Trucks*

Treb Allen
Dartmouth and NBER

David Atkin
MIT and NBER

Santiago Cantillo Cleves
University of California San Diego

Carlos Eduardo Hernández
Universidad de los Andes

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Abstract

High transportation costs in developing countries are often cited as a key hindrance to economic growth, and many billions of dollars have been invested in infrastructure in order to reduce these costs. If the transportation sector is uncompetitive, the benefits of infrastructure improvements may be attenuated or magnified depending on the pass through of cost reductions to consumers and the extent to which lower trade costs foster competition in the transportation industry. In this paper, we develop a new spatial model featuring imperfect competition in the transportation sector that highlights a "triple curse of remoteness": more remote locations face higher marginal costs for the same distance, face higher markups from less competition, and are served by worse transportation providers. Investments in infrastructure not only reduce physical costs of shipping, they also improve competition and induce better transportation firms to enter. We confirm the model predictions by examining large-scale infrastructure improvements in Colombia using a novel dataset of transactions between truck owners and shipping companies.

*Allen: treb@dartmouth.edu; Atkin: atkin@mit.edu; Cantillo Cleves: scantillocleves@ucsd.edu; Hernández: carlosehernandez@uniandes.edu.co. The authors acknowledge support by the World Bank. All errors are our own.

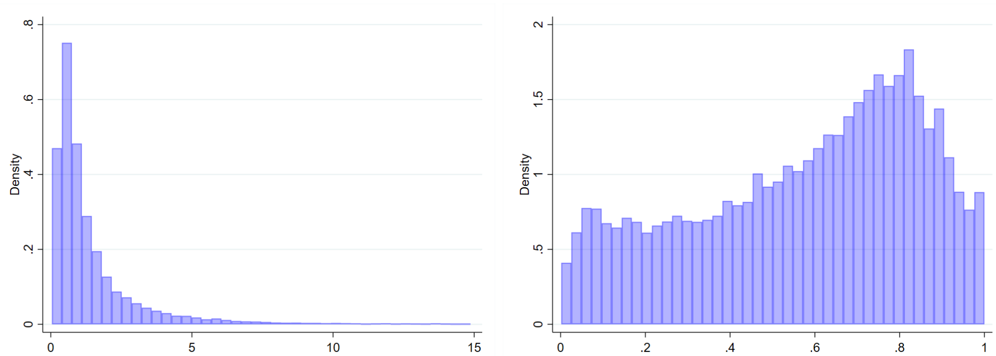
1 Introduction

The trucking sector is of vital importance in the Colombian economy. Land transportation services account for nearly 3% of GDP and trucks ship 96% of total land cargo (Ministerio de Transporte, 2018).[1] It is also a sector that has been attracting growing investment. For example, between 2002 and 2017 real investment on road infrastructure in Colombia increased seven-fold (Ministerio de Transporte, 2018). However, despite these investments, Colombia has some of the highest internal transport costs in the world Kent Londoño (2009) and the high cost of transporting goods between cities is still a key impediment to trade Duranton (2015).

At the same time, anecdotal evidence abounds about the lack of competition in the Colombian transportation sector. Some of this lack of competition may be policy driven: for example, Colombian government has intervened in the the sector by creating scrapping schemes to limit the entry of new trucks and imposing floor prices on certain routes partly in response to a number of high-profile trucker strikes (Cantillo Cleves and Hernández, 2022) And while than 300,000 trucks operated across the country, the degree of competition and variation in prices differed substantially across routes (see Figure 1).

Figure 1: Distribution of prices and competition across routes

(a) Price (per ton-mile) (b) Market concentration (HHI)



Notes: This figure shows the distribution of shipping prices per ton-mile (panel a) and the distribution of market concentration as measured by a Herfindahl–Hirschman index of market shares (panel b) across routes.

If the Colombian transportation sector is uncompetitive, will the gains from infrastructure improvements be entirely captured by the trucking industry? Or will infrastructure improvements lead to greater competition and lower prices? And ultimately, what is the impact of infrastructure improvements on the welfare of consumers?

[1]Excluding oil and coal, which are also transported by pipeline, train and boats.

Using a novel dataset of transactions between truck owners and shipping companies in Colombia, an IV strategy drawing on infrastructure improvements in one part of the network that affect competition elsewhere in the network, and a quantitative trade model with imperfect competition in the transportation sector, we highlight a triple curse of remoteness. More remote locations face higher marginal costs for the same distance, face higher markups from less competition, and are served by worse transportation providers. Thus, investments in infrastructure not only reduce physical costs of shipping, they also improve competition and induce better transportation firms to enter.

Literature review

Our research contributes to a number of literatures, most directly the nascent literature on endogenous trade costs, the rich quantitative spatial literature, and the broader literature on imperfect competition and trade.

The recent literature has highlighted three mechanisms through which trade costs may be endogenous: due to imperfect competition (Atkin and Donaldson, 2015; Hummels et al., 2009; Asturias, 2020), due to route planning (Allen and Arkolakis, 2019; Behrens and Picard, 2011; Brancaccio et al., 2020; Duranton and Turner, 2011; Fajgelbaum and Schaal, 2020; Ishikawa and Tarui, 2018), or due to the presence of intermediaries (Allen, 2014; Allen and Atkin, 2016; Antras and Costinot, 2011; Bardhan et al., 2013; Bergquist and Dinerstein, 2019; Mitra et al., 2018; Chatterjee, 2019; Grant and Startz, 2022). Our research makes two contributions to this literature. First, we study how market power is determined simultaneously with trade flows. Second, we study how market power shapes the impact of infrastructure improvements on the equilibrium distribution of economic activity.

Our research also contributes to the quantitative spatial literature (Allen and Arkolakis, 2014; Allen et al., 2020; Redding, 2016). Redding and Turner (2015) and Redding and Rossi-Hansberg (2017) provide excellent reviews of this rapidly growing field. This literature almost always assumes a perfectly competitive transportation sector where costs are born by the producers in the origin. Here we make two contributions. First, we allow agents from other locations (not just the origin) to provide transportation services. Second, we allow these agents to compete imperfectly. To do so in a realistic manner, we incorporate insights from the classic literature on imperfect competition and trade following Kreps and Scheinkman (1983) and Maggi (1996), modeling competition via a two-stage game where firms (truckers) first choose the capacity available on each route and then compete on prices on that route, resulting in Cournot outcomes. We also take advantage of our shipment level data on origins, destinations, trucker homes, truck revenues and trucker identifiers to go into more detail than previously possible and provide a plausibly exogenous identification strategy.

2 Trucking in Colombia

We begin by describing the empirical context before describing our novel data set and documenting two new facts about the Colombian trucking industry.

2.1 Empirical context

Colombia has a mountainous terrain, large heterogeneity in road quality, and large variation in population density. Unlike in other Latin American countries, the population is not heavily concentrated in the main city, Bogotá. Bogotá represents 20% of the inhabitants and 25% of GDP in Colombia. It is 1000km away from the main port in the Caribbean (N), 900km away from the main land border with Ecuador (S), 560km away from the main land border with Venezuela (NE), 500km away from the main port in the Pacific (SW), and 400km away from the second largest city, Medellín (NW). The corresponding travel times by truck are 30, 29, 22, 18, and 14 hours on average (Hernández, 2022).

Given its mountainous terrain, almost all intranational trade in Colombia is done by truck, with trucks accounted for 96% of tonnage transported within Colombia in 2019, excluding coal and oil (Ministerio de Transporte, 2018). The trucking industry has two segments. The transportation of perishable, agricultural products is almost free from economic regulations. In contrast, the transportation of most other products is subject to multiple regulations: (i) shippers cannot hire carriers directly. Instead, they must hire intermediaries that guarantee that regulations are respected, acquire insurance policies, fill paperwork required by regulation, and guarantee the fulfillment of the contract. (ii) carriers can switch intermediaries at will, except when they signed an exclusivity contract which is not mandated by regulation. (iii) intermediaries must report to the government the origin and destination of each trip, the product that the truck is transporting, and the price paid by the intermediary to the trucker.[2] In what follows, we will focus on the non-agricultural segment of the trucking industry.

2.2 A Unique Truck Dataset

Our data is ideal for measuring the effects of road infrastructure improvements when the transportation sector is not competitive. The dataset we assemble combines detailed information from five sources. First, we assemble highly granular shipment-level data on the universe of legally registered non-agricultural shipments in Colombia between 2015 and 2021 (excluding 2018), which total 50 million trips, which we collected by scraping the complete history of shipments made by

[2] Originally, this information was used to enforce price floors on freight rates. Nevertheless, these price floors were non-binding for most products and routes in our sample period (Cantillo Cleves and Hernández, 2022).

every truck in the country. For each individual shipment in the country, we observe the origin, destination, approximate start date, and truck's license plate.

Second, from the Ministry of Transportation, we received data on the average freight rate paid to the truck owner and the total quantity transported across these shipments, albeit aggregated at the origin $\times$ destination $\times$ date $\times$ truck type (i.e. number of axles) level.

Third, we combine these two datasets with truck characteristics and information on the truck owners (henceforth "truckers") that we obtained from the National Registry of Trucks by matching license plate numbers. This datasets serves two purposes: first, it allows us to identify shipments made by different trucks that were owned by the same person; second, it provides us information about the owner of the truck, most notably his or her place of residence, which will provide an important source of variation in both the theory and empirics below.

Fourth, for every month$\times$origin$\times$destination triplet, we calculate the travel time times along the optimal route given the existing road network in that given month, where the road network is the one available on Open Street Maps in that given month. In particular, in each month, we construct a speed image of the network accounting for the terrain and road quality and use the Fast Marching Method (see Sethian (1996)), as popularized in the economic geography literature by Allen and Arkolakis (2014). To account for errors in the (open-access) Open Street Maps database, we constrain all bilateral travel times to be non-increasing over time. The resulting travel times have a correlation of 0.87 with travel times calculated with GPS devices in trucks for a sample of routes, provided by Hernández (2022).

Finally, we obtain the population of each municipality from the Colombian National Census of 2018.

2.3 Two Stylized Facts

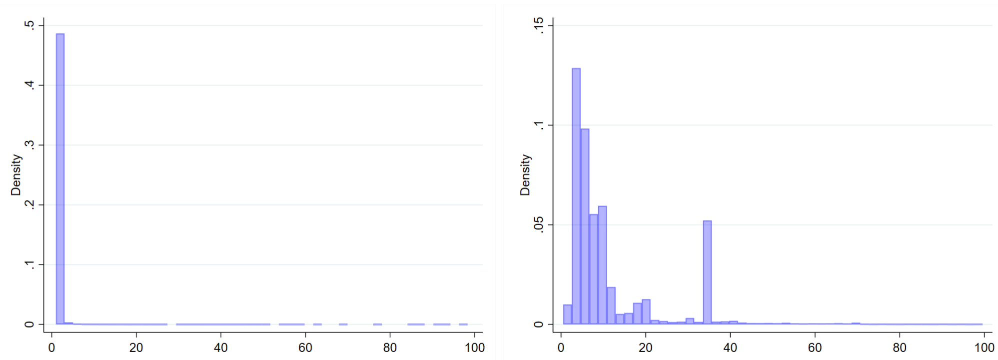
We now describe two new facts about the Colombian trucking industry.

Stylized Fact 1: There exists substantial heterogeneity in the capacity of truckers

Figure 2 depicts the distribution of trucks across owners (panel a) and capacity across owners (panel b) in Colombia. The vast majority (82%) of truckers are owner-operators who either own their own truck or share the property of a single truck with someone else—only 1% of carriers own more than ten trucks. But the few large truckers have a substantial fraction of overall capacity.

Figure 2: Heterogeneous trucker size

(a) Number of trucks (b) Capacity (tons)

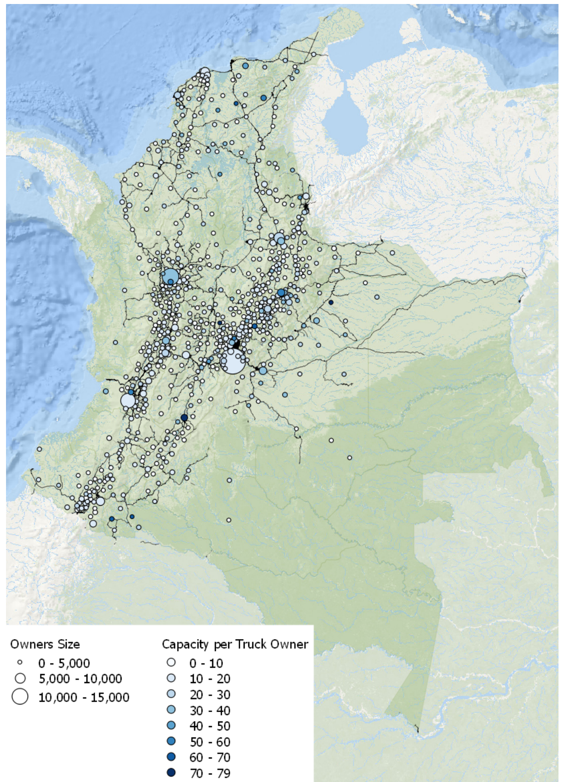


Notes: This figure shows the empirical distribution of trucking capacity across truckers in Colombia. Panel (a) depicts the distribution of number of trucks owned; panel (b) depicts the distribution of capacity (in tons).

Stylized Fact 2: There exists substantial heterogeneity in the residence location of truckers

Truckers not only vary substantially in their capacity, they also vary substantially in their location of residence. Figure 3 depicts the spatial distribution of trucker residence; as is evident, truckers live throughout the country. Truckers with higher capacities do tend to reside in larger cities.

Figure 3: Geographic distribution of truckers' place of residence



Notes: This figure shows the spatial distribution of the residences of truckers across municipalities. The population of the municipality is indicated in the size of its circle; the color of the circle indicates the average capacity (in tons) per trucker, with darker colors indicating greater capacities.

3 The Triple Curse of Remoteness: Theory

We now present a spatial economic model with two innovations: First, we include a transportation sector that allows labor (drivers) and mobile capital (trucks) to be based in one location (home) but ship goods between other locations before returning home. Second, we introduce imperfect competition in the transportation sector where capacity-constrained truckers compete on prices on any given route, following Maggi (1996). We then show that these two innovations have important implications for how the remoteness of a location shapes the welfare of its residents.

3.1 Model

Let there be N locations separated by trade costs and indexed by $o$rigin, $d$estination, and $h$ome. An origin o is endowed with L_o labor units that can work in the production of a differentiated good (producers) or in the provision of transportation services (drivers). Production is sold at the factory gate price $p_o = \frac{w_o}{A_o}$, where w_o and A_o are wages and production productivity, respectively. Production productivity is exogenous.

Consumers have standard CES preferences for final goods, so that the expenditure share in destination d on goods from o given by:

$$X_{od} = p_{od} Q_{od} = \frac{\tau_{od}^{1-\sigma} \left(p_o\right)^{1-\sigma}}{\sum_{o'} \tau_{o'd}^{1-\sigma} \left(p_{o'}\right)^{1-\sigma}} E_d, \tag{1}$$

where τ_{od} is an (endogenous) trade cost to be defined below, E_d is the total expenditure at the destination (worker + trucker income) and $\sigma \geq 1$ is the demand elasticity for goods.

3.1.1 Imperfect competition and markups

A home h is endowed with $T_{h,k}$ transportation firms (truckers) of type k.. Truckers can ship local goods or goods produced elsewhere. To do so, truckers hire local workers (drivers) to drive from their home h, load a good from o, ship it to d and return home. The productivity of truckers depends on their type k, as we will explain below.

Truckers from home h and type k play a two stage game. In the first stage, they choose the capacity available for each route. In the second stage they compete with other truckers on the route by choosing their price. Transportation services are differentiated, with each home providing a different variety of the transportation service and firms in each origin having love for variety across truckers. For example, different firms may have different preferences regarding particular trucker schedules, trucker amenities (e.g. whether or not the goods can be refrigerated), or perhaps different rapport with the particular truckers.

The equilibrium is solved by backward induction. Consider a trucker i of type k in home h. In the second stage, the trucker i has already chosen her capacity $Q^c_{od,i}$ for route od. Given $Q^c_{od,i}$, the trucker chooses her price. Quantity demanded for trucker i's service in route od is:

$$Q_{od,i} = \frac{p_{od,i}^{-\chi}}{\sum_{i'} p_{od,i'}^{1-\chi}} X_{od}, \tag{2}$$

where $\chi > \sigma$ is the demand elasticity for transportation services. Trucker i chooses her price to maximize her revenue (since capacity costs are already sunk):

$$\max_{p_{od,i}} p_{od,i} Q_{od,i} \text{ s.t. } Q_{od,i} \leq Q^c_{od,i}, \tag{3}$$

which is solved by choosing the price $p_{od,t}$ that ensures all capacity is used.

In the first stage, trucker i decides how much capacity to acquire. We assume that she can supply capacity at constant marginal cost $c_{od,h,k} = 1 + \frac{w_h}{p_o B_{od,h,k}}$, i.e. she buys the good in the origin (at factory-gate price p_o) and then hires a driver (at home wage rate w_h) for $1/B_{od,h,k}$ units of time to transport the good from origin to destination. Trucker i will then choose her capacity to maximize her profits. Assuming that she abstracts from any cross-route demand cannibalization (so that she can maximize her capacity on each route independently), she will choose her capacity so that the equilibrium price she charges for her services can be written as:

$$p_{od,h,k,i} = \mu_{od,h,k,i} \times c_{od,h,k} \times p_o, \tag{4}$$

where her endogenous mark-up $\mu_{od,h,k}$ depends on her within-route market share $s_{od,i} = \frac{\left(Q^c_{od,i}\right)^{\frac{\chi-1}{\chi}}}{\sum_{i'} \left(Q^c_{od,i'}\right)^{\frac{\chi-1}{\chi}}}$ and her across-route market share $s_{d,i} = s_{od,i} \times \frac{\left(\left(\sum_{i'} \left(Q^c_{od,i'}\right)^{\frac{\chi-1}{\chi}}\right)^{\frac{\chi}{\chi-1}}\right)^{\frac{\sigma-1}{\sigma}}}{\sum_{o'} \left(\left(\sum_{i'} \left(Q^c_{o'd,i'}\right)^{\frac{\chi-1}{\chi}}\right)^{\frac{\chi}{\chi-1}}\right)^{\frac{\sigma-1}{\sigma}}}$ as follows:

$$\mu_{od,h,k,i} \equiv \frac{\chi}{\chi-1} \left(1 - s_{od,i} \left(1 - \frac{\chi}{\chi-1} \frac{\sigma-1}{\sigma} \left(1 - s_{d,o}\right)\right)\right)^{-1}, \tag{5}$$

and the total value shipped from o to d by trucker i (who resides in h and is of type k) can be written as:

$$X_{od,h,k,i} = \frac{\left(\mu_{od,h,k,i} \times c_{od,h,k}\right)^{1-\chi}}{\tau_{od}^{1-\chi}} \times \frac{\left(\tau_{od} p_o\right)^{1-\sigma}}{\sum_{o'} \left(\tau_{o'd} p_{o'}\right)^{1-\sigma}} \times E_d. \tag{6}$$

As the number of truckers in a location increases, market shares fall and markups converge to the monopolistic competition limit $\frac{\chi}{\chi-1}$; indeed, in the limit as the number of truckers and χ both go to infinity, the trucking industry becomes perfectly competitive. This fact will be convenient below when we examine how the introduction of imperfect competition affects welfare across locations.

The inclusion of imperfect competition in our model has three direct implications: (1) truckers with larger market shares charge higher mark-ups; (2) lower cost truckers capture greater market share; and (3) profits are supermodular in market shares, so that lower cost truckers sort into the most profitable routes. Moreover, the setup above yields a convenient analytical formula for the equilibrium trade costs τ_{od}, highlighting how they depend on the degree of competition on the route:

$$\tau_{od} = \left(\sum_{h,k,i} \left(\mu_{od,h,k,i} \times c_{od,h,k,i} \right)^{1-\chi} \right)^{\frac{1}{1-\chi}} . \tag{7}$$

For example, equation (7) says that, all else equal, the fewer truckers that supply the route, the higher the trade costs will that be on that route. This is for two reasons: first, a direct love of variety effect (e.g. fewer truckers means worse match quality on average between truckers and producers); second, because each trucker will capture a greater market share, they will charge higher markups, raising the cost incurred by producers.

3.1.2 Equilibrium

Apart from the imperfect competition in the trucking industry, the rest of the equilibrium is determined by two slightly modified market clearing conditions: first, labor market clearing ensures that all workers in a location will be employed either in production or in the transit of goods, i.e.:

$$L_o = \underbrace{\frac{\sum_{d,h,k} Q_{od,h,k} T_{h,k}}{A_o}}_{\text{labor employed in production}} + \underbrace{\sum_{o',d,k} \left(\frac{Q_{o',d,o,k}}{B_{o',d,o,k}} \right) T_{o,k}}_{\text{labor employed as drivers}} . \tag{8}$$

Second, total expenditure in a location is equal to the sum of labor income and truck owner income:

$$\sum_o X_{oh} = \underbrace{w_h L_h}_{\text{income earned by labor}} + \underbrace{\sum_k T_{h,k} \sum_{od} \pi_{od,h,k}}_{\text{profits earned by truckers}} , \tag{9}$$

where $\pi_{od,h,k}$ are the profits that accrue to truckers in h of type k from route od. Note that equation (9) implies that some of the revenue from production elsewhere in the economy is captured by truckers residing in h through the profits they earn on their markups.

Similar to a standard framework, our model captures the negative effects of remoteness on consumer and producer market access. Nevertheless, our two innovations generate a new result: it is theoretically ambiguous whether the impact of remoteness on the distribution of economic activity is exacerbated or attenuated relative to a standard quantitative spatial framework. On the one hand, workers in remote areas may disproportionately benefit from the opportunity to ship goods elsewhere, as their low outside wages make them more competitive in the transportation market. On the other hand, imperfect competition in the transportation sector may create endogenously higher markups on routes serving remote locations that few truckers serve, increasing the prices that they pay as consumers.

3.2 The triple curse of remoteness

We now turn to the implications of the model on the distribution of welfare across locations. To do so, we begin by making a parametric assumption. In what follows, we assume the (inverse) unit labor requirement of shipping a good, $B_{od,h,k}$, can be written as follows:

$$B_{od,h,k} = b_k \times \left((\rho_1 \times dist_{ho}) + (\rho_2 \times dist_{od}) + (\rho_3 \times dist_{dh}) \right)^{-1}, \tag{10}$$

where $b_k \geq 1$ captures the heterogeneity in productivity of drivers of different types k, $\rho_2 \times dist_{od}$ is the trade cost incurred *along the route*, $\rho_1 \times dist_{ho}$ is the trade cost incurred *getting to the route* and $\rho_3 \times dist_{dh}$ is the trade costs incurred *getting from the route*. Note that when $\rho_1 = \infty$ and $\rho_3 = 0$, equation (10) nests the (standard) assumption that all transportation is done by labor residing in the location of production. Combined with the fact that a limiting case of our framework is perfect competition in the trucking industry, this implies that a special case of our model is the standard (perfectly competitive) trade model.

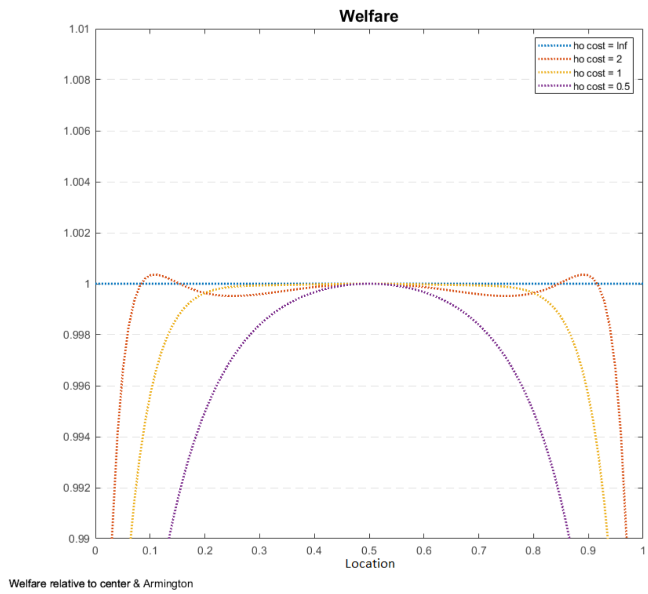
Recall that in a standard perfectly competitive trade model, agents residing in more remote locations – i.e. those with worse market access – will be worse off for two reasons: first, the goods they purchase will on average be more expensive (i.e. their consumer market access is worse); second, the demand for their products will be lower (i.e. their producer market access is worse). We now show that the introduction of our two new model features – a transportation sector where labor in one location can ship goods produced somewhere else and imperfect competition in that sector – lead to three additional reasons why agents in more remote locations may be worse off relative to a standard trade model. Each of these three "curses of remoteness" arises from a different economic mechanism in the model.

To separate the mechanisms at play, we begin with a standard perfectly competitive trade model and add the new features one by one.

Curse #1: More remote locations face relatively higher marginal costs

Consider a world comprised of a large number of identical locations arrayed on a line segment. Locations closer to the center of the segment have greater market access and locations closer to the edges are more remote. Let us initially suppose there is a large number of identical truckers (one hundred) in all locations, so that markups are constant everywhere (and hence do not affect the equilibrium welfare or distribution of economic activity), i.e. we abstract from imperfect competition. How does allowing labor in one location to transport goods produced in other locations changes the welfare in different locations relative to a standard trade model?

Figure 4: The first curse of remoteness: more remote locations face relatively higher marginal costs



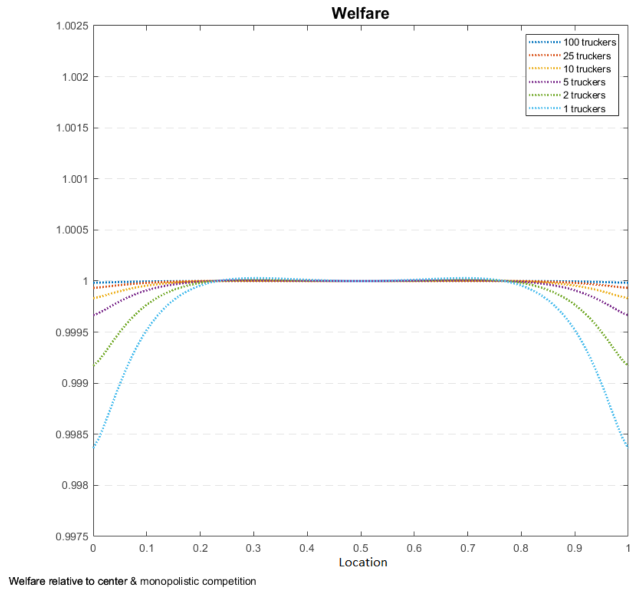
Notes: This figure considers an economy comprising a large number of identical location arrayed on a line segment. It depicts the welfare in each location relative to both the welfare of that location in a perfectly competitive trade model and the welfare of the center location in four different model extensions, each of which allow truckers in locations to ship goods produced in other locations at progressively lower costs.

To see this, we decrease ρ_1 from infinity to progressively smaller values (holding ρ_2 constant and $\rho_3 = 0$). Figure 4 presents the results. As is evident, relative to a standard trade model, more central locations have the additional benefit of being nearby more potential truckers, which means that their transportation costs fall the most with this new technology. Put another way, because it is costly for truckers to get from their place of residence to serve routes to or from more remote locations, these more remote locations benefit relatively less than central locations from the ability to use truckers elsewhere to ship their goods. As a result, in all simulations, it is the edge locations that benefit the least, and in almost all simulations, it is the central location that benefits the most. There is, however, a very interesting theoretical wrinkle here: if the wages in the most remote locations are much lower than more central locations, it may be possible for more central locations that are close to the remote locations to benefit the most by hiring workers from the most remote locations to transport their goods. This occurs in the academically interesting (but not empirically relevant) case when the travel cost of getting to the route is higher than the travel cost along the route.

Curse #2: More remote locations face higher markups

Having introduced the technology by which workers in one location can transport goods produced elsewhere, let us now add imperfect competition. How does this change the relative welfare across locations? To do so, we decrease the number of truckers in each location, which as discussed above increases their market shares along each route and their markups.

Figure 5: The second curse of remoteness: more remote locations face relatively higher markups



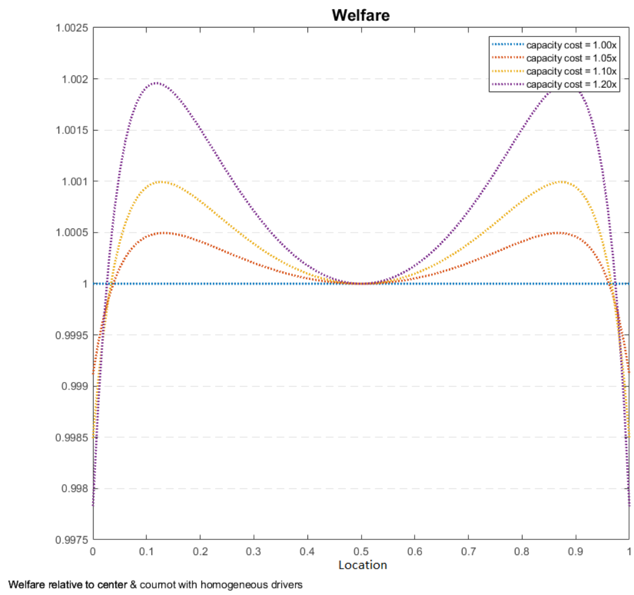
Notes: This figure considers an economy comprising a large number of identical location arrayed on a line segment. It depicts the welfare in each location relative to both the welfare of that location in the first curse and the welfare of the center location in five different model extensions, each of which increases the market power of each trucker by reducing the number of truckers with which each location is endowed.

Figure 5 presents the results. Relative to a situation where markups are constant, it is again the residents of more remote locations who are disproportionately harmed. Because there are relatively few nearby truckers who are able to serve transportation needs of more remote locations, those truckers capture greater market shares. And because they capture greater market shares, they are able to exploit their market power by charging higher markups. As a result, more remote locations face higher trade costs through these higher markups – over and above the fact that truckers serving these markups face higher marginal costs.

Curse #3: More remote locations served by less productive truckers

Up to this point, we have assumed that all truckers are identical. Now let us introduce trucker heterogeneity, dividing the truckers into an equal number of "good" and "bad" truckers, where we progressively make the "bad" truckers worse.

Figure 6: The third curse of remoteness: Better truckers sort into more competitive, longer routes



Notes: This figure considers an economy comprising a large number of identical location arrayed on a line segment. It depicts the welfare in each location relative to both the welfare of that location in the second curse and the welfare of the center location in four different model extensions, each of which divides truckers into "good" and "bad" truckers, making the bad truckers progressively less productive.

Figure 6 depicts the change in welfare of each location, relative to the previous curse of imperfect competition case (but where truckers are homogeneous). As truckers become more heterogeneous, it is again the most remote locations that are made worse off. Because the good truckers sort into the more profitable routes, it is the bad truckers that disproportionately end up supplying the transportation needs of the most remote routes. However, because there is a complementarity between the productivity of a driver and the distance of the route (see equation (10)), the locations that benefit the most are the intermediate locations (the "suburbs") where both there is enough economic activity to make the routes profitable enough and the distances traveled are long enough to make the better truckers benefit the most.

We now turn to examining whether these curses are present in empirically.

4 The Triple Curse of Remoteness: Empirical Evidence

We now turn to exploring these three curses in the data by leveraging the unique trucking dataset described above. In principle, with some measure of remoteness, these curses can all be explored by exploiting cross sectional variation alone. Specifically, we can ask whether:

Fact 1a: Trucker market shares are lower further from home—evidence that more remote locations are costlier to serve (Curse 1).

Fact 2a: There is less competition on more remote routes—evidence that more remote locations likely face higher markups (Curse 2).

Fact 3a: Truckers that supply more remote routes are less productive (Curse 3).

For example, to establish Fact 2a, we can compare routes of equal distance (which are similarly costly to travel along) and explore whether routes which truckers live further from have less competition. While suggestive, such cross sectional relationships are of course hard to interpret causally. As one example, such patterns may be driven by differences in demand between more and less remote locations.

Therefore, to provide a causal interpretation we present a second set of closely related facts that exploit the panel dimension of the data and shorter-run responses to infrastructure improvements. This approach has the benefit of being able to control for persistent differences across locations. Furthermore, rather than exploiting changes in concentration and prices resulting from infrastructure improvements along a particular route od, where we may worry the infrastructure was partly a response to changing demand conditions on that route, we exploit infrastructure improvements elsewhere in the system that shift competition on a route od, while conditioning on the od infrastructure improvements that directly affect the profitability of that route.

Specifically, we modify Facts 1a-3a and ask whether:

Fact 1b: Truckers market shares increase as time from home decreases—evidence that more remote locations are costlier to serve (Curse 1).

Fact 2b: Routes that became more accessible became more competitive—evidence that more remote locations likely face higher markups (Curse 2).

Fact 3b: More competitive routes attracted more productive truckers (Curse 3).

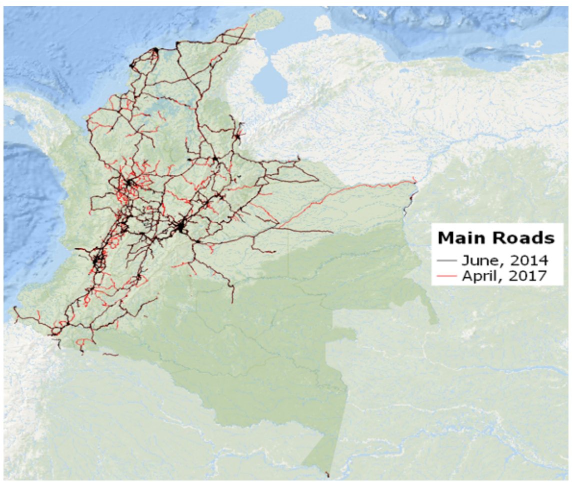
Resulting in:

Fact 4b: Decreased costs of transit on routes with more and better truckers.

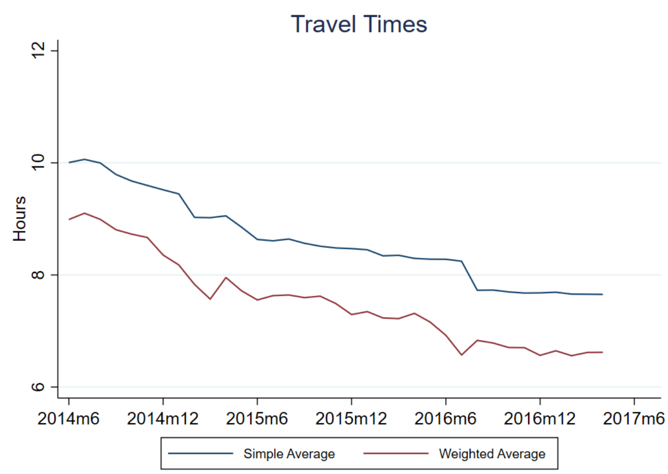
Colombia provides an appropriate setting for our analysis as it has experienced large improvements in its road network in recent years. Only between 2014 and 2017 it had a 11% increase in the length of its main roads and 22% across all types of roads (see panel (a) of Figure 7). In response, travel times between all origin-destination pairs fell by over 20% during this same period (see panel (b) of Figure 7).

Figure 7: Infrastructure improvements in Colombia

(a) Expansion of the road network



(b) Decline in travel times



Notes: This figure depicts the major road network improvements in Colombia between 2014 and 2017. Panel (a) shows the location of the new road segments constructed; panel (b) shows the corresponding decline in travel times.

Of course, to implement such an approach we require a measure of remoteness. Taking the expression for endogenous trade cost (eq. 7) and solving for transportation productivity $B_{od,h,k}$ (eq. 10) yields:

$$\tau_{od} = \left(\sum_{h,k} \left(\mu_{od,h,k} \left(\frac{w_h/b_k}{w_o/A_o} \left(\rho_1^{ho} dist_{oh} + \rho_2^{od} dist_{od} + \rho_3^{dh} dist_{dh} \right) + 1 \right) \right)^{1-\chi} T_{h,k} \right)^{\frac{1}{1-\chi}}$$

We can approximate this expression with[3]

$$\tau_{od} \approx Remote_{od} \equiv \left(\sum_{h} \left(dist_{oh} + dist_{od} + dist_{dh} + 1 \right)^{-1} T_h \right)^{-1},$$

[3]This approximation is exact when $\frac{w_h/b_k}{w_o/A_o} = \mu_{od,h,k} = \rho_1^{ho} = \rho_2^{od} = \rho_3^{od} = 1, \chi = 2$.

where $dist_{ho}$ is travel time between h and o and T_h is the share of total truckers in h (regardless of type).[4]

We now turn to sequentially establishing the sets of facts outlined above.

Curse #1: More remote locations face higher marginal costs

Fact 1a: Trucker market shares are lower further from home.

In the cross section we observe that truckers market shares are lower further from home. We estimate the following equation

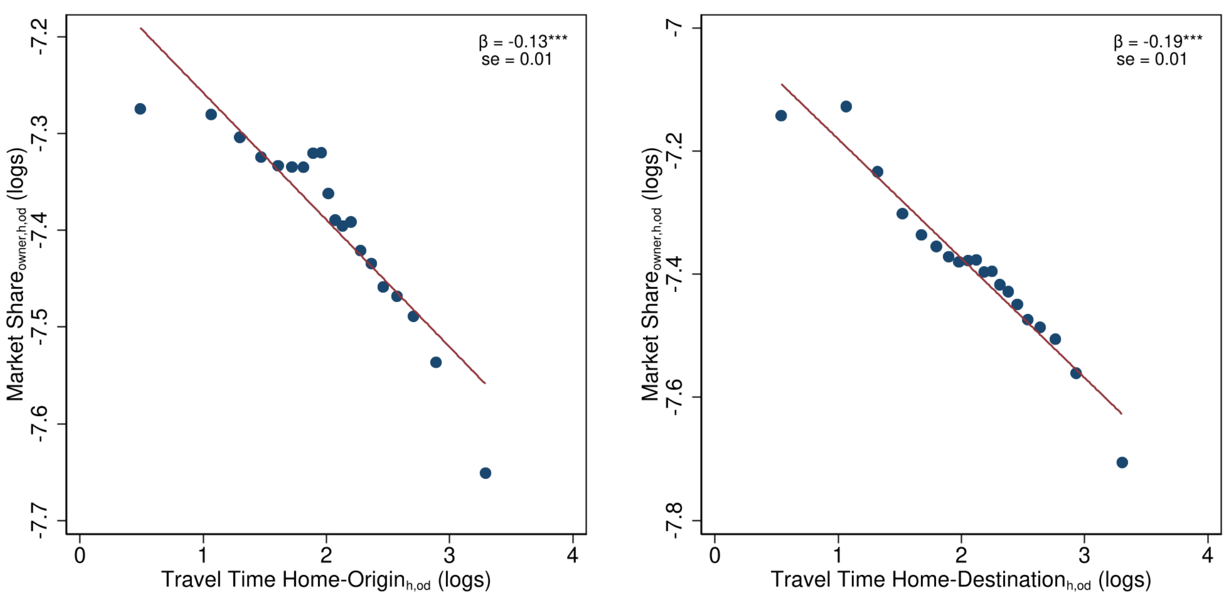
$$\ln MarketShare_{od,i} = \beta_1 \ln TravelTime_{h,o} + \beta_2 \ln TravelTime_{d,h} + \delta_i + \delta_{od} + \varepsilon_{od,i} \tag{11}$$

and find that both travel times have negative and significant coefficients. Figure 8 plots our estimates.

Figure 8: Market shares and distances

(a) Distance to route origin

(b) Distance to route destination



Notes: This figure shows that in the cross section, truckers capture smaller market shares on routes that are further from their home, where distance is either measured from the beginning of the route (panel a) or the end of the route (panel b), consistent with the first "curse" of remoteness.

[4] We construct alternative remoteness measures using straight line distances between locations instead of travel times and population share instead of trucker share.

Fact 1b: Truckers market shares increase as time from home decreases.

We now estimate equation 11 in the panel. Both coefficients have the expected negative sign, though we do not find statistical evidence that truckers market shares increase as travel time *getting to the route* decreases (table 1).

Table 1: Truckers market shares increase as time from home decreases

Market Share$_{\text{owner,od,t}}$ (logs)	(1)
Travel Times$_{\text{h,o,t}}$ (logs)	-0.022
	(0.020)
Travel Times$_{\text{d,h,t}}$ (logs)	-0.064***
	(0.022)
Fixed Effects	
- owner × month	X
- origin × destination × month	X
- home × origin	X
- home × destination	X
Observations	6,600,954
Adjusted within-R^2	0.00

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at *od* level in parentheses. *o*=origin, *d*=destination, *h*=home, *t*=month.

Curse #2: More remote locations face higher markups

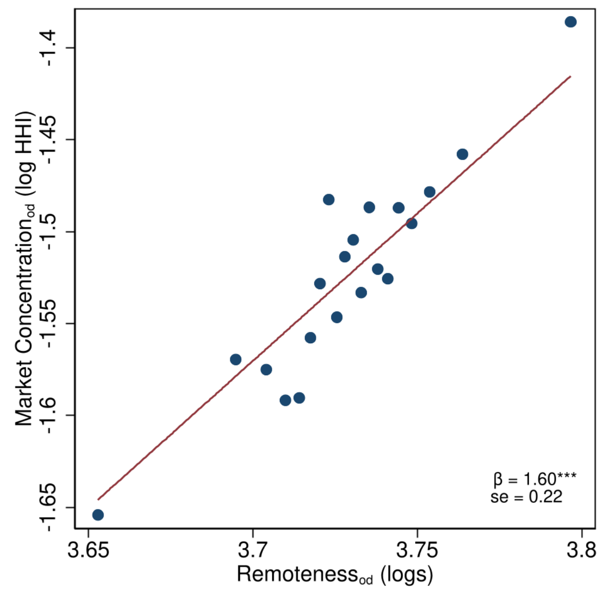
Fact 2a: There is less competition on more remote routes.

We explore this curse by asking whether locations with higher trade costs have less competition. In the cross section we run the following expression

$$\ln HHI_{od} = \beta \ln Remote_{od} + \sum_b \delta_{ob} + \sum_b \delta_{db} + \varepsilon_{od} \tag{12}$$

where HHI_{od} is the od market-share Herfindahl. We find that indeed there is less competition on more remote routes (see Figure 9).

Figure 9: Market concentration and remoteness



Notes: This figure shows that in the cross section, more remote routes have greater market concentration, as measured by the Herfindahl–Hirschman index of market shares, consistent with the second "curse" of remoteness.

Fact 2b: Routes that became more accessible became more competitive.

In the panel, we regress the route-time Herfindahl on infrastructure-induced changes in market shares

$$\ln HHI_{od,t} = \beta_1 \ln \left(\sum_h \left(\frac{\hat{Q}_{od,h,t}}{\sum_{h'} \hat{Q}_{od,h',t} \times T_{h',t}} \right)^2 \times T_{h,t} \right) + \beta_2 \ln dist_{od,t} + \delta_{od} + \delta_{ot} + \delta_{dt} + \varepsilon_{odt}, \tag{13}$$

where $T_{h,t}$ is the share of total truckers in h in period t and $\hat{Q}_{od,h,t}$ is the predicted quantities that comes from estimating trucker's capacity on route od as a function of the travel times between driver homes and the start and end of the route:

$$\ln Q_{od,h,t} = \alpha_1 \ln dist_{h,o,t} + \alpha_2 \ln dist_{h,d,t} + \delta_{od,t} + \delta_{h,t} + \varepsilon_{od,h,t} \tag{14}$$

We exclude fixed effects and use $T_{h,t=0}$ in building the prediction, with the od route fixed effects in the upper equation ensuring that we are only identifying of the temporal changes in capacity driven by infrastructure improvements.

The underlying logic is that the change in market concentration due to infrastructure improvements reducing travel times between driver homes and the route start and end point should affect observed market concentration but once we control for changes in infrastructure on the *od* route itself, it should be uncorrelated with demand shocks on that route. We draw on this same logic to construct instruments in Fact 4b below. Table 2 shows that these predicted capacity changes are predictive of concentration, with routes that became more accessible becoming more competitive.

Table 2: Observed and infrastructure-predicted market concentration

Market Concentration$_{\mathrm{od,t}}$ (log HHI)	(1)	(2)
Infrastructure-predicted market concentration$_{\mathrm{od,t}}$ (log)	0.53***	0.53***
	(0.02)	(0.02)
Travel Time$_{\mathrm{od,t}}$ (log)		0.35**
		(0.15)
Fixed Effects		
- origin × destination	X	X
- origin × month	X	X
- destination × month	X	X
Observations	31,489	31,489
Adjusted within-R^2	0.14	0.14

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at *od* level in parentheses. o=origin, d=destination, t=month.

Curse #3: More remote locations served by less productive truckers

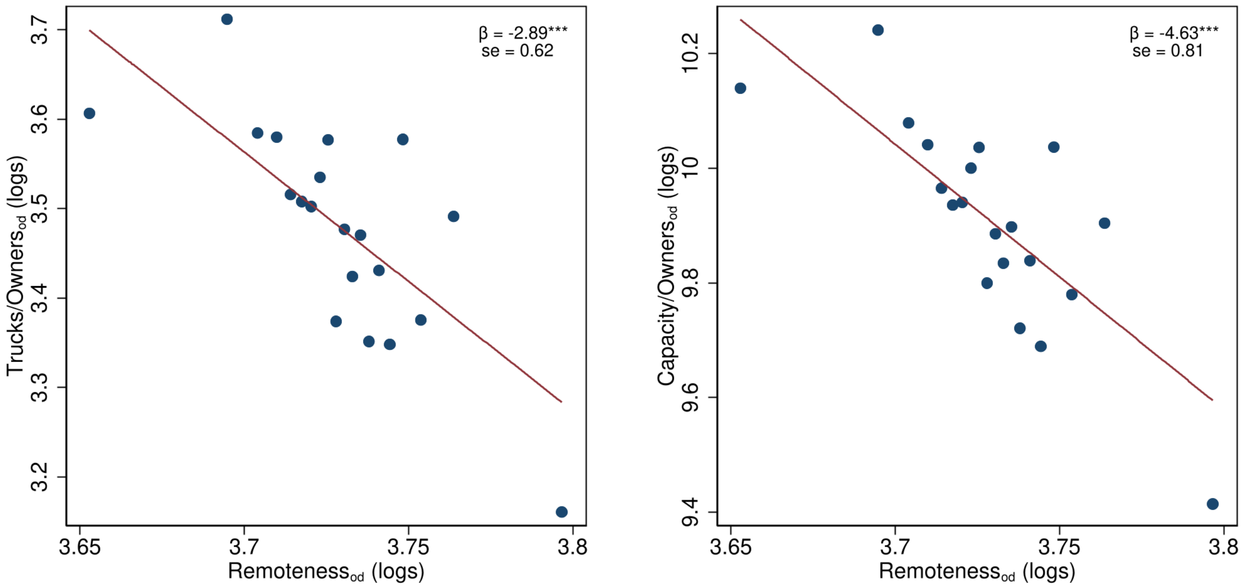
Fact 3a: Truckers that supply more remote routes are less productive.

To explore whether truckers serving more remote routes are less productive, we use two proxies for trucker quality: trucks per owner and capacity per owner. According to this measure, truckers with higher quality can provide transportation services at a lower price and might even be able to ship larger commodities than others. Figure 10 shows the result from estimating the following expression:

$$\ln TruckerQuality_{od} = \beta \ln Remote_{od} + \sum_b \delta_{ob} + \sum_b \delta_{db} + \varepsilon_{od}, \tag{15}$$

where b is an index for travel time bins (10 bins). Less productive truckers tend to serve more remote routes.

Figure 10: Trucker quality and remoteness



(a) Trucks / owner

(b) Capacity / owner

Notes: This figure shows that in the cross section, more remote routes are operated by observably worse truckers, i.e. those with fewer trucks (panel a) and those with lower capacity (panel b), consistent with the third "curse" of remoteness.

Fact 3b: More competitive routes attracted more productive truckers.

In the panel we can ask whether if routes that became more competitive attracted more productive truckers. We estimate

$$\ln \bar{Q}^{c}_{od,t} = \beta_1 \ln HHI_{od,t} + \beta_2 \ln dist_{od,t} + \delta_{od} + \delta_{ot} + \delta_{dt} + \varepsilon_{odt}, \tag{16}$$

where $\bar{Q}^{c}_{od,t}$ is the weighted average capacity of a trucker and we instrument $HHI_{od,t}$ as in equation 13. Table 3 shows worse quality truckers sorted into markets that became more concentrated.

Table 3: Market concentration and trucker quality sorting

	IV 1st stage: Market Concentration$_{od,t}$ (log HHI)	OLS: Truck Owner Capacity$_{od,t}$ (log)	IV 2nd Stage: Truck Owner Capacity$_{od,t}$ (log)
Infrastructure-predicted market concentration$_{od,t}$ (log)	0.53***		
	(0.02)		
Market Concentration$_{od,t}$ (log HHI)		-0.33***	-2.54***
		(0.02)	(0.08)
Travel Time$_{o,d,t}$ (log)	0.29*	-0.06	0.68
	(0.15)	(0.39)	(0.53)
Fixed Effects			
- origin × destination	X	X	X
- origin × year	X	X	X
- destination × year	X	X	X
SW/Cragg-Donald F-stat	1,092***		1,092***
N	31,489	31,500	31,489
Adjusted within-R^2		0.02	

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at *od* level in parentheses. *o*=origin, *d*=destination, *t*=month.

Implications of the Triple Curse of Remoteness

Fact 4b: Decreased costs of transit on routes with more and better truckers.

Taken together, the three curses above imply that routes with fewer and worse truckers should face higher transportation prices. In order to estimate such effect, we run a regression of average freight prices on trucker market shares. Given the reversal causality of prices on market shares, we use an instrumental variables strategy that builds on Fact 2b above. We first build an infrastructure-based instrument for market shares from variation in road improvements elsewhere in the network such that it is plausibly orthogonal to local demand shocks that are in the error term of the price regression.

Equations 17 and 18 show the two-step construction of the instrument:[5]

$$\ln s_{odthki} = \rho_1 \ln dist_{hot} + \rho_2 \ln dist_{dht} + \gamma_{odt} + \gamma_{ho} + \gamma_{hd} + \gamma_{it} + \epsilon_{odthki} \tag{17}$$

$$\ln Instr_{odth} = \sum_{h' \neq h} \sum_{k'} \sum_{i'} \left(s_{od,t=\bar{t},h',k',i'} \times \left(\frac{dist_{h'o,t}}{dist_{h'o,t=0}} \right)^{\hat{\rho}_1} \times \left(\frac{dist_{dh',t}}{dist_{dh',t=0}} \right)^{\hat{\rho}_2} \right) \tag{18}$$

The first equation provides estimates of the coefficients ρ_1 and ρ_2 that show how market shares respond to changes in the travel times between drivers homes and the start and end of a route od. The second equation uses those estimates and baseline shares to predict changes in market concentration at the odt level.

We then estimate an IV by regressing freight rates on predicted market shares and control for travel times and fixed effects for route-time (α_{odt}), home of trucker interacted with origin (α_{ho})

[5]The term $s_{od,t=\bar{t},h',k',i'}$ is the share of a trucker i with truck type k from home h on od, averaged across all time periods in our sample.

and destination (α_{hd}) of route and trucker-time (α_{it}) (equation 19). We also include the average share all truckers of a home h on a route od as a covariate in order to control for variation in our instrument that comes from differential home size.

$$\ln \bar{P}_{odtk} = \delta_1 \ln \hat{s_{odtkhi}} + \delta_2 \ln dist_{hot} + \delta_3 \ln dist_{dht} + \delta_4 \ln \left(\sum_{h' \neq h} \sum_{k'} \sum_{i'} s_{od,t=\bar{t},h',k',i'} \right)$$
$$+\alpha_{odt} + \alpha_{ho} + \alpha_{hd} + \alpha_{it} + \varepsilon_{odthki} \qquad (19)$$

Table 4 shows the result from such estimation in OLS and IV. The second column of each panel shows the first stage that relates market shares and our instrument. The coefficients of interest are large, negative, statistically significant and yield large F-stats, suggesting a relevant instrument. An increase in the market share of all other driver coming from home locations different to h due to declines in their travel times, reduces the market shares of drivers from h on route od. Next, the second stage of the IV strategy shows a positive sign, with prices rising when concentration increases (contrary to the OLS estimation which has a negative sign). Crucially, we control directly for price changes coming from changes in costs accessing the start or end of a route from h through the $\ln dist_{hot}$ and $\ln dist_{dht}$controls. Notably, market shares increase freight rates per ton, even when controlling for trucker-time characteristics (panel B), such as their decision to ship cargo on new routes.

Table 4: Market concentration and costs of transit

	Panel A: odt, ho, hd, i Fixed effects			Panel B: odt, ho, hd, it Fixed effects		
	(1) OLS: Price per $\text{ton}_{od,t,k}$ (logs)	(2) IV 1st stage: $\text{Shares}_{od,t,h,k,i}$ (logs)	(3) IV 2nd Stage: Price per $\text{ton}_{od,t,k}$ (logs)	(4) OLS: Price per $\text{ton}_{od,t,k}$ (logs)	(5) IV 1st stage: $\text{Shares}_{od,t,h,k,i}$ (logs)	(6) IV 2nd Stage: Price per $\text{ton}_{od,t,k}$ (logs)
$\text{Instrument}_{od,t,h}$ (logs)		-9.232***			-11.534***	
		(1.564)			(1.851)	
$\text{Shares}_{od,t,h,k,i}$ (logs)	-0.005***		0.098***	-0.003***		0.057**
	(0.001)		(0.036)	(0.001)		(0.025)
Travel $\text{Time}_{h,o,t}$ (logs)	0.015**	-1.445***	0.018**	-0.018*	-1.693***	-0.014
	(0.007)	(0.239)	(0.008)	(0.009)	(0.257)	(0.010)
Travel $\text{Time}_{d,h,t}$ (logs)	0.007	-2.260***	0.016**	0.001	-2.802***	0.006
	(0.006)	(0.371)	(0.007)	(0.007)	(0.435)	(0.007)
Share other $\text{homes}_{od,h}$ (logs)	0.020***	8.552***	0.088***	0.023***	10.847***	0.062***
	(0.004)	(1.562)	(0.024)	(0.004)	(1.846)	(0.017)
Fixed Effects						
- origin × destination × year	X	X	X	X	X	X
- home × origin	X	X	X	X	X	X
- home × destination	X	X	X	X	X	X
- owner	X	X	X	X	X	X
- year	X	X	X	X	X	X
- owner × year				X	X	X
SW F-stat		35***			39***	
Cragg-Donald F-stat		298			567	
N	4,457,876	4,457,876	4,457,876	4,432,966	4,432,966	4,432,966
Adjusted R^2	0.89		-0.22	0.90		-0.15

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at *od* level in parentheses. *o*=origin, *d*=destination, *t*=year, *k*=truck type, *h*=home, *i*=truck owner.

Furthermore, we explore heterogeneity of the effect of market concentration by route size. Table 5 shows the results from estimating equation 19 with interactions of market shares and route size.[6] We have three first stages, one for each endogenous variable, and note that for all of them we estimate significant and negative coefficients, together with large F-stats. Importantly, each instrument has a relative advantage explaining its corresponding endogenous variable compared to the other instruments. Our second stage estimates, though measured imprecisely, suggest that market concentration is more relevant in small and medium size routes. This result is consistent with truckers on the most popular routes served by hundreds of different companies having little market power.

[6]Small routes are those with less than 5,000 trips in the 6 year sample (73% of all routes in sample). Medium ones are those with trips above this threshold but below 50,000 trips (22%), while large routes are those with more than 50,000 trips in total (4%).

Table 5: Route heterogeneity in market concentration and costs of transit

	Panel A: odt, ho, hd, i Fixed effects					Panel B: odt, ho, hd, it Fixed effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS: Price per ton$_{od,t,k}$ (logs)	IV 1st stage: Shares$_{od,t,h,k,i}$ (logs)	IV 1st stage: Shares$_{od,t,h,k,i}$ (logs) × Medium routes	IV 1st stage: Shares$_{od,t,h,k,i}$ (logs) × Large routes	IV 2nd Stage: Price per ton$_{od,t,k}$ (logs)	OLS: Price per ton$_{od,t,k}$ (logs)	IV 1st stage: Shares$_{od,t,h,k,i}$ (logs)	IV 1st stage: Shares$_{od,t,h,k,i}$ (logs) × Medium routes	IV 1st stage: Shares$_{od,t,h,k,i}$ (logs) × Large routes	IV 2nd Stage: Price per ton$_{od,t,k}$ (logs)
Instrument$_{od,t,h}$ (logs)		-11.177***	-4.911***	-3.977***			-13.941***	-5.988***	-5.257***	
		(1.526)	(0.994)	(1.386)			(1.820)	(0.907)	(1.622)	
Instrument$_{od,t,h}$ (logs) × Medium routes		-0.218***	-0.441***	-0.094***			-0.228***	-0.449***	-0.095***	
		(0.015)	(0.014)	(0.013)			(0.015)	(0.015)	(0.014)	
Instrument$_{od,t,h}$ (logs) × Large routes		-0.449***	-0.110***	-0.670***			-0.466***	-0.120***	-0.677***	
		(0.025)	(0.013)	(0.025)			(0.026)	(0.014)	(0.026)	
Shares$_{od,t,h,k,i}$ (logs)	-0.016***				0.085*	-0.015***				0.034
	(0.001)				(0.047)	(0.001)				(0.035)
Shares$_{od,t,h,k,i}$ (logs) × Medium routes	0.010***				0.016	0.010***				0.032*
	(0.001)				(0.020)	(0.001)				(0.017)
Shares$_{od,t,h,k,i}$ (logs) × Large routes	0.014***				-0.019	0.014***				0.011
	(0.002)				(0.029)	(0.002)				(0.023)
Travel Time$_{h,o,t}$ (logs)	0.015**	0.008	0.021*	-0.019	0.017**	-0.018*	0.150***	0.088***	0.026	-0.014
	(0.007)	(0.021)	(0.013)	(0.017)	(0.007)	(0.009)	(0.040)	(0.020)	(0.038)	(0.010)
Travel Time$_{d,h,t}$ (logs)	0.007	0.129***	0.065***	0.039	0.015**	0.000	0.187***	0.098***	0.054	0.006
	(0.006)	(0.036)	(0.019)	(0.031)	(0.007)	(0.007)	(0.046)	(0.021)	(0.041)	(0.007)
Share other homes$_{od,h}$ (logs)	0.019***	10.786***	4.890***	3.984***	0.075***	0.023***	13.553***	5.969***	5.267***	0.057***
	(0.004)	(1.523)	(0.992)	(1.383)	(0.018)	(0.004)	(1.814)	(0.904)	(1.617)	(0.013)
Fixed Effects										
- origin × destination × year	X	X	X	X	X	X	X	X	X	X
- home × origin	X	X	X	X	X	X	X	X	X	X
- home × destination	X	X	X	X	X	X	X	X	X	X
- owner	X	X	X	X	X	X	X	X	X	X
- year	X	X	X	X	X	X	X	X	X	X
- owner × year						X	X	X	X	X
SW F-stat		72***	100***	77***			101***	176***	117***	
Cragg-Donald F-stat		188	188	188			346	346	346	
N	4,457,876	4,457,876	4,457,876	4,457,876	4,457,876	4,432,966	4,432,966	4,432,966	4,432,966	4,432,966
Adjusted R^2	0.89				-0.16	0.90				-0.13

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at *od* level in parentheses. *o*=origin, *d*=destination, *t*=year, *k*=truck type, *h*=home, *i*=truck owner.

Conclusion

Taken together, these empirical results suggest that the "triple curse of remoteness" arising from imperfect competition and the ability of truckers to ship goods in other locations highlighted in the theory are indeed present in the Colombian trucking industry. In ongoing work, we aim to quantify how these additional curses have shaped the welfare impacts of the infrastructure improvements we observe.

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