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Trucking Costs and the Margins of Internal Trade

Evidence from a Trucking Portal in India

Somik Lall
Sutirtha Sinha-Roy
Forhad Shilpi

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Abstract

This paper uses data on nearly half a million actual shipments from a trucking portal in India to provide evidence on how trucking costs depend on route characteristics and affect the intensive and extensive margins of shipment flows. The empirical analysis using pre-pandemic data (before March 24, 2020) confirms the presence of thick market externalities along a route and spillovers across routes due to network externalities, both of which confer advantages to origins and destinations with larger market sizes. The paper utilizes exogenous variations in value-added tax on gasoline across states to provide causal estimates of the elasticity of shipment flows with respect to trucking costs. The empirical estimates suggest that a 1 percent increase in trucking unit costs reduces trade flows by 2.8–3.9 percent. On the extensive margin of trade, three eastern states and several smaller territories constitute isolated regions that were largely cut off from the trading networks during the pre-pandemic period. Trucking costs increased by 32 percent during the early post-lockdown period (June 2020 to February 2021). The increase was greater along longer routes. In the short run, the increase in freight rates led to a proportionate decrease in trade flows across states. It pushed a significant number of poorer and remoter states into the ranks of isolated regions.

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Produced by the Research Support Team

Trucking costs and the margins of internal trade: Evidence from a Trucking Portal in India[1]

Somik Lall, Sutirtha Sinha-Roy, Forhad Shilpi

World Bank

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1 Introduction

Investment in physical transport infrastructure is costly. But such investment can bring economic transformation by integrating isolated regions into trade networks and intensifying trade flows within the existing network. These promises of economic integration motivated developing countries to invest generously in physical transport infrastructure during the last couple of decades. While construction of transport infrastructure is generally welfare improving,[2] much of the evaluation of its impact skirted the issue of how such investments may affect the price of transport services. Recent literature on supply chains recognizes that endogenous price responses are critically important in determining how the effect of a shock is transmitted spatially along the supply chain and is distributed unevenly across areas and people (Atkin and Donaldson, 2014; Allen, Atkin, Cantillo and Hernandez, 2020). Much of the recent evidence on the endogeneity of transport services comes from container and dry bulk shipping in international trade (Brancaccio, Kalouptsidi and Papageorgiou, 2020; Wong, 2018; Asturias, 2020). Except for the ongoing work by Allen, Atkin, Cantillo, and Hernandez (2020) on trucking in Colombia, little is known about how road transport costs vary with route characteristics and how sensitive the intensive and extensive margins of inter-regional trade are to transport costs in developing countries.[3] Similarly, evidence on the behavior of transport costs during the COVID-19 pandemic and its implications for regional trade networks is also rare in developing countries. This paper addresses these questions utilizing a unique data set consisting of nearly half a million *actual* shipment data from a trucking platform in India.

The trucking sector is the predominant carrier of freight transported domestically in both developed and developing countries. It accounts for 63 percent of internal freight in India and 58 percent in the United States, and 70 percent in Africa region.[4] In the case of international trade where ocean shipping

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[2] For a survey of the evidence, please see Donaldson (2015), Redding and Turner (2015), and Berg et al (2017).

[3] Allen, Atkin, Cantillo, and Hernandez (2020) investigate the implications of imperfect competition in trucking for trade costs in remoter areas in Colombia. Their data consist of truck shipments at the aggregate origin-destination pair level, whereas our data consists of individual-level transactions.

[4] India has about 1.8 million kilometers (km) of roads. Rail freight constitutes around 27 percent of the total freight movement in India. It consists of a large infrastructure of more than 65000 km of rail network carrying more than 1400MMT of load annually. The source of data for the USA: https://www.bts.gov/newsroom/2017-north-american-freight-

is the main transport mode, freight rates are found to be subject to various thick market and network externalities (Brancaccio, Kalouptsidi and Papageorgiou, 2020; Wong, 2018; Asturias, 2020). However, little is known about the behavior of trucking costs in developing countries due to a lack of transaction-level data. In India, several online portals have been in operation (e. g. trukky, truckguru, blackbuck, trucksuvidha, truckbhada, logisticsjunction, etc.) in recent years. These portals match truck suppliers/operators with customers where the matching is d1 through a bidding process. The transactions covered by the platform can be characterized as spot transactions. The nearly half a million *actual* transactions that took place through 1 of the platforms form the main data set for our analysis. The data set is exceptional in three ways: it recorded details of each transaction including freight cost, location of origin, and destination along with vehicle and commodity characteristics; its geographical coverage is extensive, reaching nearly all corners of India, and its temporal coverage (January 2017 to February 2021) spans the entire first wave of the COVID-19 pandemic period.

Taking advantage of this data set, we provide evidence on freight rates (per ton-km) for trucking in India during the pre-pandemic, nationwide lockdown, and post-lockdown periods, and on the determinants of trucking cost in terms of route characteristics. The evidence indicates that the freight rate per ton-km (mt-km) is relatively cheap in India (about 5 cents) and post-lockdown freight rates were about 32 percent higher compared with the immediately preceding pre-pandemic level. The rise in the freight rate during the post-lockdown period was also higher for long-distance trips. Evidence suggests several advantages for destinations with larger market sizes: the cost of incoming freight is relatively lower and consequently, their trading networks have much longer geographic reach and costs are lower if the origin is also a large city.

To see how the freight rate shock as observed during the post-lockdown period would transmit along the trade network, we estimate the elasticity of trade/shipment flow with respect to freight rate as well as

numbers#:~:text=Trucks%20carried%2057.7%20percent%20of%20the%20value%20of,carried%2084.5%20percent%20of%20the%20value%20%28Ta spatial margin of trade beyond which a location becomes relatively isolated.[5] The trade elasticity is estimated using the gravity regression in the tradition of Anderson and Van Wincoop (2004), and Head and Mayer (2014). The main estimation challenge is that freight rates and trade flows along a route are endogenous to each other, requiring an exogenous source of variations to identify the elasticity parameter. We utilize an insight from recent transport literature that the freight rate along a route depends also on the probability of securing the next trip from the destination (Brancaccio, Kalouptsidi and Papageorgiou, 2020; Wong, 2019; Behrens and Brown, 2018). Thus, a supply shock in the next probable route will affect transport cost in the current route and could act as an instrument once the supply shock in its own route is controlled for in the regression. For an exogenous supply shock to the transport sector, we rely on state-level variations in the average value-added tax (VAT) on gasoline along the next probable trip outside the current origin and destination states as an instrument for freight rate while controlling for the own route VAT rate interacted with the crude oil price. The evidence suggests that a 1 percent increase in freight rate reduces trade flow by 2.8 to 3.9 percent. These estimates are quite similar to that by Wong (2018) (elasticity=2.8-3.7) for container shipping in international trade. To identify the extensive margin of trade, we define an Indian state as isolated if more than 50 percent of its potential trade links see a negligible number of trips. The empirical evidence suggests that three remoter eastern states and two territories constituted the isolated regions during the pre-pandemic period. To simulate the very short-run effects of the post-lockdown freight shock, the estimates discussed above are used to deduce the levels of trade flows and extensive margin of trade that would be consistent with the post-lockdown freight rates. These simulation exercises find that trade flows across states decreased more or less proportionately during the post-lockdown period despite spatial heterogeneity in the increase in freight rates. However, such a large increase in freight rates led to a substantial shrinking of the spatial margin of the trade from 3,900 km in the pre-pandemic period to 1,700 km in the post-lockdown period, pushing another eleven states and three territories into isolated status. These states are poorer, remoter, and not home to major cities in India.

[5] We use shipment flow and trade flow interchangeably through out the paper.

The empirical analysis in this paper contributes to several strands of literature. First, there is now emerging literature on trade and transport emphasizing that (i) transport prices are endogenous to trade flows, (ii) there are spillovers across routes because truckers take account of the probability of finding the next trip while planning for a trip (Brancaccio et al. 2020, Wong, 2018); and (iii) the thicker trade flows along a route allow the use of larger and more efficient trucks leading to the extent of market effect observed in our data (Allen et al.,2021; Asturias, 2020). Our empirical analysis provides suggestive evidence in favor of the presence of these externalities in the Indian setting where the trucking sector is predominantly informal and unregulated with few entry barriers. The presence of these externalities suggests that the return to the construction of a road would depend on not just the reduction in travel time but also the characteristics of the places that it is connecting.

Second, trade elasticity is a key parameter in quantitative spatial equilibrium models. We provide a causal estimate of the elasticity of trade flow with respect to trucking costs which has not been --to the best of our knowledge -- available for developing countries in the existing literature. Our estimates of elasticities imply elasticities of substitution within the range of 21-29 which are much larger in magnitude than the estimates (5-6) derived from the spatial equilibrium models estimated for India (Asturias, Garcia-Santana and Ramos, 2018; van Leemput, 2021). But our estimates are very much in line with the estimates derived from direct data on freight rates by Wong (2018) (22-27). It also confirms the *a priori* expectation that this elasticity should be higher in poorer countries where consumers tend to be more sensitive to prices (Duranton, 2014).[6]

Third, developing countries are characterized by considerable regional inequality, where modern economies in larger cities coexist with subsistence economies in remoter regions, and improved transport connectivity is often offered as an important way to integrate and transform the isolated areas (Grover, Lall and Mal1y, 2022). Yet, literature on the impacts of transport connectivity as well as trade shocks on

[6] The discrepancies between estimates from annual data using distance as a measure of transport cost and ne grained transaction-level data are noted already in literature (see, Wong for a discussion) and discussed in more detail in section 4.

the extensive margin of regional integration remains sparse (Kosar and Fajgelbaum, 2014; Emran and Shilpi, 2019). In the absence of data on the universe of trucking transactions, we developed an empirical methodology to define this margin by using observable route characteristics to predict the expected number of trips for all potential routes and using a cut-off consistent with the maximum distance traveled in our data set. Simulation results for the post-lockdown transport cost shock highlight the need for considering the extensive margin. This margin shrank significantly, affecting the remoter states disproportionately.

Finally, the supply chain disruptions due to the COVID-19 pandemic have been a major cause of inflationary pressure around the world in recent months.[7] There is also considerable press coverage of the disproportionate burden of inflation falling on the poor. The evidence on the extensive margin of trade shows that the burden of the rise in transport costs also falls disproportionately on the poorer and remoter states in India. Given that enforcement of COVID-19 restrictions in India was more frequent in major cities which also experienced more frequent outbreaks, this result suggests spillovers from these restrictions in major cities to relatively poorer areas through the transport and trade networks. Any economic recovery policy in India should take account of these potential spillover effects.

The rest of the paper is organized as follows. We start with a discussion of transport platform data in section 2. Section 3 presents the evidence on the size and determinants of transport cost followed by its behavior during the pandemic and post-lockdown periods. Section 4 is devoted to the estimation of trade elasticity. Section 5 discusses the counterfactual results. Section 6 concludes the paper.

[7] Though the incidence of the pandemic was much milder in India before March 2021, the national lockdown created serious disruptions in the Indian economy during this time. The transport of essential goods was exempt from mobility restrictions duringlockdown to minimize supply chain disruptions. Yet, supply disruptions ensued because of the way the lockdown was implemented.As opposed to the developed world where supply chain disruptions did not emerge until the Christmas season of 2021, India experienced higher food prices and major disruptions in its supply chain during the early days of the pandemic due to inter- and intra-state travel/transport restrictions which were in place until July 2020 (Tomar and Mahajon, 2020).

2 Transaction data from the Trucking portal

Our main source of data is the confidential transaction-level data on trucking from a logistics company we call JDL. The data set covers 487,406 transactions that took place on its platform between January 2017 and February 2021. These transactions hauled about 8.8 million metric tons of freight. The platform was open to truckers and their customers, and a bidding process was followed leading to the ultimate transaction. Each transaction recorded its origin and destination at administrative/census code level 4 (town/village level), the types of goods transported, truck characteristics including its length, capacity, and type, and most importantly transport charge paid by the customer and weight carried by each truck. Though JDL maintains a fleet of trucks, the platform attracted many other truckers and customers beyond its own customer base. All transactions were facilitated by JDL for a small fee. About 5 percent of the transactions in the data set involve JDL's own trucks. The main analysis of the paper is based on transactions that took place before the COVID-19 lockdown on March 24, 2020. After light cleaning, we have about 470,000 transactions in the data set during this pre-COVID-19 period. The data during and after lockdown due to COVID-19 are utilized to track changes in transport costs during the pandemic period. The COVID-19 period data consists of 7,344 observations. We complemented these transactions data with distance, travel time, and crow fly distance using google distance API. This data set is further augmented with night light data from the VIIRS (Visible Infrared Imaging Radiometer Suite) which improved upon the data from the DMSP satellites.[8]

The trips in the data set cover nearly all corners of India ensuring very wide geographical coverage. About 31 percent of trips either originate or end in 7 main Indian cities highlighting the importance of economic density in trade flows.[9] Though the amount of freight hauled in this data set constitutes a small

[8] In 2011, through a partnership with NOAA and the Department of Defense, NASA launched the Suomi NPP satellite and in 2018 the NOAA-20 satellite. Both satellites carry the VIIRS instrument, which also collects NTL emissions and continues the long-term NTL data record. The VIIRS DNB improves upon the older DMSP OLS with higher spatial and radiometric resolution: VIIRS has a spatial resolution of 375 and 750 meters (depending on the band), daily temporal resolution, and more complete global coverage and higher quality data.

[9] These cities are Delhi, Mumbai, Bangalore, Chennai, Hyderabad, Ahmedabad and Kolkata.

fraction of freight hauled by trucks annually in India, the geographical coverage of the data set is quite extensive.

3 Transport costs and their determinants: Descriptive Analysis

We start with summary statistics from the pre-pandemic period trucking data set which are reported in Table 1. On average, a truck in our data set travels about 924 km and spends a little over 17 hours on the trip. The truck capacity varies from light (1 to 10 tons) to heavy-duty trucks with carrying capacity up to 35 tons. The average truck size is around 18 tons. The share of trips taken by light trucks is about 22 percent which is consistent with the national average (21 percent). The average number of trips between origin-destination is about 286 though about 8 percent of origin-destination pairs have 5 or fewer trips. We utilize the trucking data to establish key features of trucking costs in India. Table 2 reports several regression results for freight rate per ton-km as a dependent variable. The regressions are used to detect correlations between freight rate and economic density and should not be interpreted as causal relationships. We take total night light luminosity as a measure of economic density in a district. The basic regression specification controls for the log of the distance between origin and destination districts, types of vehicles used (container, trailer or open bedded) and commodity transported, size of the truck, and appropriate location fixed effects. The standard errors are clustered at the route level. In the following, we report the main stylized facts.

Stylized Fact 1: The freight rate per ton-km is relatively low in India.

The average freight rate is about Rs.3.92 per ton-kilometer (mt-km, for short) (Table 1) which translates into about 5 cents in US \$. This is much lower than about 13 cents/mt-km in the United States, and 20.5 cents/mt-km in Colombia (Allen et al, 2020) before the pandemic. Gasoline price in India was much higher (\$4.15/gallon) compared with the United States (\$3/gallon) during the pre-pandemic period. The lower labor and capital costs more than offset the higher gasoline costs, making transporting goods by trucks quite cheap in India.

Stylized Fact 2: Freight rate per ton-km is correlated negatively with economic density at the destination and positively with that at the origin. The freight rate is lower in the direction where the destination has a higher economic density.

Column 1 of Table 2 reports the results from regression of the log of freight rate on the log of night light luminosity at the destination while controlling for the origin fixed effects. The result flows a strong and negative correlation between economic density at destination and trucking freight rate. As recent literature pointed out, this correlation can arise from many reasons including a combination of imperfect market structure and technology choice as well as search and matching frictions and transport routing. Freight rate also declines with an increase in the distance which can result from less congestion in long-distance travel, lower the fixed cost per km, and use of efficient technology such as larger trucks.

Column 2 in Table 2 reports the results from a regression of the log of freight rate on economic density at the origin while controlling for destination fixed effects. The correlation between freight rate and economic density at the origin is positive. The correlations in columns (1) and (2) suggest that transport cost depends on the direction of the trip. In other words, conditional on appropriate fixed effects, the freight rate is lower for trips ending at a large city (e.g. Mumbai) but higher for trips originating in a large city. This result thus confirms the asymmetry in transport cost discussed in recent literature. This asymmetry arises due to search frictions in securing the next trip (Brancaccio et al, 2020) and/or the "round trip" effect due to joint route planning by truckers (Wong, 2020).

The joint trip planning creates spillover effects interlinking pricing of trucking services across routes. To explore this, we focus on round trips. A trip from i to j has the same cost as a trip from j to i. They differ in terms of economic densities of i and j. We take the differences between the log of freight rate between i and j (T_{ij}) and the log of freight rate between j and i (T_{ji}) and that between the log of NL_j and log of NL_i where NL stands for night lights luminosity*:* We then fit a polynomial regression between the two. Figure 1 plots the prediction from this polynomial regression and a smooth fitted line through them. Except for extreme differences between origin and destination economic densities, the relationship is downward sloping. This suggests that truckers set a lower price while going to a larger city and a higher price when coming back to the same origin but with a smaller market size.

Stylized Fact 3: Trucking freight rate per ton-km is negatively correlated with the economic density of a route.

Is the freight rate lower if a route has higher densities at both ends? To check this, we add night light luminosity for origin and destination to define the thickness of each route, as two locations with higher GDP are expected to have higher trade flow as well. We then run the same regression as in column 1, this time with this measure of the thickness of a route replacing destination night light luminosity. The estimated coefficient of this economic density variable is negative and about 76 percent larger than that reported in column 1 (column 3). This correlation is robust to using the log of the number of trips between OD pairs as an indicator of the thickness of trade flow. Thus, the freight rate is lower not only when the destination is larger in terms of economic density but even more so when both origin and destination are large economically. 1 possible explanation for such a strong correlation is that larger economic density allows the adoption of better transport technology in terms of larger truck sizes which have a lower marginal cost of transporting goods. Another possibility is that thicker routes attract more competition reducing markups for truckers.

Stylized Fact 4: Distance traveled is longer when the economic density of the origin is larger.

Do large cities/origins have larger hinterlands with which they trade actively? To answer this question, we take the distance between OD pairs as the dependent variable and regress it on the log of night light density of origin while conditioning on destination fixed effects. The result reported in column 4 indicates a significant positive correlation implying a longer reach of origins with a larger size of the economy.

3.1 **Transport costs during the COVID-19 pandemic**

Our trips data set covers trips that took place during the COVID-19 national lockdown period (March 24-May 30, 2021) and various localized lockdown periods that lasted till November 30, 2020. It also has information on trips during post-lockdown up to February 24, 2021. The pandemic period covered in our data set corresponds to the first wave of COVID-19 infections and deaths which were milder in India (Figure 2). The vertical lines in Figure 2 show the start and end of the lockdown period (red and green lines respectively), and the end date for our data set (dark orange line). As clear from Figure 2, fatality rates were quite low by February 24, 2021, and many observers reas1d (and perhaps hoped) that India escaped much of the scourge of COVID-19. That hope was dashed soon with the arrival of the next wave (Delta variant) in March 2021 which caused a serious rise in infections and deaths in the following months.

1 caveat with the data set is that in October 2020, the logistics company (JDL) completed a reorganization in which it restricted access to its platform only to its own trucks. This led to a very large reduction in the number of transactions recorded on the platform. We restrict our sample to JDL trucks for the analysis of freight rate behavior before, during, and after the lockdown period. There are 7,344 trips after March 24, 2020, in our data set. To avoid the uncertainty during re-organization, we define a pre-lockdown sample from November 1, 2019. There are 9,220 trips during the pre-lockdown sample period. To show trends in freight rate, we collapse data by date and fit a time trend to both pre-and post-lockdown periods. Figure 3 plots the observed trend in freight rate from November 1, 2019, to February 24, 2021, and the red vertical line indicates the date when the nationwide lockdown was imposed. Before the lockdown in March 2020, the freight rate had been completely flat. The freight rate doubled during the first week of lockdown and started to come down quickly though it was about 37 percent higher even in February 2021.[10] The negative shocks to production and trading due to lockdown and COVID-19 reduced demand for transport services. Similarly, the price of crude oil dropped substantially during much of 2020 compared with the pre-pandemic period. Both of these changes should in principle result in a lower freight rate. Two factors -directly relevant to the transport sector itself could potentially explain the

[10] This rise in trucking prices during the pandemic period is confirmed in the month-to-month comparison as well (Figure A.1 in the online appendix). This pattern in India is quite different from those observed in developed countries over the same period. Trucking costs increased only for a short while during early 2021 in the US due to the shipping backlog during the Christmas season. For the rest of the time, it remained stable with no disruptions in the internal supply chain, though supply chain issues re-emerged during the latter half of 2021.

rise in trucking costs. The lower probability of securing the next trip from the destination may have led to an increase in cost in the current route. Drivers needed to be compensated for higher health risks.

To establish the average increase in freight rate during the lockdown and post-lockdown periods, we revert back to trip level data from JDL trucks. We define two dummies to capture the national lockdown ("lockdown") and post-lockdown ("post") periods. We run a before-after (single difference) regression of the log of freight rate on the post dummy which takes the value of unity if the date is after June 30, 2020, and zero otherwise.[11] This regression includes the log of the distance between OD pair and origin and destination fixed effects. Column 1 of Table 3 reports the estimates from this simple regression excluding the lockdown period from the sample. The coefficient of post dummy indicates a nearly 32 percent increase in freight rate during this period. To capture the heterogeneity with respect to distance, the regression in column 2 introduces the interaction of post with the log of distance. The interaction term has a positive sign indicating a larger increase in freight rate for longer distance trips. The regressions so far excluded the lockdown period. In column 3, we include the lockdown period (March 24- June 30, 2020) in the sample and the lockdown dummy in the regression. Consistent with Figure 3, the estimate indicates about a 39 percent increase in freight rate during the lockdown period (column 3). When interaction with distance is introduced (column 4), the estimate implies a doubling of the average freight rate for shorter trips and a lower increase for longer distance trips during the lockdown period. The results for post-lockdown in column 4 are similar to that in column 2.

The regression results suggest a heterogeneous increase in freight rates between lockdown and post-lockdown periods, and with respect to the distance between OD pairs. With such heterogeneity, the policy-makers may want to know how such heterogeneous increases in freight rates may affect inter-regional trade. To answer this question, we examine two aspects of the trade: (i) intensive margins of trade focusing on how shipment flow will be affected among OD pairs already trading with each other; (ii)

[11] Though the national lockdown was lifted in early June 2020, many of the restrictions including restrictions on mobility were still in place until the end of June. Those restrictions were removed by June 30, 2020. We take June 30th as the end date of the lockdown.

extensive/spatial margin of trade where an increase in transport cost can sever the link between OD pairs who were engaged in trading during the pre-pandemic period. We use the trade flow and freight rate data during the pre-pandemic period to estimate elasticity and spatial margin of trade. The shift in freight rate during the post-lockdown period is then used to simulate the effects of this shock on these two margins of trade. The pandemic has affected every facet of the economy, including the way goods are transported, how people migrate across areas and how preferences shift in response to it. The exercise is not intended to predict the overall spatial effects of the pandemic or even trade flows and trucking costs in the long run. Taking the observed changes in freight rates as given, we limit our analysis in favor of providing a suggestive view of how trade flows and spatial margin of trade may be affected in the short run.

4 Estimating trade gravity regression during the pre-pandemic period

The first step in analyzing the impacts of the increase in trucking costs on inter-regional trade flows is the estimation of elasticity of trade flow with respect to the freight rate, which to the best of our knowledge is not available from existing literature for developing countries, particularly for India. We start by describing how values of trade flows across districts are constructed.

The volume of goods transported is reported for each transaction in our trucking data set. Using these data, we construct district to district flow of volumes of goods by aggregating over all trips for each OD pair. However, the data set does not provide information on the value of traded goods which is needed for the estimation of trade elasticity. To estimate the value of trade, we web-scrapped daily prices of essential commodities reported by the Reserve Bank of India for 114 cities. As noted in Atkin and Donaldson (2014), it is important to establish the origin of comparable goods to trace out the trading and transport cost over distance. We select two commodities loose tea and palm oil whose qualities are comparable across markets. For each of these commodities, the origin can be ascertained easily from ports for palm oil which is mostly imported, and auction houses for tea. For each commodity, we select two cities nearest to the port or auction house. Origin is then selected as the city which has the lower wholesale price. We use Google Map API to compute distances between origin and destination cities. These daily price data for OD pairs are then merged with trucking cost data.

The trading margins tend to vary over distances when intermediaries operate in an imperfectly competitive market structure (Atkin and Donaldson,2014). Appendix Figure A.2 provides a scatter plot of the ratio of freight costs over retail product prices at the destination. Evidence in Figure A.2 confirms that the share of freight cost in destination retail price increases with an increase in distance from the origin. To allow for this heterogeneity, we estimate a regression of the ratio of freight cost to destination price on distance. Using the estimates of intercept and distance coefficient from this regression, we predict the freight cost to product price ratio for the trips in our trucking data set. As trucking cost is already known, we invert predicted prices using these observed trucking costs. The quantity is then multiplied by this predicted price to estimate the value of freight for each transaction. Summing it up by OD pairs provides the value of trade flow across districts.

4.1 Econometric Specification

To estimate the trade elasticity with respect to trip cost, we utilize the canonical gravity equation for trade flow:

$$X_{ij} = \beta_0 + \beta_1 T_{ij} + \beta_2 Z_{ij} + \mu_i + \eta_j + \varepsilon_{ij} \tag{1}$$

Where X_{ij} is the value of trade flow (export) from origin i to destination j; T_{ij} is the freight rate for the trip, Z_{ij} is the set of controls relevant for the OD pair (i, j) including the distance between them, μ_i is the origin fixed effects, η_j is the destination fixed effects and ε_{ij} is the residual term. Note that the specification in equation (1) lacks a time subscript because trade flow data do not have time variation. All regressions include the log of the distance between OD pair as a control in Z_{ij}. The main identification challenge in the estimation of equation (1) is that trip cost is determined by the demand for and supply of trucks.

Demand for trucks in a route depends on the trade flow itself, making trip costs endogenous. Consider a negative trade shock for a route. It reduces trade flow along the route, shifting truck demand downward and reducing trip costs. The shock thus produces a positive correlation between trade flow and transport cost and biases the OLS estimate of β_1 downward. To identify the coefficient of interest β_1; we need to find an exogenous source of variations that affect trip cost but not trade flow in route (*ij*) directly.

4.2 Instrumenting the Freight Rate

To instrument the trip cost, we rely on key insights from recent papers on transport costs across routes (Brancaccio et al, 2020; Wong, 2019; Hummels, Lugovskyy and Skiba, 2009; Behren and Picard, 2011; Behren and Brown, 2018). A truck going to a destination needs to catch its next trip be it back to its origin or some other destination. This means that T_{ij} depends not only on its demand along route *ij* but also on the probability of catching the next trip from destination *j*: This probability in turn is determined by trade flows and transport costs originating at *j* to other destinations leading to network effects. In other words, a shock to transport cost along a route originating at *j* affects T_{ij} directly and X_{ij} indirectly through T_{ij}. We utilize this key insight to derive an instrument for T_{ij} focusing particularly on cost shock for the transport sector itself.

In India, gasoline is exempt from its common Goods and Services Tax (GST) umbrella. The GST reform enacted in 2017 eliminated tax differential across states, particularly for inter-state sales of most goods and services. The indirect tax on petroleum is an important contributor to both central and state tax revenue and remains under the old regime of central taxes, state-level Value Added Tax (VAT), and other taxes. India imports much of its crude oil at international prices and has refining capacity under different ownership arrangements. The refined gasoline is marketed through dealers with a fixed commission rate and subject to central excise and customs tariffs which vary by product but not by location. The major variations in petrol and diesel prices across locations come from variations in the state-level VAT which vary from 6 percent in Andaman and Nicobar Island to 28 percent in Odisha. In addition, many states also impose additional cess per liter. The differential rates of VAT across states along with variations in the international price of crude oil provide us the exogenous variations to identify trade elasticity with respect to trucking cost.

To construct the instrument for transport price along route ij, we consider possible routes for the next trip originating from j. We define an instrument as follows:

$$\bar{v}_j = \frac{1}{K}\sum_{k=1}^{K} v_{jk} \text{ where } k \neq j, i$$

where v_{jk} is VAT rate in destination state k which is different from state i or state j. In other words, the instrumental variable estimation will drop all within state trips originating in district j and all across state trips between ji, and ik. We also define an alternative instrument by interacting v_j with the price of crude oil. This interaction instrument utilizes temporal variations in crude price over the period that corresponds to month-year during which trips in our data set had taken place. The instrumental variable regressions control for the interaction of crude price with own route VAT rate directly and for the origin and destination district fixed effects.[12] Our instruments are similar in spirit to instruments in Bronccacio et al (2019) who used tariff rates on the next possible routes as an instrument for freight rate in the current route. The difference is that we utilize cost shifters (in terms of VAT) instead of demand shifters in Bronccacio et al (2019). Since instruments are defined at destination (j) of route ij, we cluster standard errors at the destination district level.[13]

4.3 Empirical Results

Trade Gravity Equation

Table 4 reports the results from the simple OLS regressions of the trade gravity equation (1). All regressions include origin and destination fixed effects at the district level. For each destination district, all destinations for the next trip which are within the same state are dropped, and so are potential back

[12] The VAT rate along its own route drops out of regressions since origin and destination fixed effects are controlled. However, the interaction with crude price has temporal variations and does not drop out because of variations in the timing of trips between OD pairs.

[13] Standard errors are much smaller if we cluster at the route level. As a result, empirical conclusions are unaffected if standard errors are clustered at the route level.

trips to origins (ji, and ik), giving us a total sample of 362,436 trips between 491 origin and 589 destination districts. The dependent variable in panel A of Table 4 is the log of value of trade flow and in Panel B, the log of total quantity hauled, both estimated from trip data. All regressions control for the log of distance but the sets of control variables vary across columns.

The first column in Table 3 reports the estimates when the log of the distance between OD pairs and interaction of crude price with average VAT rate between OD pairs are the controls in Z_{ij}. The second column adds the log of diesel prices along the route to controls in column 1. The sample for this third specification is smaller as we have daily diesel prices in different districts only for 2019. The third column adds the log of night light luminosity along the route to the set of controls in the first column. It should be noted that both diesel price and night light luminosity are endogenous to trade flows and transport costs and could be argued to be bad controls in our context. These specifications are estimated to check the robustness of IV results later. The OLS estimate of trade elasticity with respect to the freight rate has the expected negative sign and is statistically significant in each of the three regression specifications. The estimates are remarkably consistent across specifications and fall within a narrow bound of -0.24 to -0.27. The estimates imply an average elasticity of trade with respect to the freight rate of around -0.25. The elasticity of volume of trade with respect to the freight rate is larger in magnitude (-0.79) than the average value of trade elasticity.

To take care of the potential endogeneity of freight cost in the trade gravity regression, we start with first stage estimates which are reported in Table 5. The instrument is the average VAT rate for the next trip from destination district j (v_j) as defined earlier. The controls in each column are the same as in Table 4. The coefficients of the instrument in all three Specifications are positive and statistically significant at a 1 percent level. The estimate implies that an increase in the average VAT rate in the next possible destination increases the freight rate in the current route. An increase in the VAT rate in the next possible route (jk) will decrease trade flow along that route, decreasing the probability of getting a match for the next trip. The estimates for the current route interaction term also suggest a positive pass-through of the crude price shock, though it does not fully capture the pass-through because of regression specification.[14] Note that VAT rate along own route is dropped out of regression because of origin and destination fixed effects.

Table 6 reports the IV regression results. The first stage F-statistics are above or near the threshold of Stock-Yogo critical value for 10 percent maximal IV size (F=16.38). The estimated coefficient of freight rate has the correct negative sign and is statistically significant in all specifications at a 1 percent level. The estimate in column 1 of Panel A suggests that a 1 percent increase in transport cost reduces the value of trade by 3.9 percent. The elasticity estimate increases slightly to 3.94 percent when we control for the own route average night light luminosity (column 3). The estimate becomes slightly smaller when the current route diesel price is controlled for. However, all of the estimates fall within each other's confidence intervals. They are slightly larger than estimates reported in Wong (2018) for containerized shipping (elasticity: 2:8 3:7) and much larger than that for dry bulk shipping (Branccacio et al, 2020) (elasticity= 1:03). In panel B, the elasticity estimates are for the log of trade volume. The elasticity estimates range between 4.3 to 4.48. These estimates fall within the interval [3.6-4.8] estimated by Wong (2019). Our preferred specification is in column 1 which excluded two potential endogenous variables (diesel price and night light luminosity) from the regression.

We perform a robustness check by repeating the estimation for our second IV which is the interaction of average VAT rate and crude price in potential destinations. The results reported in Table 7 again show that estimates fall within a narrow bound both for value and volume of trade. The estimates are, however, smaller in magnitude. Our preferred specification in column 1 provides an estimate of 2.79 for value and 3.4 for the volume of trade.

[14] The estimated coefficient of own route interaction term captures only a fraction of actual pass-through of gasoline price. A regression of freight rate on diesel price suggests a passthrough rate of 92 percent in our sample.

The elasticity estimate in the gravity model relates directly to the estimate of the elasticity of substitution in consumption:

$$\frac{\partial \ln X_{ij}}{\partial \ln T_{ij}} = (\sigma - 1)\frac{P_{ij}}{T_{ij}} = \hat{\beta}_1$$

Where σ is the elasticity of substitution. The share of trip cost (T_{ij}) in destination price (P_{ij}) in our price data is about 0.133. This provides us with estimates of σ= [21,29] with an average of 25*:* These estimates are much larger than typical estimates used in quantitative spatial equilibrium models (σ= [5,6]). However, they are only slightly larger than those reported in Wong (2018) [average= 22]. The estimates from trip costs tend to be larger for several reasons. First, the elasticity of substitution is typically larger for consumer goods which constituted the single largest category transported by trucks in our data set (35 percent of all trips) followed by food and agriculture (21 percent). The second reason for the higher elasticity estimate is that transport hubs at destinations are substitutable and the elasticity parameter captures not only substitution among goods but also that among hubs. Finally, poorer consumers are in general more price-sensitive leading to a higher estimate of σ.

4.4 Estimation of the spatial margin of trade

To define the extensive margin of trade, we leverage the number of trips between OD pairs recorded in our data set. Though trip data appear to cover nearly all corners of India, there are about 28,794 unique OD pairs in the data set. Excluding two smaller island territories (Andaman and Nicorbor, Lakshwadeep) and a few districts for which we have no trip data, there are 618 districts in our data set, which gives us a total of 381,924 potential OD pairs. We define the extensive margin of trade in two steps. First, we predict the potential freight rate between OD pairs given their observable characteristics (night light luminosity at the origin and destination, along a route, and distance between them, as well as VAT rate along the route and potential next trip). Second, we estimate the responsiveness of the number of trips to freight rate following the IV strategy described above and then predict the number of trips for all potential OD pairs given the predicted freight rates. We define two alternative cut-offs for an OD pair to be considered isolated: if the predicted number of trips between an OD pair is either the bottom 10 or bottom 15 percent of the distribution of the number of trips. The respective cut-offs for the number of trips are 1.57 (lower) and 1.76 (higher). An OD pair is considered at or beyond the extensive margin of trade if the predicted number of trips between them is less than the cut-off considered.

Table 8 reports the regression results for the steps described above. All regressions included the same set of controls such as the log of distance and interaction of crude price with own route VAT rate as in column 1 in Tables 5 and 6. As these regressions are also used to predict freight rates and the number of trips for all OD pairs, the origin and destination fixed effects are not controlled for. Instead, we use the log of night light luminosity at origin, destination as well as along each route to control for local effects. All regressions are run using the actual trips observed in our data set. All standard errors are clustered at the destination district level. Column 1 of Table 8 reports results when the log of freight rate is regressed on our instrument VAT rate in the next potential trip along with other controls menti1d above. Consistent with expectation, the estimated coefficient is positive and highly statistically significant. This small set of controls explains about 33 percent of variations in the freight rates. The regression in column 1 is used to predict freight rates for all potential OD pairs. The dependent variable in columns 2 and 3 of Table 8 is the log of the number of trips between OD pairs. The OLS estimate in column 2 suggests a negative correlation between the number of trips and freight rate along an OD route. According to the IV estimate in column 3, a 1 percent increase in freight rate reduces the number of trips by 1.23 percent. We use this IV regression to predict the number of trips between all potential OD pairs. Armed with data on the expected number of trips, we define a dummy that takes a value of unity if an OD expects less than the cut-off number of trips and zero otherwise. This dummy indicates all OD pairs which can be considered at or beyond the extensive margin of trade and thus are isolated. About 13.6 percent of OD pairs are isolated by our higher cut-off and about 9.1 percent by the lower cut-off. Figure 4 plots the local polynomial regression of the dummy for the extensive margin with respect to the distance between OD pairs for the alternative cut-offs. Consistent with a priori expectation, the probability of being isolated increases with an increase in distance between the OD pair. We consider an OD pair isolated if the predicted probability is more than 0.5 (blue dashed horizontal line in Figure 4). The higher cut-off implies an extensive spatial margin at around 3,900 km which coincides with the maximum distance we observe in our trip data. We use the higher cut-off for the rest of the analysis. When the probability of being isolated is averaged by states, the estimates indicate that three Indian states (Mizoram, Nagaland, and Sikkim) and two territories (Puducherry, Daman and Diu) can be considered isolated in the sense that 50 percent of the potential trade links in these states and territories see very few trips between them (Figure 7).

5 Short-term Impact of the Pandemic

5.1 Impact of transport cost shock on the intensive margin

In this subsection, we use the estimates from Tables 3 and 6 to simulate the impacts of the freight rate increase on trade flows focusing on the post-lockdown period. This exercise limits its scope to look at the immediate impacts of a freight rate increase in the very short-run and thus does not attempt to utilize the general equilibrium framework. The rationale behind the narrow focus is that the COVID-19 shock has affected nearly all facets of the economy, and a broader evaluation of its impacts on spatial development would have to wait in light of the more devastating wave that started after March 2021.

The simulation exercise takes the heterogeneous pattern of freight rate changes during the post-lockdown period from Table 3 (column 2) and predicts freight rates along existing pre-pandemic routes. These predicted rates are then used in conjunction with trade elasticity to predict the change in trade flow along each route. The estimated decrease in trade flows under two alternative trade elasticity estimates (2.8 and 3.9) are plotted in Figure 5. The average decrease in trade flow due to freight rate shock is about 70 percent when we take the elasticity of trade with respect to the freight rate as equal to (3.9) and 58 percent when elasticity is equal to (2.8). Figure 5 confirms a sharper reduction in trade flows between OD pairs that are farther from each other. Average reduction in trade flow by states falls within a narrow interval of [0.56, 0.60] for trade elasticity=3.29 and [0.68, 0.72] for elasticity=4.5. All states saw a substantial decline in trade flow during the post-lockdown period, but inter-state differences were quite small despite the heterogeneous increase in freight rate over distance.

5.2 Impact of transport cost shock on the spatial margin of trade

Using an approach similar to that described above for the intensive margin of trade, we use estimates from Tables 3 and 8 (column 3) to predict the number of trips between OD pairs under the scenario of higher freight rates during the post-lockdown period. In Figure 6, we plot the predicted probabilities of being isolated during pre-pandemic and post-lockdown periods. Figure 6 indicates an upward rotation in these probabilities during the post-lockdown period relative to the pre-pandemic period as a result of which the spatial margin of trade shrank significantly in the post-lockdown period to about 1,700 km compared with about 3,900 km in the pre-pandemic period. Figure 7 plots the percentage of districts isolated in each state of India for pre-pandemic and post-lockdown periods. During the post-lockdown period, 11 states and 3 territories joined the rank of isolated states in addition to 3 states and 2 territories during the pre-pandemic period. As can be seen from the maps, remoter and poorer states became nearly autarkic due to such a large increase in freight rates during the post-lockdown period. The results for intensive margins indicated nearly a proportionate downward shift in trade flows for all states. This proportionate shift has pushed more than half of Indian states and territories into relative isolation. Interestingly, though lockdowns were enforced more frequently in large metropolitan cities, it is the relatively poorer and remoter states that were pushed to near autarkic situations.

6 Conclusions

There is keen interest in the impacts of road transport investment on economic integration and development in developing countries in light of the heavy investment needed for the construction of such infrastructure. Not surprisingly, a large body of recent literature is devoted to evaluating the impacts of transport investment using various innovative modeling and empirical strategies. However, much of the existing literature models transport improvement as a reduction in travel time or distance while taking the transport prices as given. Recently there is increasing realization in the literature mostly on international shipping that transport services are subject to thick market and network externalities which make transport costs themselves endogenous to trade flows. In this paper, we use half a million actual shipment data from a trucking portal in India to provide evidence on how trucking costs depend on route characteristics and affect the intensive and extensive margins of trade/shipment flow. The empirical analysis using the pre-pandemic period data confirms the presence of thick market externality along a route and spillovers across routes due to network externality, both of which confer advantages to origins and destinations with larger market sizes. These findings suggest that returns to the construction of a road would depend on not just the reduction in travel time but also the characteristics of the places that it is connecting. This may explain why studies find large benefits from the construction of the Golden Quadrilateral that connected major cities in India (Ghani et al, 2016; Asturias, Garcia-Santana and Ramos, 2018) but at best modest returns from India's vast rural road construction projects (Asher and Novosad, 2020).

We utilize exogenous variations in value-added tax on gasoline across states to provide a causal estimate of the elasticity of shipment flow with respect to trucking cost. Using the VAT rate along the next probable route as an instrument while controlling for VAT along its own route, we find that a 1 percent increase in trucking unit cost reduces trade flow by 2.8-3.9 percent which is larger in magnitude than estimates from international shipping data by Brancaccio et al (elasticity=1.03) and but similar to Wong (2018) (elasticity=2.8-3.7). The implied elasticity of substitution derived from the above estimate of trade elasticity is about 21-29, confirming the a priori expectation that this elasticity should be higher in poorer countries where consumers tend to be more sensitive to prices (Duranton, 2014).

In the absence of data on the universe of trucking transactions, we developed an empirical methodology to define the extensive/spatial margin of trade by using observable route characteristics to predict the expected number of trips for all potential routes and using a cut-off consistent with the maximum distance traveled in our data set. Empirical evidence suggests that three eastern states (Nagaland, Mizoram, and Sikkim) and two smaller territories constituted the isolated region during the pre-pandemic period as more than 50 percent of potential trade links in these states saw negligible actual trips.

Data for the post-lockdown period suggests a substantial increase in trucking costs (32 percent). The simulation results using the estimated trade elasticity suggest a proportionate decrease in trade flows across states despite heterogeneity in the increase in trucking costs across routes. The increase in trucking cost pushed an additional 11 states and 3 territories into the rank of isolated regions. These states are poorer and not home to major cities in India. Given that enforcement of COVID-19 restrictions in India was more frequent in major cities, this result suggests spillovers from these restrictions in major cities to relatively poorer areas through the transport and trade networks. Any economic recovery policy in India should take account of these potential spillover effects.

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Table 1: Summary Statistics for transaction data from a trucking portal

	Mean	Standard Dev.	Minimum	Maximum	N
Freight rate (mt-km)	3.92	3.44	0.62	23.77	469974
Freight Cost/trip	43562	37311	10000	850000	469974
Average Distance/trip	924.25	700.34	7.05	3935	469974
Hours traveled/trip	17.25	12.75	0.14	79.21	469974
Truck capacity	18.18	8.35	1	35	469974
Share of light Trucks (10mt or less)	0.22	0.42	0	1	469974
Number of trips	286.43	425.21	1	2701	469974

Source: India Trucking Database

Table 2: Determinants of Trucking Freight Rate (per mt-km)

	Ln (Freight Rate (mt-km))			Ln(distance)
	(1)	(2)	(3)	(4)
Ln (Av. Nightlights luminosity at destination)	-0.108***			
	(0.008)			
Ln (Av. Nightlights luminosity at origin)		0.031***		0.007***
		(0.010)		(0.002)
Ln (Av. Nightlights luminosity at route level)			-0.169***	
			(0.016)	
Ln (Distance)	-0.683***	-0.682***	-0.677***	
	(0.008)	(0.007)	(0.007)	
Intercept	6.483***	4.960***	7.256***	6.422***
	(0.098)	(0.114)	(0.176)	(0.020)
Destination FEs	No	Yes	No	No
Origin FEs	Yes	No	Yes	No
Vehicle type, Year FEs	Yes	Yes	Yes	No
Vehicle Size FEs	Yes	Yes	Yes	No
Observations	469,954	469,968	469,954	469,974
R-squared	0.808	0.798	0.806	0.000
Number of origins	517	517	517	
Number of destinations	589	589	589	

Note: Standard errors are clustered at the route level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: Changes in Freight Rate during lockdown and post lockdown periods

Dependent Variable: ln (Freight Rate)

	(1)	(2)	(3)	(4)
Lockdown dummy			0.388***	1.004***
			(0.005)	(0.068)
Post-lockdown dummy	0.316***	0.209***	0.317***	0.230***
	(0.003)	(0.044)	(0.003)	(0.046)
Lockdown*ln(distance)				-0.087***
				(0.010)
Post-lockdown*ln(distance)		0.015**		0.012*
		(0.006)		(0.006)
Intercept	2.957***	2.979***	3.057***	3.015***
	(0.022)	(0.024)	(0.023)	(0.025)
Observations	28,227	28,227	29,690	29,690
R-squared	0.813	0.813	0.805	0.805

Note: All regressions control for ln(distance). Lockdown spans (from March 24, 2020, to June 30, 2020). On July 1, 2020, India entered the unlock phase 2 when inter and intra- state travel restrictions were removed though many of the NPI restrictions were still in effect at the local level. Post lockdown spans July 1, 202,0 to February 24, 2021. Standard errors are clustered at the route level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Estimation of trade gravity regression: OLS Results

	Control 1	Control 2	Control 3
Ln (value of trade)	(1)	(2)	(3)
Ln (Freight rate)	-0.241***	-0.270***	-0.240***
	(0.060)	(0.064)	(0.060)
Ln (Volume of trade)			
Ln (Freight rate)	-0.792***	-0.807***	-0.790***
	(0.061)	(0.070)	(0.061)
Origin Fixed Effects	Yes	Yes	Yes
Destination Fixed Effects	Yes	Yes	Yes
No. Absorbed FEs	1080	1003	1080
No. OD pairs	23288	13793	23288

Note: Dependent variables are in bold. Each cell represents a coefficient estimate from separate regressions. The column heading corresponds to the set of controls for regressions results reported in that column. Control 1: ln (distance between origin and destination (OD)) and ln (average VAT in potential next destinations*crude price). Control 2: Control 1 plus ln (diesel price/litre along OD route). Control 3: Control 1 plus ln(average nightlight luminosity along OD route). The sample for column 2 is smaller because diesel price data is available only for 2019. Standard errors are clustered at the destination level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: First Stage Regression Results

Dependent variable: Ln (Freight Rate)

	Control 1	Control 2	Control 3
	(1)	(2)	(3)
Av. VAT rate at next probable destination	5.557***	5.191***	5.567***
	(1.405)	(1.410)	(1.401)
Ln (Av. VAT rate in own route*Crude price)	0.109***	0.101***	0.115***
	(0.025)	(0.026)	(0.026)
Intercept	-1.468	-3.491**	-1.802
	(1.664)	(1.756)	(1.653)
No. OD pairs	23288	13678	23288
No. Absorbed FEs	1080	1003	1080
R-squared	0.514	0.514	0.514

Note: Each column represents a coefficient estimate from separate regressions. The column heading corresponds to the set of controls for regressions results reported in that column. Control 1: ln (distance between origin and destination (OD)) and ln (average VAT in potential next destinations*crude price). Control 2: Control 1 plus ln (diesel price/litre along OD route). Control 3: Control 1 plus ln (average nightlight luminosity along OD route). The sample for column 2 is smaller because diesel price data is available only for 2019. Standard errors are clustered at the destination level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Estimation of trade gravity regression: IV Results

IV: VAT rate in the next potential destination

	(1)	(2)	(3)
	Control 1	Control 2	Control 3
Ln (value of trade)			
Ln (Freight rate)	-3.904***	-3.677***	-3.936***
	(1.160)	(0.888)	(1.169)
Ln (Volume of trade)			
Ln (Freight rate)	-4.445***	-4.295***	-4.479***
	(1.142)	(0.884)	(1.152)
Kleibergen-Paap F statistic	15.65	28.81	15.79
Origin Fixed Effects	Yes	Yes	Yes
Destination Fixed Effects	Yes	Yes	Yes
No. Absorbed FEs	1080	1003	1080
No. OD pairs	23288	13678	23288

Note: Dependent variables are in bold. Each cell represents a coefficient estimate from separate regressions. The column heading corresponds to the set of controls for regressions results reported in that column. Control 1: ln (distance between origin and destination (OD)) and ln (average VAT in potential next destinations*crude price). Control 2: Control 1 plus ln (diesel price/litre along OD route). Control 3: Control 1 plus ln (average nightlight luminosity along OD route). The sample for column 2 is smaller because diesel price data is available only for 2019. Standard errors are clustered at the destination level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Estimation of trade gravity regression: IV Results

IV: Crude oil price*VAT rate in the next potential destination

	Control 1	Control 2	Control 3
Ln (value of trade)	(1)	(2)	(3)
Ln (Freight rate)	-2.790**	-3.656***	-2.836**
	(1.277)	(0.880)	(1.269)
Ln (Volume of trade)			
Ln (Freight rate)	-3.410***	-4.275***	-3.459***
	(1.229)	(0.877)	(1.221)
Kleibergen-Paap F statistic	14.54	28.67	14.59
Origin Fixed Effects	Yes	Yes	Yes
Destination Fixed Effects	Yes	Yes	Yes
No. Absorbed FEs	1080	1003	1080
No. OD pairs	23288	13678	23288

Note: Dependent variables are in bold. Each cell represents a coefficient estimate from separate regressions. The column heading corresponds to the set of controls for regressions results reported in that column. Control 1: ln (distance between origin and destination (OD)) and ln (average VAT in potential next destinations*crude price). Control 2: Control 1 plus ln (diesel price/litre along OD route). Control 3: Control 1 plus ln (average nightlight luminosity along OD route). The sample for column 2 is smaller because diesel price data is available only for 2019. Standard errors are clustered at the destination level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Estimation for Extensive margin of trade

	Ln (Freight Rate)	Ln (number of trips)	
	OLS	OLS	IV
	(1)	(2)	(3)
Av. VAT rate at next probable destinations	10.485***		
	(1.672)		
Ln (Freight rate)		-0.175***	-1.232***
		(0.045)	(0.409)
Kleibergen-Paap F statistic			39.31
No. OD pairs	24,445	24,445	24,445

Note: Each column represents a coefficient estimate from separate regressions. The column heading corresponds to the dependent variable. All regression includes the following controls: ln (distance between origin and destination (OD)) and ln (average VAT in potential next destinations*crude price), ln (night lights at origin), ln(night lights at destination), ln(night lights at the route level). Standard errors are clustered at the destination level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Trucking unit cost and economic density in destination

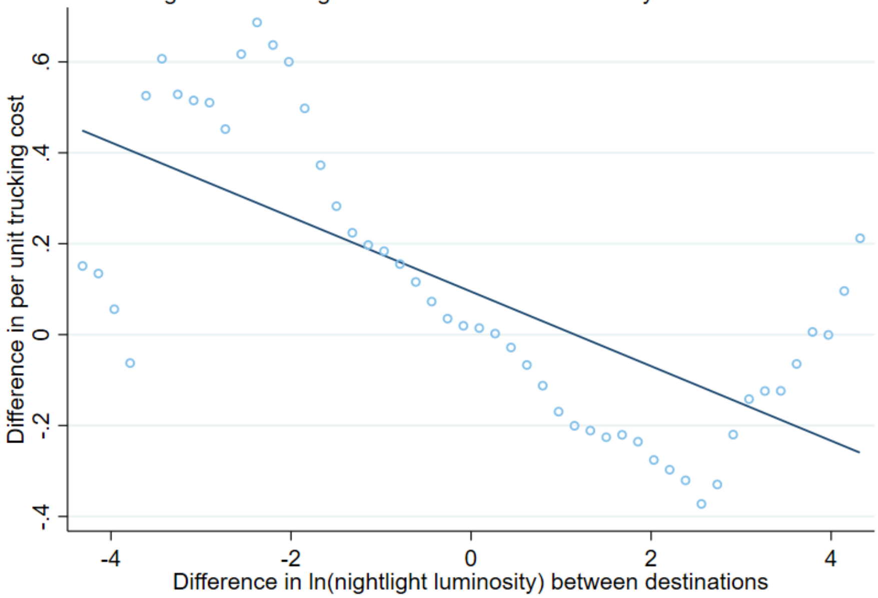


Figure 2: COVID19 daily deaths in India: 7days moving average

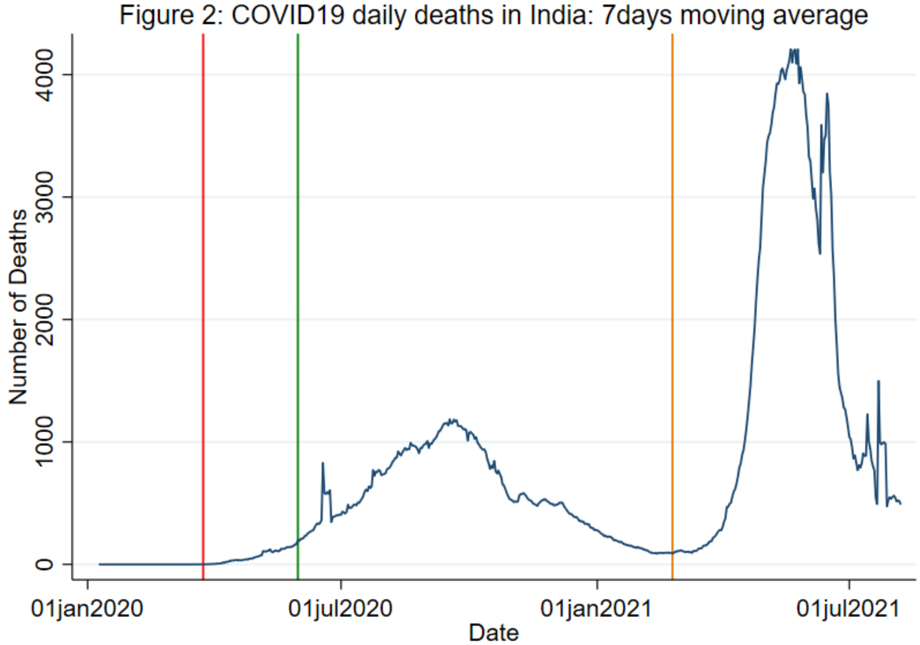


Figure 3: Freight rate per Ton-Km during pre-pandemic and pandemic period

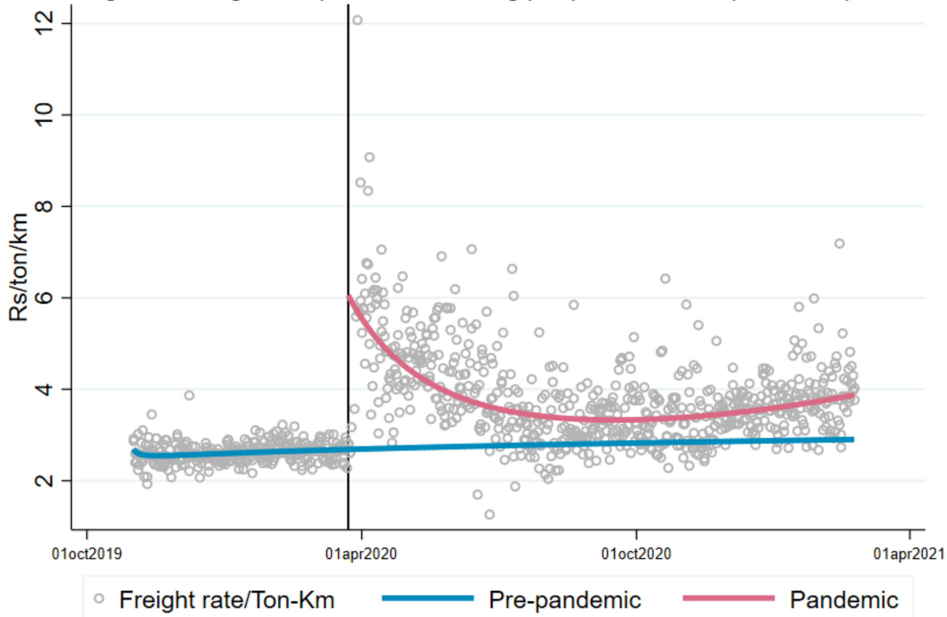


Figure 4: Predicted Probability of being isolated by distance

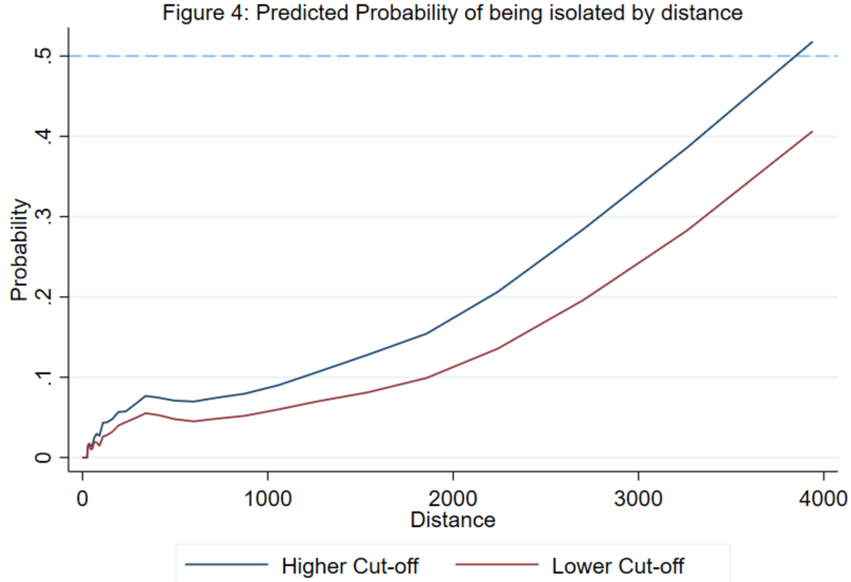


Figure 5: Predicted reduction in trade flows by Distance

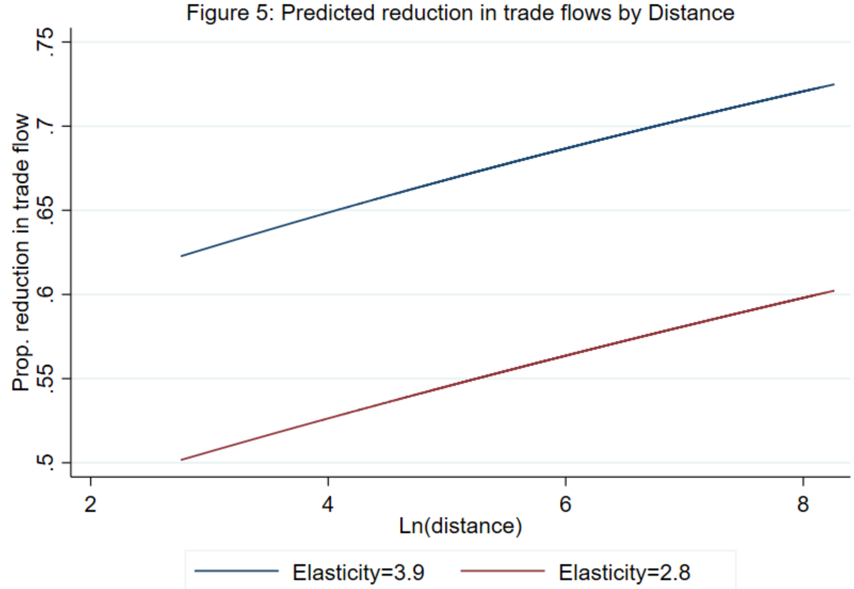
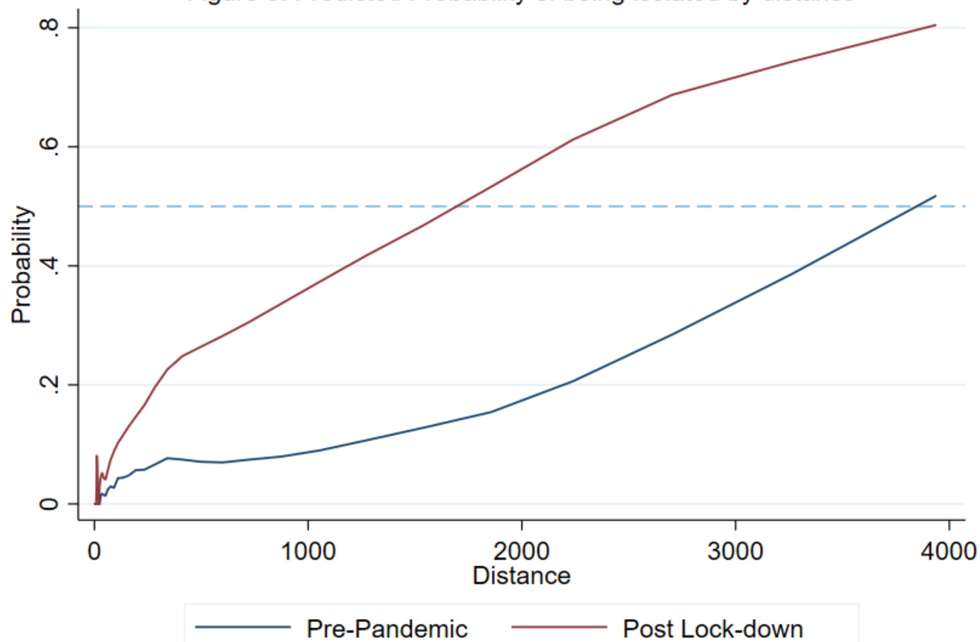


Figure 6: Predicted Probability of being isolated by distance



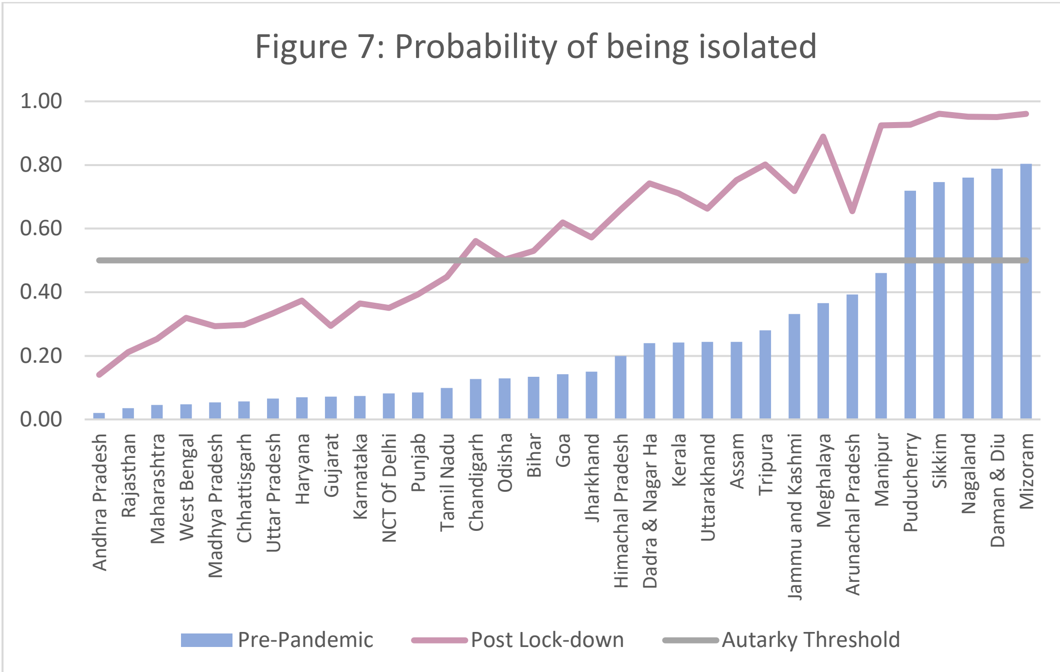


Figure 7: Probability of being isolated
1.00
0.80
0.60
0.40
0.20
0.00
Andhra Pradesh
Rajasthan
Maharashtra
West Bengal
Madhya Pradesh
Chhattisgarh
Uttar Pradesh
Haryana
Gujarat
Karnataka
NCT Of Delhi
Punjab
Tamil Nadu
Chandigarh
Odisha
Bihar
Goa
Jharkhand
Himachal Pradesh
Dadra & Nagar Ha
Kerala
Uttarakhand
Assam
Tripura
Jammu and Kashmi
Meghalaya
Arunachal Pradesh
Manipur
Puducherry
Sikkim
Nagaland
Daman & Diu
Mizoram
Pre-Pandemic
Post Lock-down
Autarky Threshold

Appendix A:

Figure A.1:Comparison of Freight rates: Pandemic vs. pre-Pandemic

Coefficient and 95% CI

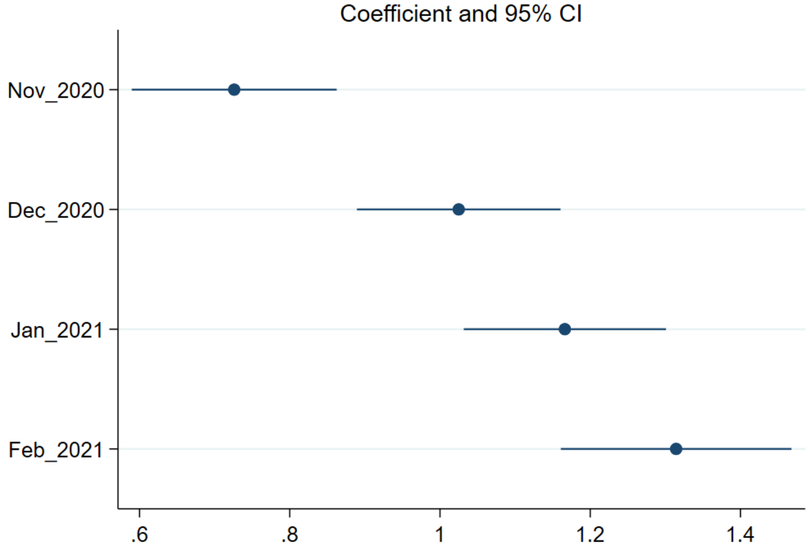


Figure A.2: Trucking's Share in Product Price at Destination