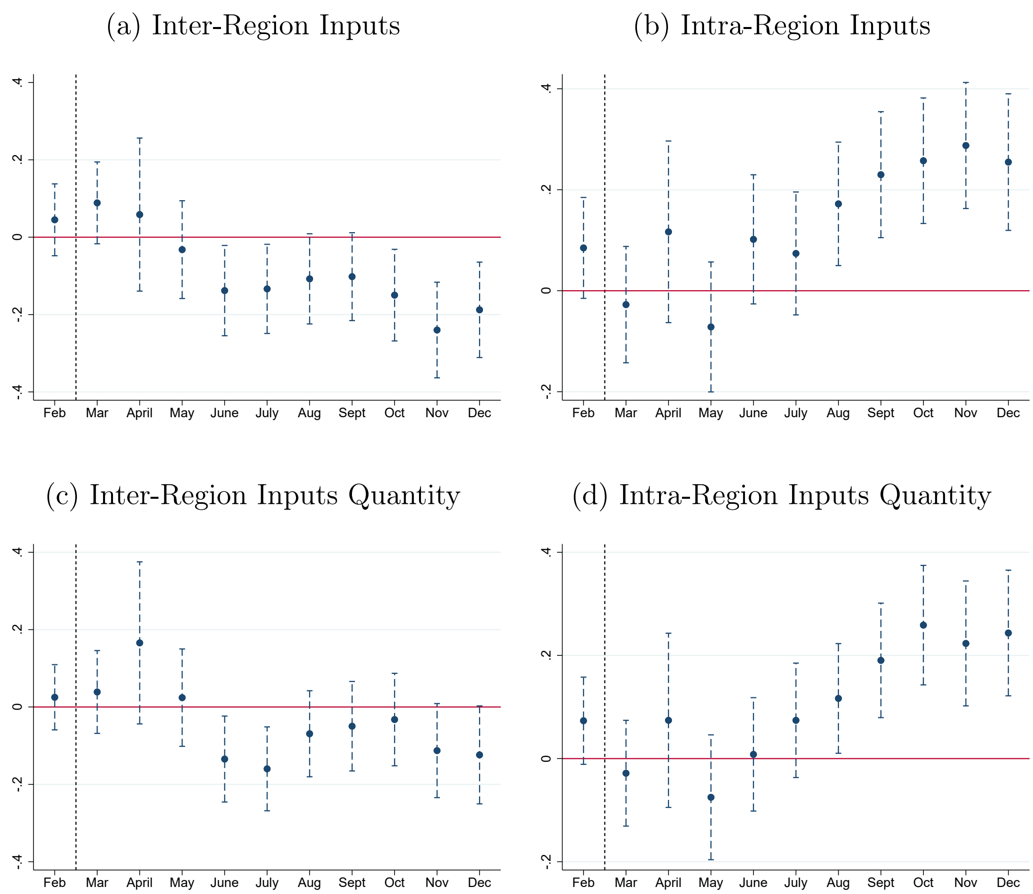
Inter-regional Dependence: We first construct a measure of product's dependence on outside regions for sales. It is similar to the one used to measure plant level inter-regional dependence. For a product k produced in region r, this dependence is given by:

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

where $f_{kr,sales}$ is the fraction of inter-region sales over home-region production in 2019, i.e. a pre-pandemic measure.Here, $\text{Sales}_{kr}^{inter}$ refers to the inter-region sales and $\text{Sales}_{kr}^{intra}$ is the intra-region sales of product k produced in region r. A high $f_{kr,sales}$ shows a higher dependence of region r on outside regions to sell k. The third row of Panel (c) in Table 1 reports the summary statistics for $f_{kr,sales}$. The average for this fraction is 0.53 and is similar in magnitude to the regional dependence measure obtained using plant sales data.

[27] We introduce another variable defined as $(\mathbb{1}_m \times \mathbb{1}_{2020} \times X_{ir}^c)$ where $X_{ir}^c = Border_{ir}$. We do not find any significant effect of this variable on either inter-region sales (inputs) or intra-region sales (inputs). It shows that border effect continues to impede inter-region trade more relative to distance of a plant from the border. Such home bias or border effect has been well reported in the within country trade context (Wolf (2000)).

Figure 5: Realignment in Plant Inputs: By Inter-Region Inputs Fraction



Notes: The figures in Panels (a) and (b) plot the monthly coefficients (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region inputs and intra-region inputs respectively (inputs refers to value of inputs, unless otherwise mentioned), by plant-level Inter-Region 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 (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region inputs E-Way Bills and intra-region inputs E-Way Bills respectively, by plant-level Inter-Region 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-Region 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.

Scope for Home Expansion: The $f_{kr,sales}$ measure defined above does not completely capture the production and demand constraints that need to be satisfied for regional realignment. Let's present the limitation of $f_{kr,sales}$ through an example. Consider Tamil Nadu, a region in India, that sells a large quantity of coffee to other regions. At the same time, it also buys a considerable quantity of coffee from other regions, displaying the *love for variety* effect. The excess home production and consumption of coffee from outside regions allow for the possibility of replacement of outside coffee with coffee produced within Tamil Nadu.

We capture both the constraints presented in the above example through a new measure that we call *scope for home expansion*, defined at the product-region level. As its first attribute, our measure captures the capacity constraints after the lockdown. Based on plant-level results we know that plants with higher inter-region sales diverted their sales to home region after the lockdown. The plants with high intra-region sales in the pre-pandemic period could not increase their intra-region sales as much possibly due to capacity constraints. A similar reasoning at product-level would imply that products with a possibility of diversion of inter-region sales to home region are the ones that would undergo realignment. The second attribute incorporates the constraint from the demand side. It requires that the home region would be able to absorb the extra supply created by diversion of inter-region sales to intra-region. Therefore, the overall demand for a given product in a given region should include a significant fraction of outside home region imports in the pre-pandemic period, similar to non-Tamil Nadu coffee consumed in the above example.

Formally, we define the scope for home expansion for product k in region r as:

$$\sigma_{kr} = \min\left[\frac{\text{Sales}_{kr}^{inter}}{\text{Sales}_{kr}^{inter} + \text{Sales}_{kr}^{intra}}\ ,\ \frac{\text{Receivables}_{kr}^{inter}}{\text{Receivables}_{kr}^{inter} + \text{Sales}_{kr}^{intra}}\right]. \tag{5}$$

The first ratio (Inter-Region Sales Fraction) determines the share of inter-regional sales of product k produced in region r. Suppose region r does not sell any k outside its home region before the pandemic. In that case, the first term is zero and r would be capacity constrained and cannot divert k for home consumption, i.e., have a zero value of σ_{kr}. The second ratio (Inter-Region Receivables Fraction) measures the share of consumption of product k bought from outside region r. Therefore, if region r does not buy k from other regions before the pandemic, then the second term in the minima function is zero and makes σ_{kr} also zero. Only when both these fractions are large, σ_{kr} is large, and the outside region receipts for product k in region r can be substituted by home production. As earlier, We calculate σ_{kr} as a pre-pandemic measure using 2019 data.[28]

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

5.2 Empirical Strategy

We now describe our empirical strategy to measure heterogeneous impact on product level outcomes after the lockdown by the above product attributes, denoted by $g_{kr} \in \{f_{kr,sales}, \sigma_{kr}\}$. We use the following specification:

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

where $z_{kr,my}$ is the outcome variable for product k produced in region r, in month m and year y. Here, $\delta_{kr,m}$ is product×region specific month fixed-effects and accounts for product-region level monthly seasonality.[29] $\delta_{k,my}$ are the product-specific time

[28] To measure intra-industry substitution across countries, the prior literature has considered Grubel-Lloyd index which captures intra-industry trade at the product level. For the i-th product, it 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 σ_{kr} instead of the Grubel-Lloyd index stems from two reasons. First, our objective is to estimate the impact on intra-region sales, and not just the change in inter-region trade. The presence of intra-region sales in the denominator of σ_{kr}, therefore, captures the potential for change in intra-region sales. Under Grubel-Lloyd index, this dimension is absent. Second, Grubel-Lloyd index does not respond to total production capturing inter- and intra-region sales whereas the proposed measure σ_{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-region sales to mitigate against future uncertainty. While Grubel-Lloyd index does not capture this, σ_{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-region sales value, say 10, the latter pair would provide greater potential for the plant to shift towards the home region. Our proposed measure captures this possibility too.

[29] Inclusion of $\delta_{kr,m}$ also preclude the need to control for $\mathbb{1}_m \times g_{kr}$.

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 g_{kr} of a product in a region, net of any demand effect. $\mathbb{X}_{kr,my}$ includes a vector of time-varying product×region level controls.[30] Thus, our identification strategy is similar to that for plant level data. Note that the double interaction term $(\mathbb{1}_m \times g_{kr})$ is subsumed in $\delta_{kr,m}$. Standard errors are clustered at the product×region level.

Again, this specification is akin to a DID estimation strategy with heterogeneous effects. The main coefficient of interest is π_2^τ, which captures the impact of g_{kr} on outcomes for product k in region r in period τ. Again, 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.

5.3 Results: Product Realignment

We first estimate the heterogeneous impact of inter-region sales dependence on product outcomes. We estimate Equation 6 with inter-region sales and intra-region sales as the dependent variables and report the π_2^τ coefficients in Panel (a) and (b) of Figure 6, respectively.

There is a sharp fall in inter-region sales at the start of the pandemic during April 2020 for products with a higher inter-regional 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-region sales for a one-standard-deviation increase in inter-region sales fraction. We find no impact on the intra-region sales initially (March–June 2020). However, we see an increase in intra-region sales from July–December 2020 (coefficients are positive and significant) for products that have higher initial inter-regional 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-region sales for a one-standard-deviation increase in inter-region sales fraction. Thus, decline in inter-region sales is offset by the increase in the intra-region

[30] These controls are of the form $\sum_{\tau \in (m2020)} \phi^\tau (\mathbb{1}_m \times \mathbb{1}_{2020} \times X_{ir})$ and the relevant double interactions. Here, X_{kr} = Inter-Region Receivables Fraction, which is defined as the fraction of sales for a product within a region sourced from outside regions in 2019.

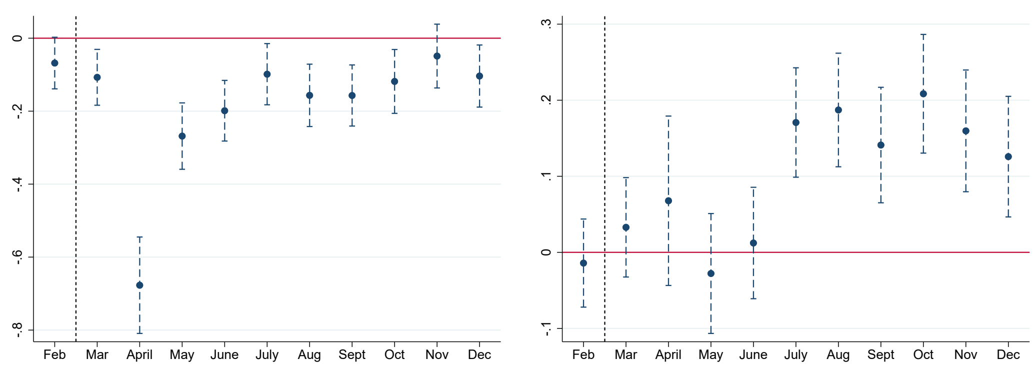
sales in the recovery phase, for products that had a greater reliance on outside regions for sales.[31] In addition, we find that the above change in sales value is driven by the change in quantity (Appendix Figure C.4, Panels (a) and (b)).

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

Figure 6: Realignment in Product Sales: By Inter-Region Sales Fraction

(a) Inter-Region Sales

(b) Intra-Region Sales



Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-region sales of a product originating in a region by product-region level Inter-Region 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-region level Inter-Region Receivables Fraction (2019) for every month in 2020. The regressions include a set of products in a region for which total sales information is available for every month. All specifications include product×region×month and product×month×year fixed effects. The standard errors are clustered at product×region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Next, we test the scope for home expansion hypothesis as outlined in Section 5.1.

[31] 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 C.3. All the results presented in this section go through for this specification as well.

We estimate Equation 6 with $g_{kr} = \sigma_{kr}$ and plot the π_2^τ coefficients in Figure 7. Panels (a) and (b) report the impact of σ_{kr} on inter- and intra-region sales respectively. We find that σ_{kr} matters for the decline in inter-region sales throughout the period post-lockdown but the effect declines over time. The largest relative decline in inter-region product sales is in April and May 2020 where a one standard-deviation increase in σ_{kr} leads to $0.2 \times 0.26 \times 100 = 5$ percent decline in inter-region sales. The coefficients remain negative during July–December 2020 but are insignificant during November 2020–December 2020. On the other hand, we find that the impact of σ_{kr} is positive and significant for intra-region 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 σ_{kr}). Thereafter, the impact remains positive and significant, though the magnitude declines. Even during August–December 2020, when there were no border restrictions, intra-region product sales are higher by 6.5 percent for every standard-deviation increase in σ_{kr}. Again, 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 hold for change in quantity as well (Appendix Figure C.4).[32]

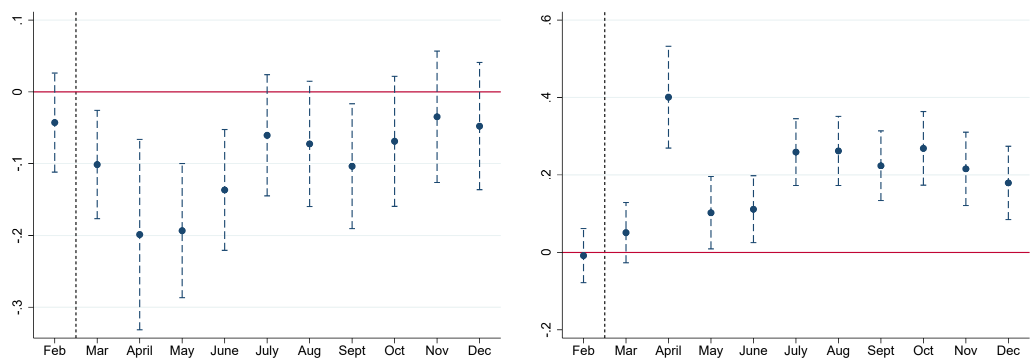
These results demonstrate that intra-region sales increase immediately for products that are easy to substitute with home-region production during the lockdown (April 2020). This result is consistent with closure of regional borders in the initial lockdown phase. It is, therefore, natural that regional production, sold inter-region earlier, was diverted to satisfy demand within the home region when the need for local substitutes was the most critical. The large positive and significant impact on intra-region product sales of σ_{kr} in April 2020 therefore provides us the key product attribute behind the realignment results. The same set of products that witness higher intra-region sales in April 2020 also continue to see higher sales within the home region until the end of the year.[33] At the same time, σ_{kr} has an opposite impact on inter-region sales. The

[32] Panels (c) and (d) in Appendix Figure C.4 show the effect of σ_{kr} on quantity (proxied by the log of count of E-way Sale Bills) for inter-region and intra-region product sales respectively. The results for quantity are similar to the results for sales value. We find an increase in intra-region quantity sold and a decline in inter-region quantity sold immediately post-lockdown and this persists for products having a higher scope for home expansion.

[33] Plants can continue to sell these products more within the home region for multiple reasons; for instance, to minimize the risk of losing sales against future lockdowns that could have led to the closure of regional borders. Alternatively, lockdown provided an opportunity to discover demand within their home region, and plants continue to fulfill it beyond the initial shock period. Unfortunately, our data do not allow us to explore whether new connections (extensive margin) or more supply to

Figure 7: Realignment in Product Sales: By Scope for Home Expansion

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



Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2 in Equation 3) for the heterogeneous impact on log of inter-region and intra-region sales of a product originating in a region by product-region 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-region level Scope for Home Expansion (2019) is defined as the minimum of Inter-Region Sales Fraction (2019) and Inter-Region Receivables Fraction (2019). The regressions include a set of products in a region for which total sales information is available for every month. All specifications include product×region×month and product×month×year fixed effects. The standard errors are clustered at product-region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

outside home region sales decrease for these products immediately after the lockdown and the effect persists until December 2020.

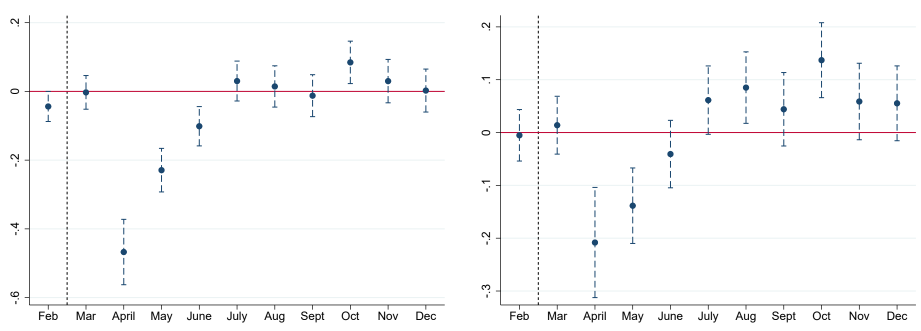
To summarize, the post-lockdown increase in intra-region sales is associated with a commensurate decline in inter-region sales for products with high σ_{kr}. The products that managed to shift their sales from outside to home region in the early phase of the pandemic permanently upended their sales destination. These results demonstrate how temporary realignment can lead to a persistent switch in sales destination. Simultaneously, we also see that the impact of trade collapse on the aggregate output is ameliorated through the reconfiguration of trade via high σ_{kr} products.

Impact on Total Sales: We next estimate the impact on total sales for a product based on these attributes. We plot the impact on the log of total sales by inter-region sales dependence and scope for home expansion in Figure 8, Panel (a) and

existing connections (intensive margin) at the plant level has led to the increase in intra-region trade after the lockdown.

Figure 8: Impact on Total Product Sales

(a) By Inter-Region Sales Fraction (b) By Scope for Home Expansion



Notes: The figure in Panel (a) plots the monthly coefficients (π_2 in Equation 3) for the heterogeneous impact on log of total sales of a product originating in a region by product-region level Inter-Region 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-region level Inter-Region Receivables Fraction (2019). The figure in Panel (b) plots the monthly coefficients (π_2 in Equation 3) for the heterogeneous impact on log of total sales of a product originating in a region by product-region 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×region×month and product×month×year fixed effects. The standard errors are clustered at product-region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

(b) respectively, by estimating Equation 6. Comparing the two panels we can see that the total sales fall relatively more in April 2020 for products having higher inter-regional dependence and scope for home expansion. This is because the relative fall in inter-region sales is higher than the relative gain in intra-region 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 σ_{kr} suffer less immediately after the lockdown. This is primarily on account of higher intra-region sales that help improve total sales for higher σ_{kr} products (Panel (b) in Figure 7). In fact, Figure 8, Panel (b) shows that products with higher σ_{kr} witness a relatively higher increase in total sales in the later months of 2020. The point estimates give $0.1\times0.26\times100{=}2.6$ percent increase in total sales for one-standard-deviation increase in σ_{kr} until the end of 2020. Similar level of persistent increase is absent for products that have high inter-region dependence only (Panel (a)).

6 Robustness

In this section, we provide main robustness checks for our empirical results based on additional controls, alternate data samples, and specifications.

6.1 Robustness: Plant Level

In this part, we report robustness of plant-level results. We estimate Equation 3 and report the coefficients γ_2^τ in each case.

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 single difference strategy while beset with plant-level seasonality concerns, can give us pre-trends before February 2020.[34] 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-regional dependence. We do this until the last quarter of 2019 to minimize seasonality from months farther away from February. Appendix Figure C.5 plots the monthly coefficients of the heterogeneous impact of inter-regional dependence obtained from this specification. There are no significant pre-trends, and we still find a decline in inter-region sales and inputs and an increase in intra-region sales and inputs post-lockdown, as plant-level inter-regional dependence increases. However, these results do not correct for plant-level seasonality in outcomes and hence are not our preferred specification.

Firms' Financial Conditions: The evidence in Amiti & Weinstein (2011) and Chor & Manova (2012) suggest trade credit channel as the main factor behind the trade collapse after the GFC. This channel is less likely to be active in our case as within-country trade cycles are relatively shorter than those for international trade. Also, it is less likely to be significantly different for plants selling/buying within or outside the home region. Nevertheless, we test if our results are robust after controlling for a plant's pre-pandemic level of financial condition. To do this, we merge our data

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

with Prowess data (2019) to get information on firm-level financial variables.[35] Our approach is similar to Behrens *et al.* (2013), and we use cash-to assets and leverage ratio (interacted with $(\mathbb{1}_m \times \mathbb{1}_{2020})$) as additional controls in our specification.[36] We continue to see that inter-regional dependence matters even after using financial variables as controls (Figure C.6). We do not find any differential effect of these financial variables on either inter-region sales or intra-region sales in the domestic trade context. The results are omitted for brevity but available on request.

Alternate Plant Sample: 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. We use this approach as we cannot perfectly observe entry and exit given the nature of our dataset. We do not know whether a plant sells (or buys) zero value of goods in a given month or simply drops out of the top 1,000 plants sample due to low sales (inputs). Figure C.7 shows that our main results continue to hold for this sample of plants.

Regional Variation in Stringency: While all economic activities returned to normalcy across most regions after August 2020, some localities within a region could still enforce restrictions to contain the COVID-19 spread. Therefore, we include district×month×year fixed-effects to control for time-varying heterogeneity in stringency on mobility restrictions at the lowest administrative level observed in our plant data. Controlling for the geographical variation in stringency does not change our results (Figure C.8).

Other Robustness: Our results are also robust to using an above median indicator measure of regional dependence (Figure C.9). In this specification, we use a dummy variable to capture whether a plants' outside region dependence is above the median level. Finally, heterogeneous impacts due to plant location (lying in border district), plant parent-firm structure (part of a multi-plant firm), and plant size (total sales in 2019) also do not change the main results (Figure C.10). This allays any concerns that outside region dependence is correlated with other plant characteristics and those

[35] 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 the Prowess data.

[36] We also control for all the relevant double interaction of the control variables.

factors drive the results.[37]

6.2 Robustness: Product Level

In this part, we check that the product-level results are robust to a variety of additional specifications. We report the coefficients π_2^τ in each case below.

Longer Pre-trends: To report longer pre-trends, we once again report single difference estimates with February 2020 as the baseline month. Appendix Figure C.11, Panels (a) and (b), plot the monthly coefficients from the single difference estimates for inter-region and intra-region sales as a function of inter-region sales dependence. Panels (c) and (d) report the impact on sales based on scope for home expansion. All panels rule out pre-trends in the last quarter of 2019 and our main results go through.

Non-essential Products: We check that our main results are not limited to essential products like food and medical supplies that faced fewer movement restrictions during the lockdown. We drop these essential items and plot the re-estimated coefficients in Figure C.12, Panels (a) and (b), with respect to outside region dependence, and in Panels (c) and (d), with respect to scope for home expansion. All the previous results continue to hold for non-essential products as well.

Alternate Product Sample: In the main estimation, we restricted our analyses to products that report total sales for every month during January 2019–December 2020. We test if our results are robust for a larger sample of products by including all products that appear for a minimum of six months in 2019. Again, given the nature of the data, we cannot measure strict entry or exit as we do not know whether a product is not produced or is not present in the top 1,000 products in a given month. Figure C.13 shows that our main results continue to hold for this larger sample of products as well.

Regional Variation in Stringency: We include region$\times$ month$\times$year fixed-effects to control for time-varying heterogeneity in stringency measures at the region level, the

[37] We also show robustness of our results for the impact on total sales, total inputs, and count of E-way Bills in Tables C.5 and C.6.

lowest administrative level observed in product data. We find that the geographical variation in lockdown intensity does not change the realignment results (Figure C.14).

Above Median Product Attributes: Our results are robust to using indicator measures for inter-regional dependence and scope for home expansion. The indicator variable takes a value of one if a product attribute is above the median level. This alleviates any concern of bias in our estimates due to measurement error and extreme values in product attributes. We continue to find that our main results hold for these measures too (Figure C.15).

7 Realignment: Contribution to Sales Growth

We now measure the quantitative importance of the realignment channel by estimating the impact of realignment on aggregate product sales. In Section 6, we show that regional realignment results hold when inter-regional dependence and scope for home expansion are defined as indicator variables for above median values. We divide products into three categories based on the above/below median value of inter-region sales dependence and scope for home expansion. Products with above-median σ_{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 σ_{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 realignment. 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 realignment 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).[38] We find a 1.2 percent relative growth in sales for products with above-median inter-region sales

[38]This is obtained by estimating Equation 6 where the dependent variable is log of total product sales, and instead of $f_{kr,sales}$, the indicator variables for the two product categories 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 Realignment (October–December 2020)

	Below-Median σ_{kr} & Above-Median $f_{kr,sales}$	Above-Median σ_{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 (region-product level) as the dependent variable. The independent variables include the interaction of two dummy variables (product categories based on above-median inter-region sales dependence and below-median σ_{kr}, and above-median σ_{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 realignment case with sales growth equal to zero for both types of products. Scenario II is the case with realignment only for above-median σ_{kr} products. Here, in the absence of realignment, 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 σ_{kr}.

dependence and below-median σ_{kr} (column (1)), while it is 2.6 percent for products with above-median σ_{kr} (column (2)), compared to the baseline group.

In counterfactual Scenario I (column (3)), we calculate the overall impact of realignment on growth due to the non-baseline products (total share 18+29 = 47%). In the absence of realignment, 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 realignment.

Scenario II corresponds to the case with no realignment only for the above-median σ_{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 realignment as captured in counterfactual Scenario I, $(100 \times 0.75/0.97 =)$ 77 percent comes from the above-median σ_{kr} products. Finally, Scenario III (column (5)) gives the impact on above-median σ_{kr} products over and above the impact on products in the first group (below-median σ_{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 realignment as seen in Scenario I. The decomposition through Scenario II and III suggests that the contribution of products with the above-median σ_{kr} to realignment is higher than those with higher f_{kr}.

Overall, the realignment 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 realignment to this growth is equal to $(100 \times 0.97/12.8 =) = 7.6$ percent, confirming that the realignment channel plays a crucial role in the recovery phase.[39]

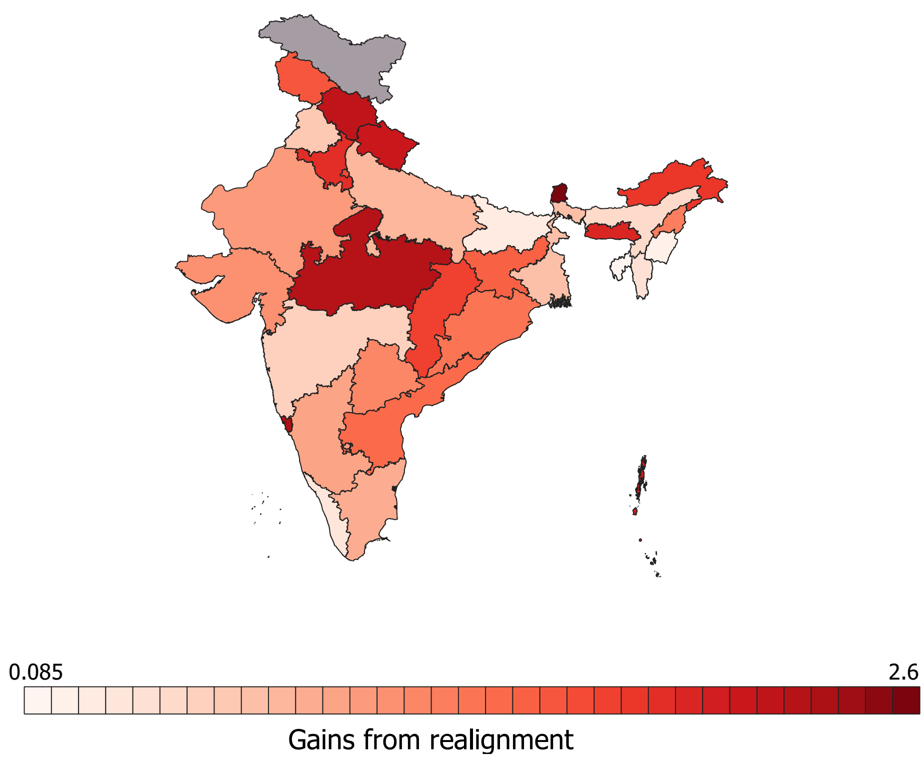
Finally, we evaluate the variation in recovery across regions based on the realignment channel. Given that regions differ based on the product mix that they produce and consume, we expect substantial heterogeneity in their scope for home expansion and hence sales recovery. To gauge this heterogeneity, we perform the counterfactual exercise for each region in the absence of realignment. We find the share of products (by value) in each of three product categories in each region and calculate the impact under counterfactual Scenario I. The gains from realignment are reported in Figure 9.[40] We find that all regions gain through realignment, however, there is substantial heterogeneity in the magnitude. While some regions see a minimal change of 0.08 percentage points, others gain as much as 2.6 percentage points in aggregate sales. From a planner's perspective, these results suggest that policy response to such aggregate shocks can vary across regions based on their realignment potential.

In general, a decline in inter-region trade after a shock can lead to loss in both producer and consumer welfare. Our results suggest that the realignment channel would partially arrest such loss in welfare.

[39] 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.

[40] Appendix Table C.7 shows the gains in total sales in each region under each of the three scenarios along with average value of scope for home expansion in each region (column (4)).

Figure 9: Impact of Realignment on Total Product Sales: Regional Heterogeneity



Notes: The map plots the increase in total sales (percentage points) under Scenario I, due to realignment, for each region. The region with no products included in the analyses (given the condition of balanced products) are reflected in grey.

8 Conclusion

This paper is the first to document within-country trade collapse after an aggregate shock and explains it through a new channel of regional realignment. Using monthly plant- and product-level data on sales and inputs from 35 trading regions in India, we provide causal evidence for home-ward realignment in sales and input-sourcing using the COVID-19 pandemic as an exogenous shock. This shift happens for plants that were more dependent on outside region sales and inputs before the pandemic and leads to a persistent decline in inter-region trade while increasing intra-region trade and restoring GDP. We find that the shift in sales 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-region sales, they also witness relatively higher growth in total sales towards the end of 2020, compensating for the decline in their inter-region sales. Overall, regional realignment accounts for 7.6 percent of the sales growth in October–December 2020.

Our analyses accounts for changes in demand, regional variation in movement stringency and other plant (e.g. financial conditions) and product characteristics. The domestic trade context allows us to rule out other channels such as protectionism and exchange rate movements. The large quantitative impact of regional realignment after ruling out other competing channels, makes it an important candidate that can explain trade collapse. Importantly, we show that a product's scope for home expansion determines its extent of realignment. Since countries differ in their import-export baskets, our proposed measure can explain the heterogeneous recovery in output and international trade across countries after a global shock.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. 2012. The network origins of aggregate fluctuations. *Econometrica*, **80**(5), 1977–2016.

Amiti, Mary, & Weinstein, David E. 2011. Exports and financial shocks. *The Quarterly Journal of Economics*, **126**(4), 1841–1877.

Andrews, M., Areekal, B., Rajesh, K., Krishnan, J., Suryakala, R., Krishnan, B., Muraly, C., & Santhosh, P. 2020. First confirmed case of COVID-19 infection in India: A case report. *The Indian Journal of Medical Research*, **151**(5), 490.

Antràs, P. 2020. *De-Globalisation? Global Value Chains in the Post Covid-Age*. NBER Working Paper No. 28115.

Asturias, Jose, García-Santana, Manuel, & Ramos, Roberto. 2019. Competition and the welfare gains from transportation infrastructure: Evidence from the Golden Quadrilateral of India. *Journal of the European Economic Association*, **17**(6), 1881–1940.

Atkin, David. 2013. Trade, tastes, and nutrition in India. *American Economic Review*, **103**(5), 1629–63.

Atkin, David, & Donaldson, Dave. 2015. *Who's getting globalized? The size and implications of intra-national trade costs*. Tech. rept. National Bureau of Economic Research.

Atkin, David, & Khandelwal, Amit K. 2020. How distortions alter the impacts of international trade in developing countries. *Annual Review of Economics*, **12**, 213–238.

Baker, S. R, Bloom, N., & Davis, S. J. 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, **131**(4), 1593–1636.

Balajee, A., Tomar, S., & Udupa, G. 2020. *Fiscal Situation of India in the Time of COVID-19*. SSRN Working Paper No. 3571103.

Baldwin, Richard, & Evenett, Simon. 2009. *The collapse of global trade, murky protectionism and the crisis: Recommendations for the G20*. Cepr.

Baqaee, D., & Farhi, E. 2020. *Nonlinear production networks with an application to the covid-19 crisis*. NBER Working Paper No. 27281.

Barrot, J.-N., & Sauvagnat, J. 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, **131**(3), 1543–1592.

Behrens, K., Corcos, G., & Mion, G. 2013. Trade crisis? What trade crisis? *Review of Statistics*, **95**(2), 702–709.

Bems, R., Johnson, R. C., & Yi, K. 2013. The great trade collapse. *Annual Review of Economics*, **5**, 375–400.

Bernard, A. B., Moxnes, A., & Saito, Y. U. 2019. Production networks, geography, and firm performance. *Journal of Political Economy*, **127**(2), 639–688.

Bonadio, B., Huo, Z., Levchenko, A. A., & Pandalai-Nayar, N. 2020. *Global supply chains in the pandemic*. NBER Working Paper No. 27224.

Bricongne, J., Fontagné, L., Gaulier, G., Taglioni, D., & Vicard, V. 2012. Firms and the global crisis: French exports in the turmoil. *Journal of International Economics*, **87**(1), 134–146.

Carvalho, V. M. 2014. From micro to macro via production networks. *Journal of Economic Perspectives*, **28**(4), 23–48.

Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. 2021. Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics*, **136**(2), 1255–1321.

Chakrabarti, A. S., & Tomar, S. 2021. Granular Origin of Synchronization in Regional Business Cycles. *Working Paper*.

Chor, D., & Manova, K. 2012. Off the cliff and back? Credit conditions and international trade during the global financial crisis. *Journal of International Economics*, **87**(1), 117–133.

Coşar, A Kerem, & Fajgelbaum, Pablo D. 2016. Internal geography, international trade, and regional specialization. *American Economic Journal: Microeconomics*, **8**(1), 24–56.

Donaldson, Dave. 2018. Railroads of the Raj: Estimating the impact of transportation infrastructure. *American Economic Review*, **108**(4-5), 899–934.

Eaton, Jonathan, Kortum, Samuel, Neiman, Brent, & Romalis, John. 2016. Trade and the global recession. *American Economic Review*, **106**(11), 3401–38.

Evenett, S. J. 2020. Sicken thy neighbour: The initial trade policy response to COVID-19. *The World Economy*, **43**(4), 828–839.

Gopinath, Gita, & Neiman, Brent. 2014. Trade adjustment and productivity in large crises. *American Economic Review*, **104**(3), 793–831.

Gopinath, Gita, Itskhoki, Oleg, & Neiman, Brent. 2012. Trade prices and the global trade collapse of 2008–09. *IMF Economic Review*, **60**(3), 303–328.

Korovkin, V., & Makarin, A. 2020. Production Networks and War. *arXiv preprint arXiv:2011.14756*.

Levchenko, A. A., Lewis, L. T., & Tesar, L. L. 2010. The collapse of international trade during the 2008–09 crisis: in search of the smoking gun. *IMF Economic Review*, **58**(2), 214–253.

Mahajan, K., & Tomar, S. 2021. COVID-19 and Supply Chain Disruption: Evidence from Food Markets in India. *American Journal of Agricultural Economics*, **103**(1), 35–52.

Novy, Dennis, & Taylor, Alan M. 2020. Trade and uncertainty. *Review of Economics and Statistics*, **102**(4), 749–765.

Ramondo, Natalia, Rodríguez-Clare, Andrés, & Saborío-Rodríguez, Milagro. 2016. Trade, domestic frictions, and scale effects. *American Economic Review*, **106**(10), 3159–84.

Sotelo, Sebastian. 2020. Domestic trade frictions and agriculture. *Journal of Political Economy*, **128**(7), 2690–2738.

UNCTAD. 2020. Key Statistics and Trends in International Trade 2019. *United Nations Conference on Trade and Development.*

Van Leemput, Eva. 2021. A passage to india: Quantifying internal and external barriers to trade. *Journal of International Economics*, 103473.

Wolf, Holger C. 2000. Intranational home bias in trade. *Review of Economics and Statistics*, **82**(4), 555–563.

WTO. 2021. *World trade primed for strong but uneven recovery after COVID-19 pandemic shock.* Tech. rept. WTO.

ONLINE APPENDIX

A Appendix: Model

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

$$Y_i = A_i L_{p,i}^{1-\mu} X_i^{\mu} \tag{A.7}$$

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-region inputs Z_i and inter-region inputs M_i, combined together through a CES aggregator:

$$X_i = \left[Z_i^{\rho} + M_i^{\rho}\right]^{\frac{1}{\rho}}. \tag{A.8}$$

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

$$Z_i = \left[\int_j z_{ij}^{\theta} dj\right]^{\frac{1}{\theta}} \quad , \quad M_i = \left[\int_{k \in \Omega_i} m_{ik}^{\theta} dk\right]^{\frac{1}{\theta}}. \tag{A.9}$$

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

$$F(|\Omega_i|) = f|\Omega_i|^{\lambda} \tag{A.10}$$

where $f > 0, \lambda > 0$. The fixed costs are increasing in number of inter-region 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:

$$Y_i = g_i + z_i = g_i + \int_j z_{ji} dj. \tag{A.11}$$

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-region prices p_j, and inter-region prices as given. It chooses labor $L_{p,i}$, the intra-region nputs z_{ij}, the number of inter-region inputs Ω_i and their amount m_{ik}. The price of inter-region inputs is p_m and is the same for all varieties, which also makes m_i same across all k.[1] 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-region 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:

$$C_i = \frac{1}{\mu^\mu (1-\mu)^{(1-\mu)}} \frac{w^{1-\mu} P_{X_i}^\mu}{A_i}. \tag{A.12}$$

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

$$P_{X_i} = \left[P_Z^{\frac{\rho}{\rho-1}} + P_{M_i}^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}}. \tag{A.13}$$

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

$$P_Z = \left[\int_j p_i^{\frac{\theta}{\theta-1}} di\right]^{\frac{\theta-1}{\theta}} \quad , \quad P_{M_i} = \left[\int_k p_m^{\frac{\theta}{\theta-1}} dk\right]^{\frac{\theta-1}{\theta}} = p_m |\Omega_i|^{\frac{\theta-1}{\theta}}. \tag{A.14}$$

The home-region price index P_Z is the same across all firms, while the inter-region price index varies depending on the number of inter-region 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

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

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-region input price p_m, increases the share of domestic inputs in total inputs for firm i.*

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

$$\frac{\partial\, ln\gamma_i}{\partial\, lnp_m} = \frac{\rho(1-\gamma_i)}{1-\rho}\left[1 - \frac{\partial\, lnP_Z}{\partial\, lnp_m} + \frac{\theta-1}{\theta}\frac{\partial\, ln\Omega_i}{\partial\, lnp_m}\right] > 0. \tag{A.15}$$

Intuitively, the share γ_i would fall after an increase in p_m under two sufficient conditions. First, the home-region 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-region 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-region inputs is larger for firms with a higher dependence on inter-region intermediate inputs after an increase in uncertainty captured by an increase in p_m.*

Taking a derivative of Equation A.15 w.r.t. γ_i gives the above sufficient condition (see Gopinath & Neiman (2014) for details).

B Appendix: Alternate Test for Trade Collapse

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

$$\begin{aligned} ln(z_{ijtr,my}) = \beta_0 \quad &+ \sum_{\tau\in(m2020)} \beta_1^\tau(\mathbb{1}_m \times \mathbb{1}_{2020}) + \sum_{\tau\in(m2020)} \beta_2^\tau(\mathbb{1}_m \times \mathbb{1}_{2020} \times \mathbb{1}(Inter)) \\ &+ \quad \mathbb{1}_{2020} \times \mathbb{1}(Inter) + \mathbb{1}_{2020} + \delta_{itr,m} + \delta_{j,my} + \varepsilon_{ijtr,my} \end{aligned} \tag{B.1}$$

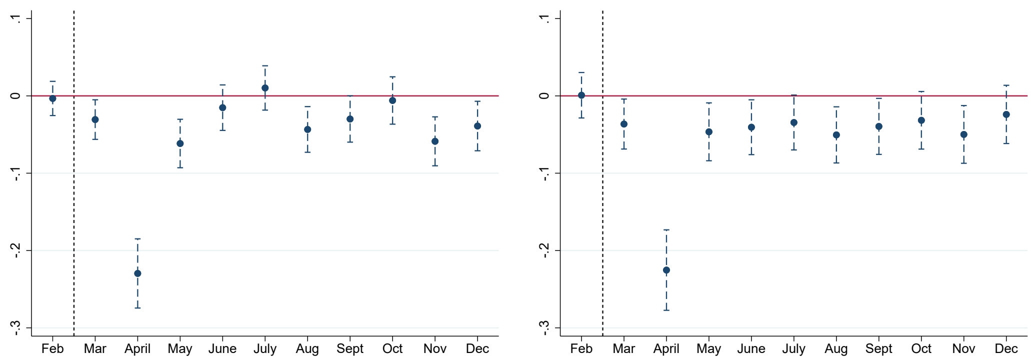
where $z_{ijtr,my}$ is the outcome of sales (or inputs) differentiated by region type $t \in \{inter-region, intra-region\}$ for plant i belonging to sector j in region r in month m and year y. The variable $\mathbb{1}(Inter)$ takes a value of one if type t belongs to inter-region, else it is zero. Compared to Equation 1, here we have an additional interaction term $\mathbb{1}_m \times \mathbb{1}_{2020} \times \mathbb{1}(Inter)$ that captures the differential impact on inter-region sales (or inputs) after the lockdown. Once again, January 2020 serves as the baseline month. The coefficient β_1^τ captures the average impact on outcome variable in month τ in year 2020 over January 2020, relative to the same months in 2019, while β_2^τ captures the heterogeneous impact on the inter-region sales (or inputs). For instance, in the regression with sales as outcome variable, if inter-region sales fall more in a month, then β_2^τ will be negative.

We also include plant×type×months fixed-effects, $\delta_{itr,m}$, which account for plant-type level unobserved heterogeneity and plant-type monthly seasonality in outcomes, the two important confounding factors in identifying the trade collapse. In addition, we include controls for sector×month×year fixed effects denoted by $\delta_{j,my}$. It ensures that the estimated impact on inter-region trade is not driven by plants in certain industrial sectors which are more likely to trade inter-region and that also suffered a larger change in demand post-lockdown. Thus, our identification uses within-plant variation in a given month-year across its intra-region and inter-region sales (inputs). Lastly, if the impact is driven by the lockdown then we should observe no differential pre-trends between intra- and inter-region sales (inputs) in February and the corresponding β_2^τ should be insignificant.

We plot the coefficients β_2 that capture the differential impact of lockdown on inter-region sales and inputs relative to the intra-region outcomes in Panel (c) and (d) of Figure B.1. Panel (c) shows that the initial fall (April 2020) in inter-region 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 (d). The initial fall in inter-region inputs is larger at 21 percent in April 2020 and continues to remain subdued by 5 percent for the rest of the year.

Figure B.1: Domestic Trade Collapse: Alternate Specification

(a) Sales: By Inter-Region (b) Inputs: By Inter-Region



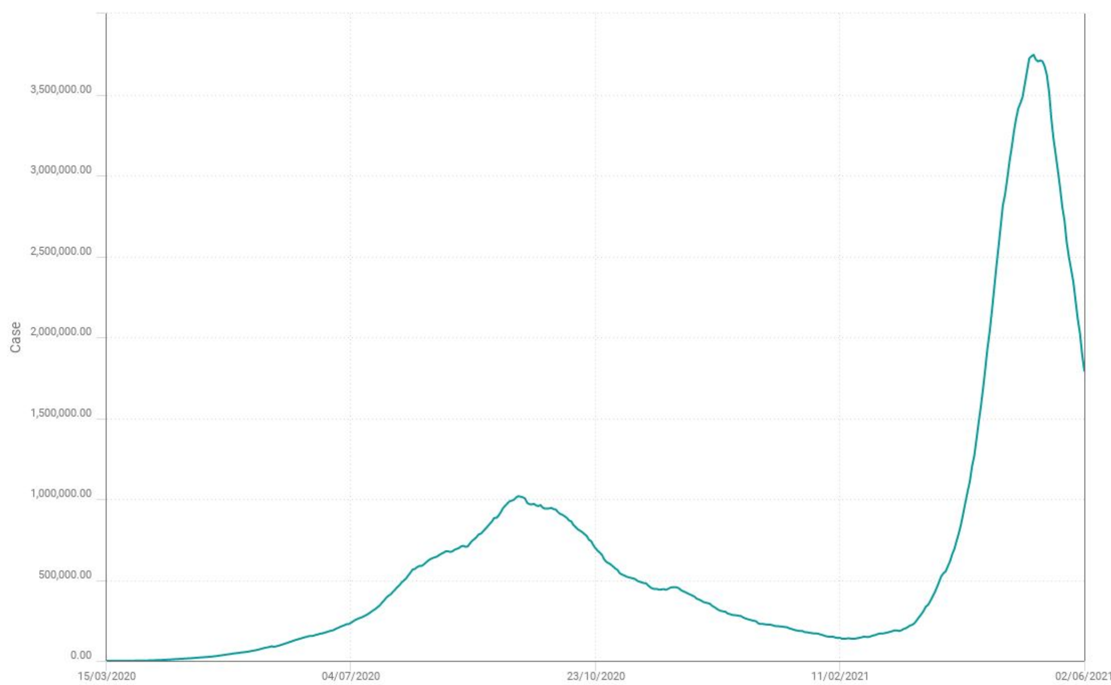
Notes: The figures plot the coefficients β_2^τ from the estimated Equation B.1. Panel (a) plots the monthly coefficients for the impact on log of inter-region plant sales versus intra-region plant sales, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Panel (b) plots the monthly coefficients for the impact on log of inter-region plant inputs versus intra-region 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-month fixed effects and sector×type×month×year fixed effects, where type is inter- or intra-region 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.

C Appendix: Figures and Tables

Figure C.1: Regional Border Closure post the National Lockdown in India

Source: Business Standard

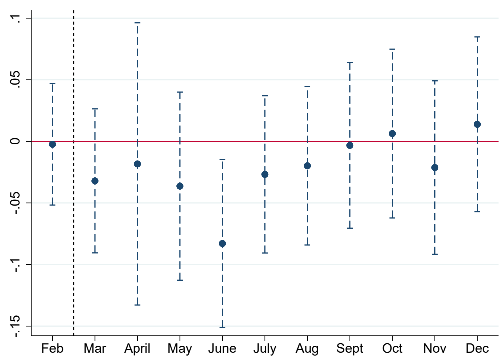
Figure C.2: Evolution of Active COVID-19 Cases in India



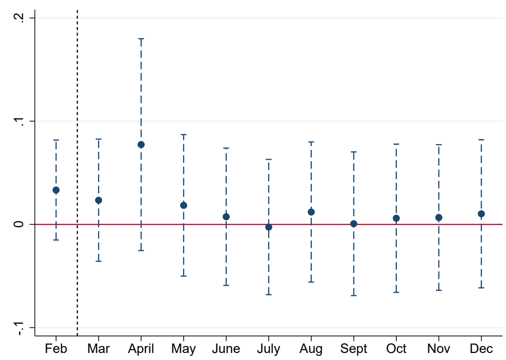
Notes: The figure plots the evolution of active COVID-19 cases in India.

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

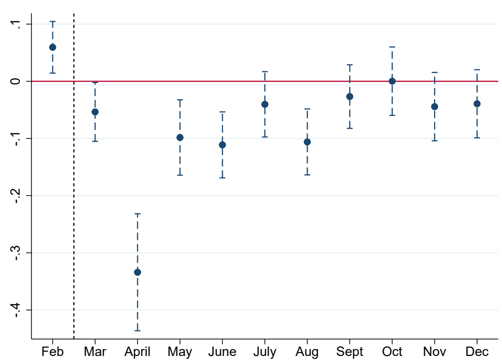
(a) Inter-Region Sales: By Inputs Fraction



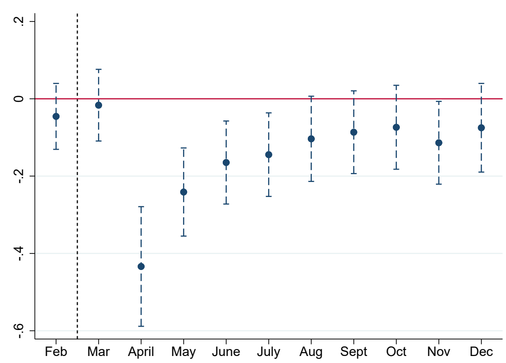
(b) Intra-Region Sales: By Inputs Fraction



(c) Inter-Region Inputs: By Sales Fraction



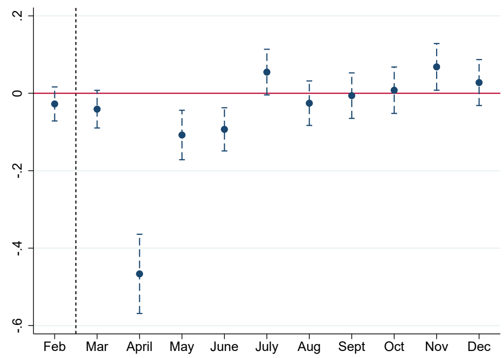
(d) Intra-Region Inputs: By Sales Fraction



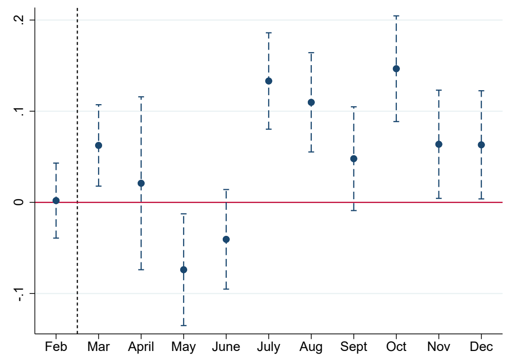
Notes: The figures in Panels (a) and (b) plot the monthly coefficients on $\mathbb{X}^{c}_{ir,my}$ (Equation 3) for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by plant-level Inter-Region Inputs Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-Region 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 3) for the heterogeneous impact on log of inter-region inputs and intra-region inputs respectively, by plant-level Inter-Region 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-Region 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 C.4: Realignment in Quantity (Products)

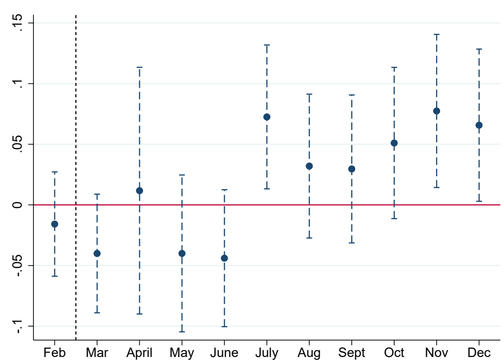
(a) Inter-Region: By Sales Fraction



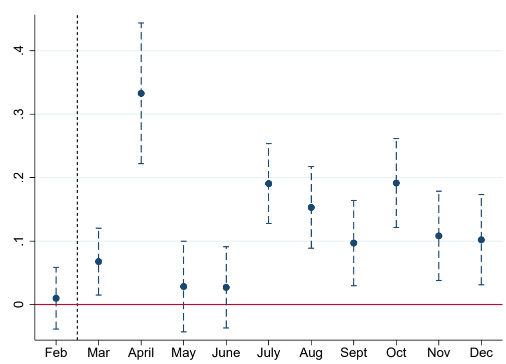
(b) Intra-Region: By Sales Fraction



(c) Inter-Region: By Scope for Home Expansion



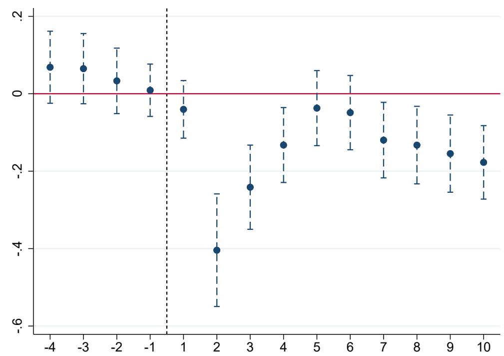
(d) Intra-Region: By Scope for Home Expansion



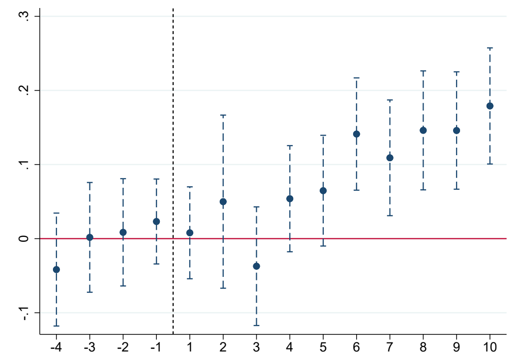
Notes: The count of E-Way Bills is used as a proxy for quantity in these regressions. The figures in Panels (a) and (b) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-region E-Way sale bills of a product originating in a region by product-region level Inter-Region 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. The figures in Panels (c) and (d) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-Region E-Way sale bills of a product originating in a region by product-region 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-region level intra-region Scope for Home Expansion (2019) is defined as the minimum of Inter-Region Sales Fraction (2019) and Inter-Region Receivables Fraction (2019). Panels (a)–(b) additionally control for the heterogeneous impacts of product-region level Inter-Region Receivables Fraction (2019) for every month in 2020. The regressions include a set of products in a region for which total sales information is available for every month. All specifications include product$\times$region$\times$month and product$\times$month$\times$year fixed-effects. The standard errors are clustered at product-region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure C.5: Realignment (Plants): Single Difference Estimates

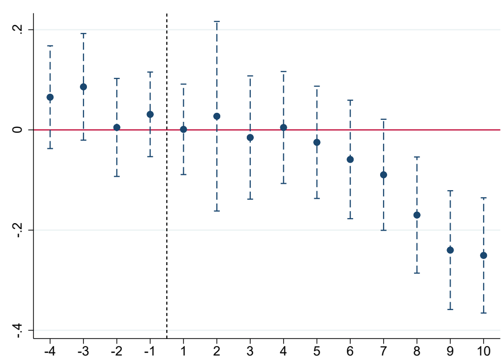
(a) Inter-Region Sales: By Sales Fraction



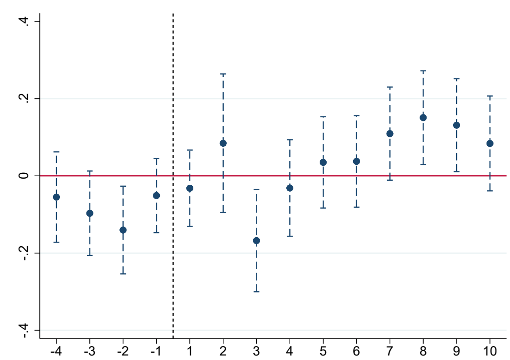
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Inputs: By Inputs Fraction



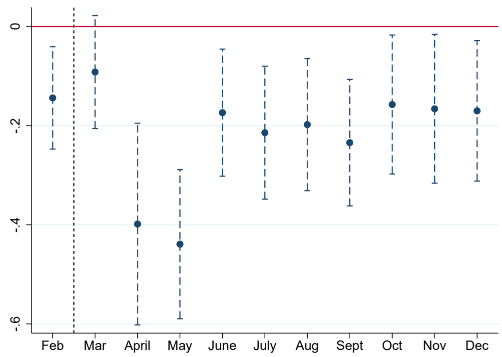
(d) Intra-Region Inputs: By Inputs Fraction



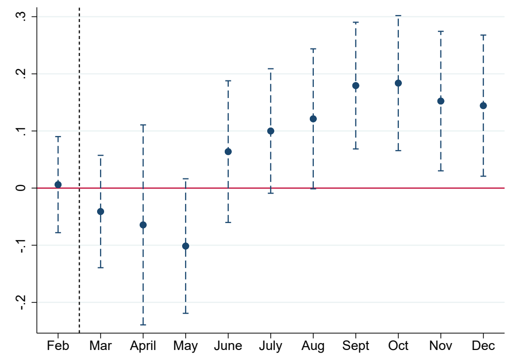
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by plant-level Inter-Region Sales Fraction (2019), for four months before February 2020 (-4=October 2019, -3=November 2019, -2=December 2019, -1=January 2019) 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-Region 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-Region Inputs and Intra-Region Inputs respectively, by plant-level Inter-Region 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-Region 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-region×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 C.6: Realignment (Plants): Robustness (Additional Plant and Firm Level Controls)

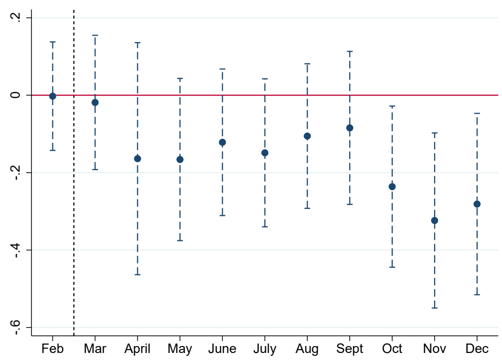
(a) Inter-Region Sales: By Sales Fraction



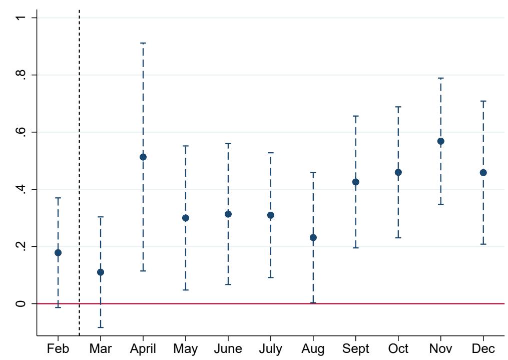
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Inputs: By Inputs Fraction



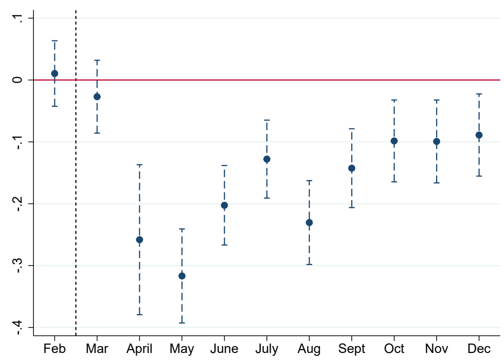
(d) Intra-Region Inputs: By Inputs Fraction



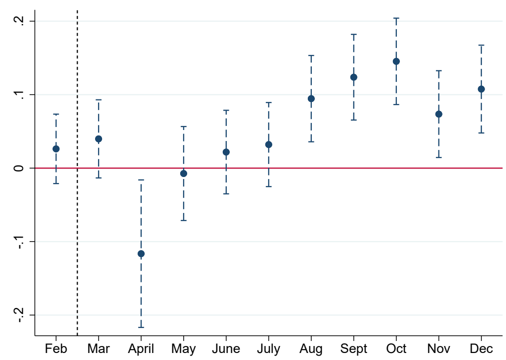
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by plant-level Inter-Region Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative 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 (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region inputs and intra-region inputs respectively, by plant-level Inter-Region 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-Region Inputs fraction (2019) for every month in 2020 (Panels (a) and (b)) and plant-level Inter-Region 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$\times$month and sector$\times$month$\times$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 C.7: Realignment (Plants): Robustness (Unbalanced Plants)

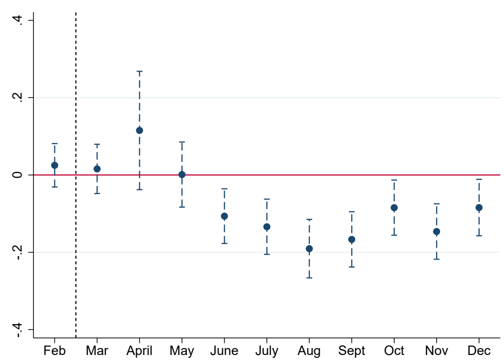
(a) Inter-Region Sales: By Sales Fraction



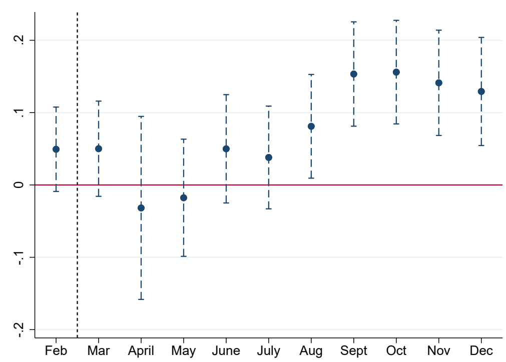
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Inputs: By Inputs Fraction



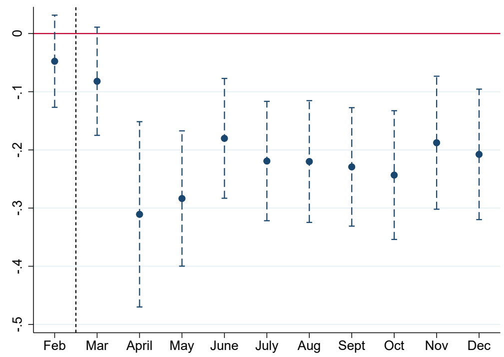
(d) Intra-Region Inputs: By Inputs Fraction



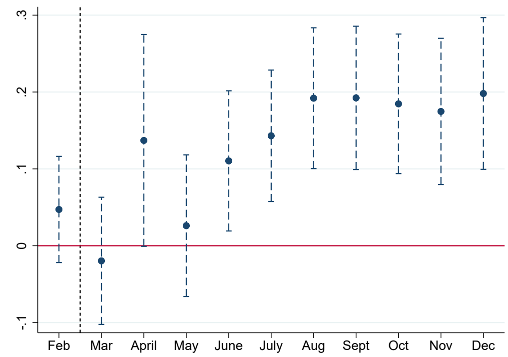
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by plant-level Inter-Region Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-Region 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 (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region inputs and intra-region inputs respectively, by plant-level Inter-Region 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-Region 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 C.8: Realignment (Plants): Robustness (Variation in Regional Stringency)

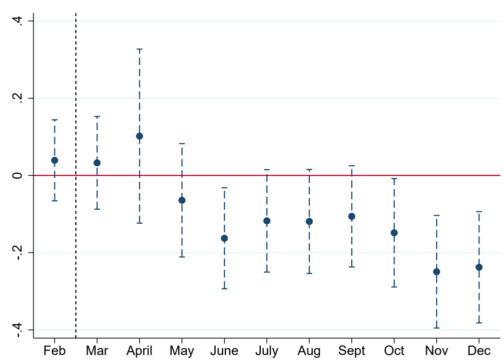
(a) Inter-Region Sales: By Sales Fraction



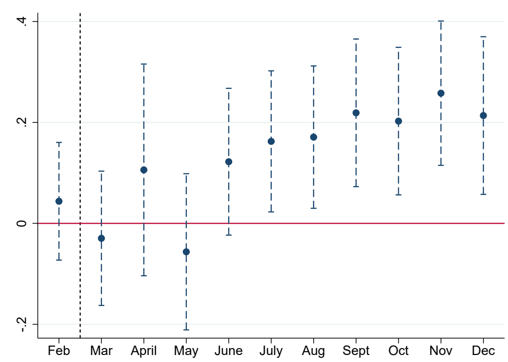
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Inputs: By Inputs Fraction



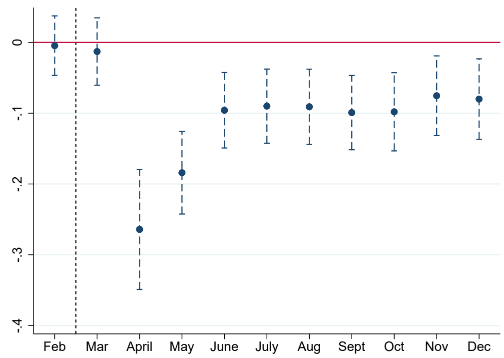
(d) Intra-Region Inputs: By Inputs Fraction



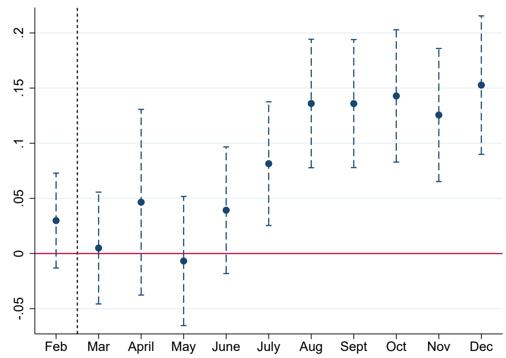
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by plant-level Inter-Region Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-Region 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 (γ_2 in Equation 3) for the heterogeneous impact on log of inter-region inputs and intra-region inputs respectively, by plant-level Inter-Region 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-Region 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 C.9: Realignment (Plants): Robustness (Above Median Fraction)

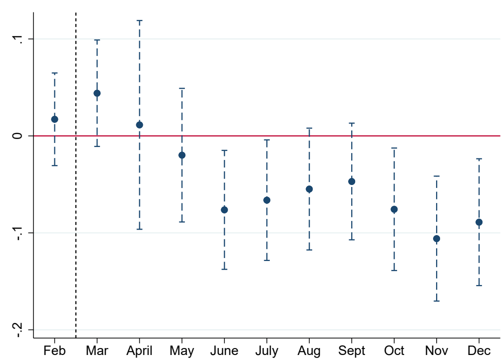
(a) Inter-Region Sales: By Sales Fraction



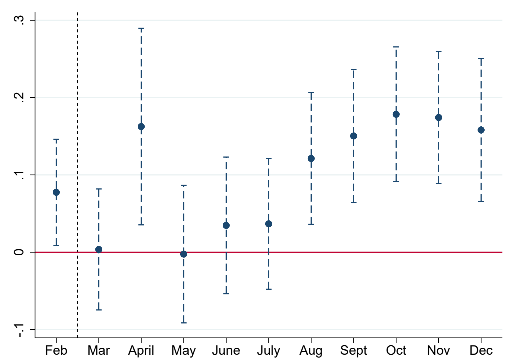
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Inputs: By Inputs Fraction



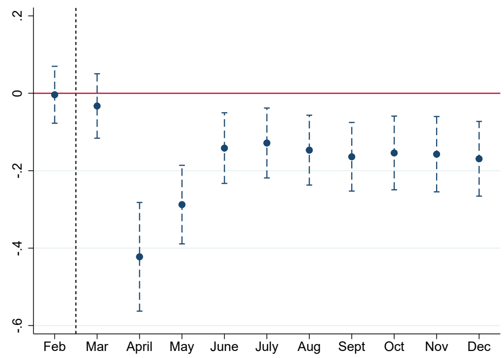
(d) Intra-Region Inputs: By Inputs Fraction



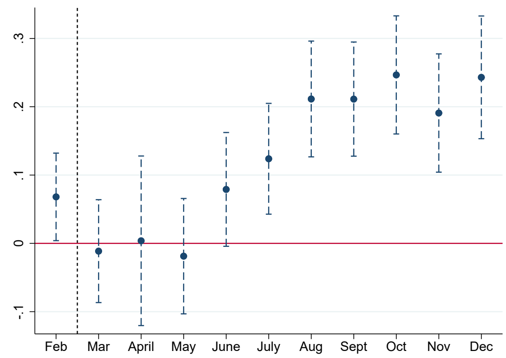
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by an indicator variable, that takes a value of one for above median measure of plant-level Inter-Region Sales Fraction (2019) and zero 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-Region 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-region inputs and intra-region inputs respectively, by an indicator variable, that takes a value of one for above median measure of plant-level Inter-Region 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-Region 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 C.10: Realignment (Plants): Robustness (Additional Plant Controls)

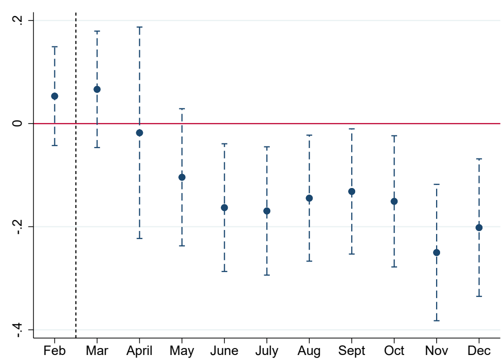
(a) Inter-Region Sales: By Sales Fraction



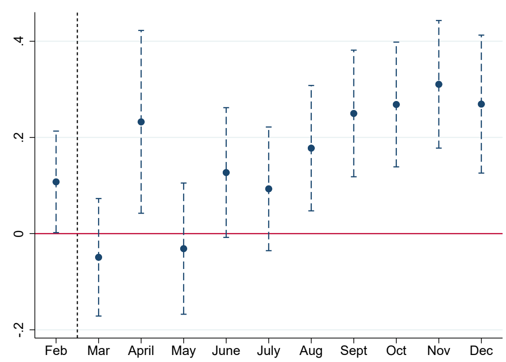
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Inputs: By Inputs Fraction



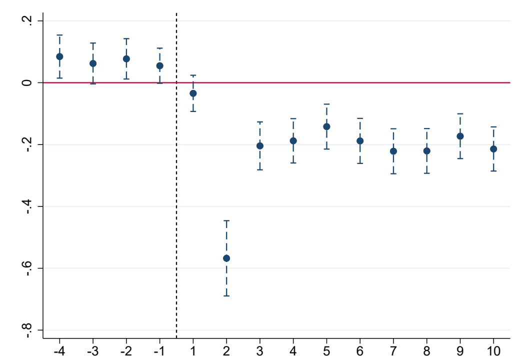
(d) Intra-Region Inputs: By Inputs Fraction



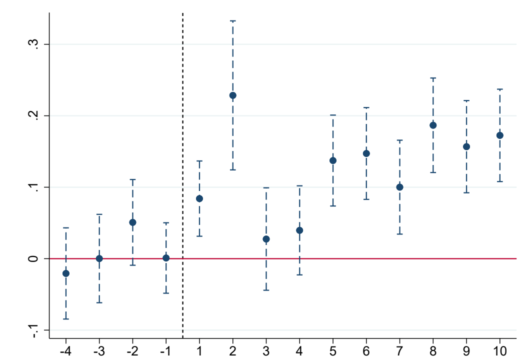
Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by plant-level Inter-Region Sales Fraction (2019), for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. We additionally control for heterogeneous impacts of plant-level Inter-Region 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-region inputs and intra-region inputs respectively, by plant-level Inter-Region 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-Region 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 additionally control for 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. 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 C.11: Realignment (Products): Single Difference Estimates

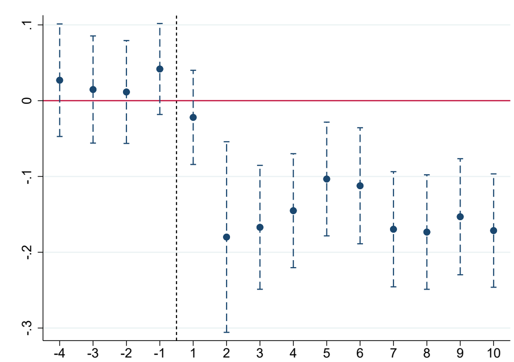
(a) Inter-Region Sales: By Sales Fraction



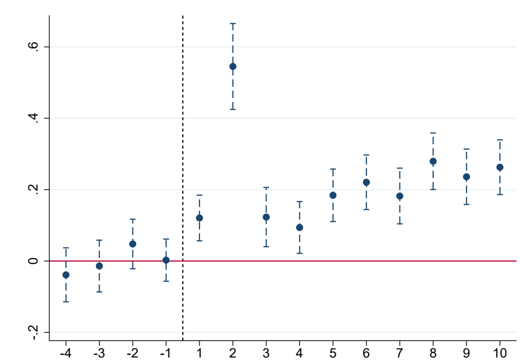
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Sales: By Scope for Home Expansion

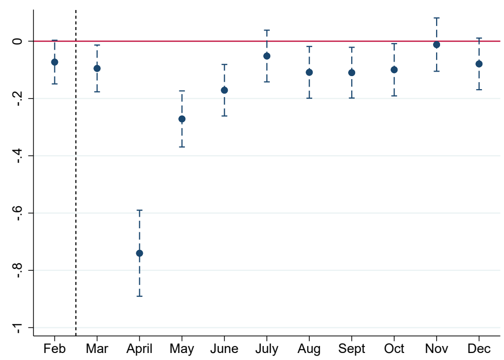


(d) Intra-Region Sales: By Scope for Home Expansion

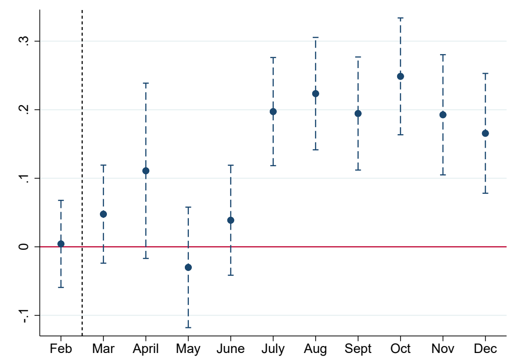


Notes: The figures in Panels (a) and (b) plot the monthly coefficients for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by product-region level Inter-Region Sales Fraction (2019), for four months before February 2020 (-4=October 2019, -3=November 2019, -2=December 2019, -1=January 2019) 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 product-region level Inter-Region Receivables Fraction (2019) for each of the month-year combinations. The figures in Panels (c) and (d) plot the monthly coefficients for the heterogeneous impact on log of inter-region sales and intra-region sales respectively, by product-region level Scope for Home Expansion (2019), for the last quarter in 2019 and every month in 2020, with February 2020 as the base month. 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-region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

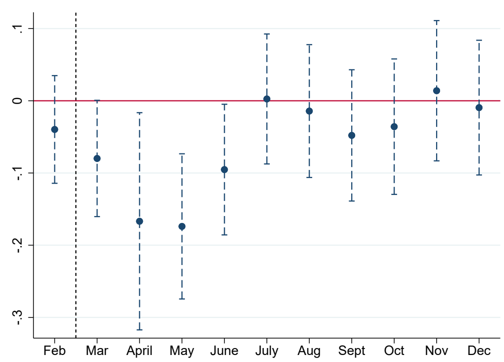
Figure C.12: Realignment (Products): Robustness (Non-Essential Products)



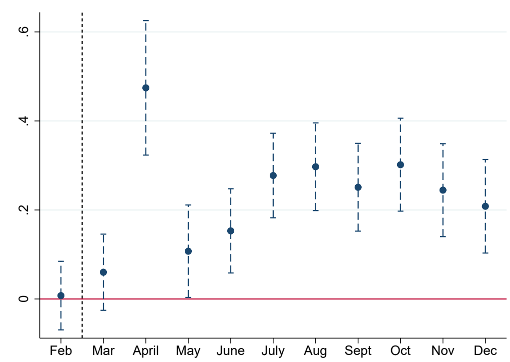
(a) Inter-Region Sales: By Sales Fraction



(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Sales: By Scope for Home Expansion

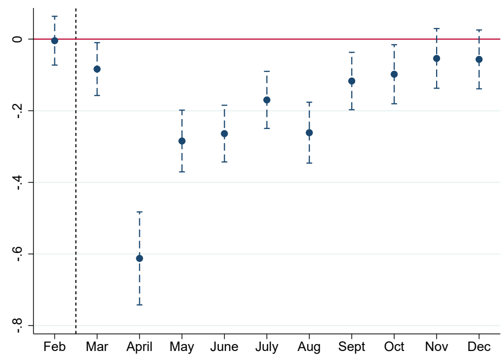


(d) Intra-Region Sales: By Scope for Home Expansion

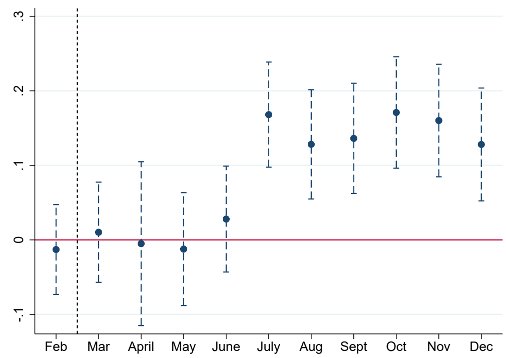
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-Region E-Way sale bills of a product originating in a region by product-region level Inter-Region Sales Fraction (2019) respectively, for every month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

Figure C.13: Realignment (Products): Robustness (Unbalanced Products)

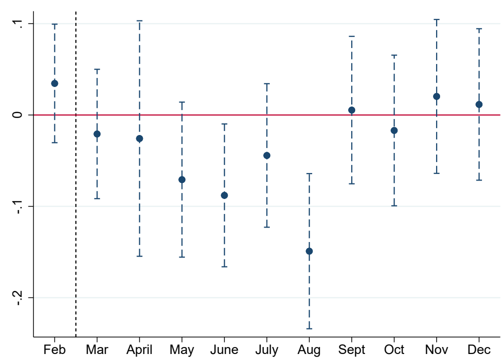
(a) Inter-Region Sales: By Sales Fraction



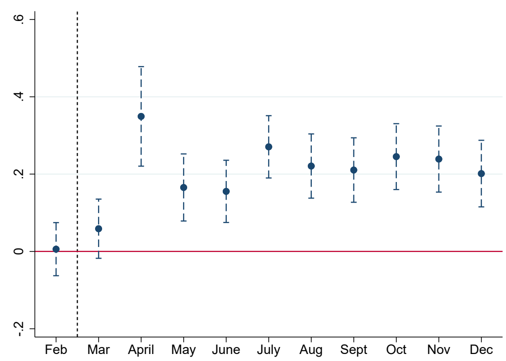
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Sales: By Scope for Home Expansion



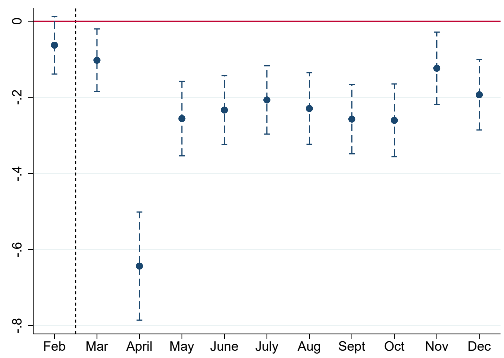
(d) Intra-Region Sales: By Scope for Home Expansion



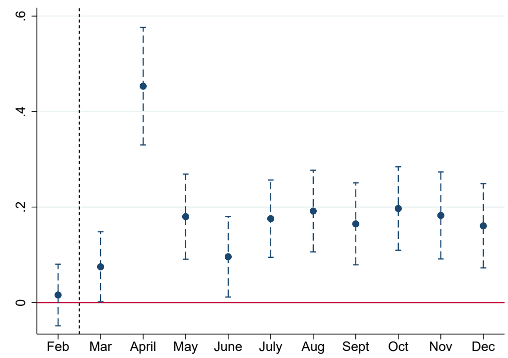
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-region sales of a product originating in a region by product-region level Inter-Region Sales Fraction (2019) respectively, for every month in 2020 with January 2020 as the base month, relative to change between the same months in 2019. Panels (c) and (d) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-region sales of a product from a region respectively, by the product-region 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-region level intra-region Scope for Home Expansion (2019) is defined as the minimum of Inter-Region Sales Fraction (2019) and Inter-Region Receivables Fraction (2019). Panels (a) and (b) additionally control for the heterogeneous impacts of product-region level Inter-Region Receivables Fraction (2019) for every month in 2020. 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-region-month and product-month-year fixed effects. The standard errors are clustered at product-region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Figure C.14: Realignment (Products): Robustness (Variation in Regional Stringency)

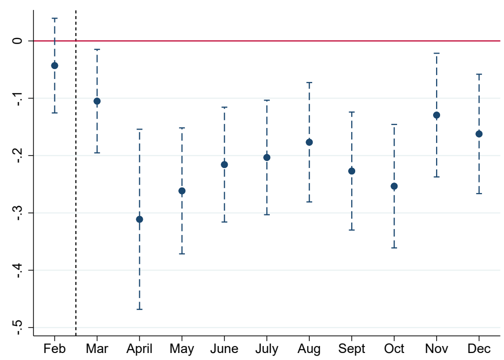
(a) Inter-Region Sales: By Sales Fraction



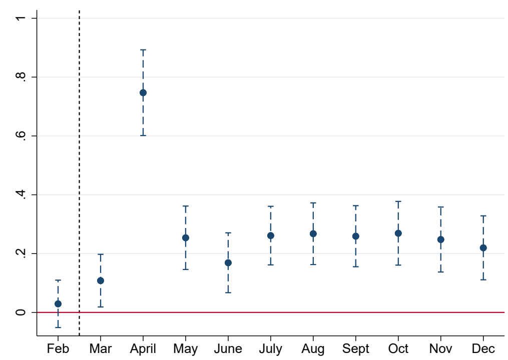
(b) Intra-Region Sales: By Sales Fraction



(c) Inter-Region Sales: By Scope for Home Expansion



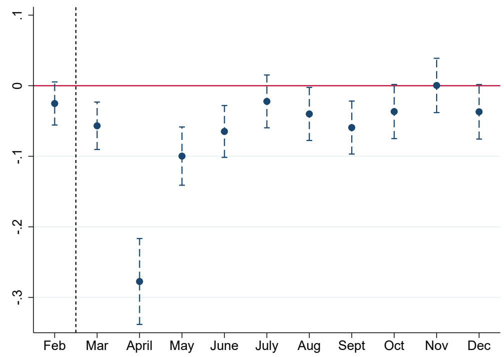
(d) Intra-Region Sales: By Scope for Home Expansion



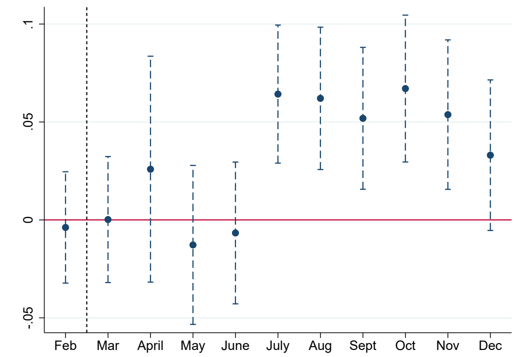
Notes: The figures in Panels (a) and (b) plot the monthly coefficients (π_2 in Equation 6) for the heterogeneous impact on log of inter-region and intra-region sales of a product originating in a region by product-region level Inter-Region Sales Fraction (2019) respectively, for every month in 2020 with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

Figure C.15: Realignment (Products): Robustness (Above Median Product Attributes)

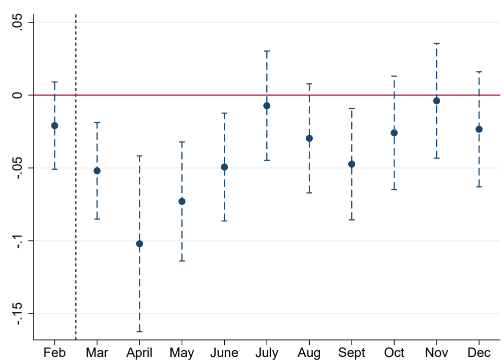
(a) Inter-Region Sales: Above Median Dependence



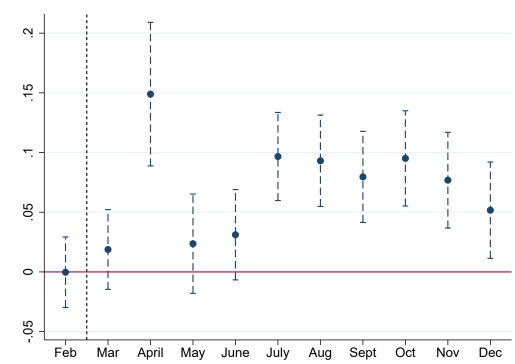
(b) Intra-Region Sales: Above Median Dependence



(c) Inter-Region Sales: Above Median Scope for Home Expansion



(d) Intra-Region 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-region and intra-region sales of a product originating in a region by an indicator variable at product-region level which takes a value of one for above median Inter-Region Sales Fraction (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 regressions additionally controls for the heterogeneous impacts of above median level product level Inter-Region Receivables Fraction (2019) for each month in 2020. The figures in Panels (c) and (d) plot the monthly coefficients for the heterogeneous impact on log of inter-region and intra-region sales of a product originating in a region by an indicator variable at product-region 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 regressions include a set of products in a region for which total sales information is available for every month. All specifications include product×region×month and product×month×year fixed effects. The standard errors are clustered at product-region level and 95% confidence intervals are plotted. The vertical line corresponds to the first national lockdown in India.

Table C.1: Realignment (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)
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
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 (3). Columns with heading γ_1 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 γ_2 show the heterogeneous impact on the dependent variable, by plant level Inter-Region 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 γ_2 show the heterogeneous impact on the dependent variable, by plant level Inter-Region 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-Region Inputs Fraction (2019); Columns (5)-(8) include interaction of each month in 2020 with plant Inter-Region 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 C.2: Impact on Plant Sales and Inputs: By Inter-Regional Dependence

Dependent variable:	log(Sales)			log(Inputs)		
	(1)	(2)	(3)	(4)	(5)	(6)
Reg. Dependence=	Inter-Region Sales Fraction ×			Inter-Region 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-Region 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-Region 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-Region Input Fraction (2019) in columns (2)-(3), interaction of each month in 2020 with plant Inter-Region 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 C.3: Realignment (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-Region Sales Fraction				Scope for Home Expansion			
	π_1	π_2	π_1	π_2	π_1	π_2	π_1	π_2
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 ($\mathbb{X}^c_{ir,my}$)	✓		✓					
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 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 show the heterogeneous impact on the dependent variable, by product level Inter-Region 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 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-Region 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 C.4: Average Scope for Home Expansion across Products (HSN 2-digit)

HSN Code (1)	Product Description (2)	σ_{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 (σ_{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 C.5: Impact on Plant Sales: By Inter-Regional Dependence (Robustness)

Dependent variable:	log(Sales)			log(E-Way Bills)
	(1)	(2)	(3)	(4)
Reg. Dependence=	Inter-Region Sales Fraction (2019) ×			
Feb 2020	−0.01	0.00	0.02	−0.00
	(0.02)	(0.01)	(0.01)	(0.01)
Mar 2020	−0.07***	−0.03**	0.01	−0.04***
	(0.02)	(0.01)	(0.01)	(0.02)
Apr 2020	−0.29***	−0.26***	−0.33***	−0.36***
	(0.05)	(0.03)	(0.03)	(0.04)
May 2020	−0.15***	−0.12***	−0.16***	−0.17***
	(0.03)	(0.02)	(0.02)	(0.02)
June 2020	−0.06**	−0.05***	−0.07***	−0.08***
	(0.03)	(0.02)	(0.02)	(0.02)
July 2020	−0.03	−0.01	−0.01	0.00
	(0.02)	(0.02)	(0.01)	(0.02)
Aug 2020	−0.05**	−0.05***	−0.12***	−0.04*
	(0.03)	(0.02)	(0.02)	(0.02)
Sep 2020	−0.05*	−0.04**	−0.04***	−0.04*
	(0.03)	(0.02)	(0.02)	(0.02)
Oct 2020	−0.02	−0.01	0.02	0.04*
	(0.03)	(0.02)	(0.02)	(0.02)
Nov 2020	−0.05*	−0.05**	−0.06***	−0.04*
	(0.03)	(0.02)	(0.02)	(0.02)
Dec 2020	−0.04	−0.03	−0.03**	−0.05**
	(0.03)	(0.02)	(0.02)	(0.02)
Plant-Month FE	✓	✓	✓	✓
Sector-Month-Year FE	✓	✓	✓	✓
Additional Controls ($\mathbb{X}^c_{ir,my}$)	✓	✓	✓	✓
Specification	District-Month -Year FE	Median	Unbalanced	Quantity
N	161736	164736	425930	164736

Notes: The dependent variable in column (1)-(3) is log of total sales and in column (4) is log of total number of E-way sale bills for a plant. The coefficients in columns (1), (3) and (4) show the heterogeneous impact, by plant level Inter-Region 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 coefficients in column (2) similarly show the heterogeneous impact, by an indicator variable, that takes value one for above median measure of plant level Inter-Region Sales Fraction (2019) and zero otherwise. The regressions include a balanced set of plants in columns (1)-(2) and (4) for which total sales information is available for every month whereas column (3) uses data on all plants for which more than six months of total sales data was available in 2019. Additional controls: interaction of each month in 2020 with plant Inter-Region Inputs Fraction (2019) in columns (1), (3) and (4); interaction of each month in 2020 with an indicator variable for above median plant Inter-Region Input Fraction (2019) in column (2). 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 C.6: Impact on Plant Inputs: By Inter-Regional Dependence (Robustness)

Dependent variable:	log(Inputs)			log(E-Way Bills)
	(1)	(2)	(3)	(4)
Reg. Dependence=	Inter-Region Inputs Fraction (2019) ×			
Feb 2020	–0.02	0.00	0.02	–0.02
	(0.03)	(0.02)	(0.01)	(0.02)
Mar 2020	–0.02	–0.02	0.00	–0.07***
	(0.03)	(0.02)	(0.02)	(0.03)
Apr 2020	–0.13**	–0.09**	–0.28***	–0.19***
	(0.06)	(0.04)	(0.04)	(0.05)
May 2020	–0.21***	–0.10***	–0.13***	–0.19***
	(0.04)	(0.03)	(0.02)	(0.03)
June 2020	–0.12***	–0.08***	–0.09***	–0.14***
	(0.03)	(0.02)	(0.02)	(0.03)
July 2020	–0.04	–0.04*	–0.06***	–0.09***
	(0.03)	(0.02)	(0.02)	(0.03)
Aug 2020	–0.03	–0.03	–0.09***	–0.05
	(0.03)	(0.02)	(0.02)	(0.03)
Sep 2020	–0.02	–0.02	–0.05***	–0.03
	(0.03)	(0.02)	(0.02)	(0.03)
Oct 2020	–0.03	–0.00	–0.00	0.01
	(0.03)	(0.02)	(0.02)	(0.03)
Nov 2020	–0.05	–0.04	–0.06***	–0.06*
	(0.04)	(0.02)	(0.02)	(0.03)
Dec 2020	–0.03	–0.01	–0.02	–0.01
	(0.04)	(0.02)	(0.02)	(0.03)
Plant-Month FE	✓	✓	✓	✓
Sector-Month-Year FE	✓	✓	✓	✓
Additional Controls ($\mathbb{X}^c_{ir,my}$)	✓	✓	✓	✓
Specification	District-Month -Year FE	Median	Unbalanced	Quantity
N	119688	122712	384576	122712

Notes: The dependent variable in column (1)-(3) is log of total inputs and in column (4) is log of total number of E-way input bills for a plant. The coefficients in columns (1), (3) and (4) show the heterogeneous impact, by plant level Inter-Region 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 coefficients in column (2) similarly show the heterogeneous impact, by an indicator variable, that takes value one for above median measure of plant level Inter-Region Inputs Fraction (2019) and zero otherwise. The regressions include a balanced set of plants in columns (1)-(2) and (4) for which total inputs information is available for every month whereas column (3) uses data on all plants for which more than six months of total inputs data was available in 2019. Additional controls: interaction of each month in 2020 with plant Inter-Region Sales Fraction (2019) in columns (1)-(2) and (4); interaction of each month in 2020 with an indicator variable for above median plant Inter-Region Sales Fraction (2019) in column (3). 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 C.7: Gains in Sales from Realignment and Scope for Home expansion: Regional Heterogeneity

Region	(1) CF Scenario I	(2) CF Scenario II	(3) CF Scenario III	(4) Average σ_{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 realignment case with sales growth equal to zero for both types of products. Scenario II is the case with realignment only for above-median σ_{kr} products. Scenario III captures the effect due to scope for home expansion alone. Column (4) shows the product sales weighted average value of σ_{kr} for a region in 2019. Greater the value of σ, larger is the gains from home expansion in a region.