COMPETITION AND THE WELFARE GAINS FROM TRANSPORTATION INFRASTRUCTURE: EVIDENCE FROM THE GOLDEN QUADRILATERAL OF INDIA

Jose Asturias
Georgetown University Qatar

Manuel García-Santana
UPF, Barcelona GSE

Roberto Ramos
Bank of Spain

Abstract
A significant amount of resources is spent every year on the improvement of transportation infrastructure in developing countries. In this paper, we investigate the effects of one such large project, the Golden Quadrilateral in India. We do so using a model of internal trade with variable markups. In contrast to the previous literature, our model incorporates several channels through which transportation infrastructure affects welfare. In particular, the model accounts for gains stemming from improvements in the allocative efficiency of the economy. We calibrate the model to the Indian manufacturing sector and find real income gains of 2.7%. We also find that allocative efficiency accounts for 7.4% of these gains. The importance of allocative efficiency varies greatly across states, and can account for up to 18% of the overall gains in some states. The remaining welfare gains are accounted for by changes in labor income, productive efficiency, and average markups that affect states' terms of trade. (JEL: F15, H54, O18, O22, R42)

1. Introduction

Poor transportation infrastructure is a common feature in low-income countries. For example, in 2000, it would take a truck four to five days to drive the 1,500 km distance between Delhi and Calcutta, which is five times longer than it would in the United States. International organizations and policymakers have not overlooked this fact: between 1995 and 2005, upgrades to the transportation network constituted around

The editor in charge of this paper was Dirk Krueger.

Acknowledgments: We thank the CEPR for financial support of this project and the Private Enterprise Development in Low-Income Countries (PEDL) program. The authors would like to thank Tasso Adamopoulos, Reshad Ahsan, Chris Edmond, Ben Faber, Rob Feenstra, Thomas Holmes, Oleg Itskhoki, Joe Kaboski, Timothy Kehoe, Dirk Krueger, Virgiliu Midrigan, Michael Peters, Scott Petty, Andres Rodriguez-Clare, John Romalis, Jim Schmitz, three anonymous referees, and seminar participants at multiple seminars and conferences. The views expressed in this paper are of the authors and do not necessarily reflect the views of the Bank of Spain or the Eurosystem. Manuel García-Santana is a Research Affiliate at CEPR.

E-mail: jga35@georgetown.edu (Asturias); manuel.santana@upf.edu (García-Santana); roberto.ramos@bde.es (Ramos)

Journal of the European Economic Association 2019 17(6):1881–1940 DOI: 10.1093/jeea/jvy039

12% of total World Bank lending. Out of this, 75% was allocated to upgrading roads and highways. Given the resources that are invested into transportation infrastructure, understanding the impact of large-scale transportation infrastructure projects is a matter of importance to both researchers and policymakers.

We use the example provided by a recent large-scale highway development project in India to quantitatively evaluate the welfare gains that stem from improving the transportation infrastructure within a country. We study the construction of the Golden Quadrilateral (GQ), which provided India with 5,800 km of modern highway that connected India's four major metropolitan areas (Delhi, Mumbai, Chennai, and Calcutta). Construction was rapid for a project of this scale, starting in 2001 and 90% being completed by the end of 2006.

Our main contribution is to quantify the gains from the construction of the GQ in a setting that allows us to distinguish among various channels that can affect welfare. One channel that we consider is the traditional Ricardian channel. This channel has been emphasized by prominent papers in the existing literature, such as Donaldson (2018) and Donaldson and Hornbeck (2016). Another channel that we study is how the GQ affected the allocative efficiency of the economy. Thus, we examine how new transportation infrastructure improves the allocation of resources across firms and how this affects the aggregate gains from new transportation infrastructure.

We use a quantitative trade model à la Atkeson and Burstein (2008) in which all of the states of India trade with each other. Firms compete oligopolistically, which implies that firms charge variable markups depending on the level of competition in a market. This framework is useful to study the effects of high transportation costs on the allocative efficiency of the economy. The reason is that firms with high markups are inefficiently small relative to firms with low markups. Changing transportation costs, by affecting the pattern of spatial competition, will thus impact the distribution of markups and allocative efficiency.

To discipline the parameters of our model, we use plant-level data of India's manufacturing sector and transportation network. We derive a set of structural equations to estimate these parameters. In particular, we use a two-step approach that allows us to estimate transportation costs and the elasticity of the sectoral demand curve even without having access to direct information on trade flows across Indian regions. This methodology provides a straightforward way of identifying these parameters in a manner that is fully consistent with the model.

In the first step, we estimate transportation costs between Indian states using a methodology similar in spirit to the one used by Donaldson (2018). We show that in the model transportation costs can be identified by comparing the prices charged across locations by firms that are monopolistic producers at the national level. This is the case because the prices charged by these firms only depend on transportation costs since the level of competition they face is constant across space. To implement this strategy, we first identify all the goods that are produced by only one plant in India. For these goods, we regress the prices paid across destinations with the effective distance between origin and destination. This measure of effective distance is the lowest cost path given the infrastructure quality in place at the time. We find that the transportation costs implied by this method are similar to those found in additional microlevel pricing data that we collect.

In the second step, we estimate the elasticity of the sectoral demand curve. This parameter is important since it governs the size of markups for firms with a large degree of market power. We use the fact that, for goods produced by monopolistic producers, the model implies a standard gravity equation that relates internal flows to transportation costs. Using the transportation costs from the first step, we find the elasticity of the sectoral demand curve that is consistent with the gravity equation for monopolistic products in the data.

We use our calibrated model to quantify the effects of the construction of the GQ. To do so, we compare outcomes from the model when we feed in the estimated transportation costs with and without the GQ. We find real income gains of 2.72% in the Indian manufacturing sector, equivalent to $4.2 billion per year.[1] A back of the envelope calculation shows that these gains are large relative to the initial construction costs, which are $5.6 billion. Thus, our results imply that it would take less than two years for India to recover the initial construction cost. We also find a high degree of heterogeneity in income changes across states, including some states that lose.

We decompose the welfare gains into different components using the theoretical result developed by Holmes, Hsu, and Lee (2014). The *Ricardian* component is simply the gains in real income if all firms charged their marginal cost. This component maps back to welfare in models in which all firms have the same markup or operate in perfect competition. The *allocative efficiency* component relates to the welfare loss resulting from misallocation arising due to heterogeneous markups charged by firms. Finally, the *markups terms of trade* component compares the average markup of the goods sold with the average markup of the goods purchased by a state. Ceteris paribus, states with high markups on the goods that they sell relative to the goods that they buy will enjoy a higher real income.

From a research perspective, understanding the effects of new infrastructure on allocative efficiency is perhaps the most interesting part of our analysis. First, it is a channel that has been previously unexamined in the literature that quantifies the welfare gains from transportation infrastructure. At the same time, papers such as Hsieh and Klenow (2009) suggest that allocative efficiency is an important driver in explaining cross-country income differences and our understanding of the particular forces driving these inefficient allocations is still limited. If high transportation costs lead to low levels of allocative efficiency, then lowering transportation costs in countries like India could result in gains previously not considered by the literature through the allocative efficiency channel.

We find that the *allocative efficiency* component accounts for 7.4% of the overall gains. We also find that there are large differences in the importance of allocative efficiency gains across states. In fact, allocative efficiency can account for up to 18%

1. We arrive at this number by multiplying the manufacturing value added share in India (16%) by the Indian GDP in 2006 ($949 billion) by 2.72%. The implied gains as a fraction of total national income is 0.44% (2.72% $\times$ 16%).

of the overall gains at the state level. These gains are concentrated in the largest states since these are the states with the initial lowest levels of allocative efficiency. This is because firms located in the largest states tend to have on average lower marginal costs. These lower marginal costs provide a cost advantage to local firms, which allows them to charge high markups.

Finally, we conduct a reduced form empirical exercise to examine if there is evidence in the data for the main mechanisms of the model. We estimate a differences-in-differences specification in which we compare economic outcomes for locations close to the GQ with those that are far away, before and after the construction of the highway. First, we show that prices paid for intermediate inputs declined more in areas close to the GQ. Second, we find that the Olley and Pakes (1996) covariance term between size and productivity increased more in areas close to the GQ, suggesting that the GQ improved allocative efficiency. These empirical findings are consistent with the model output.

The remainder of the paper is organized as follows. In Section 2, we present the related literature. In Section 3, we describe the main characteristics of the road network in India. In Section 4, we present the model. In Section 5, we describe the data used. In Section 6, we discuss the calibration of the model. In Section 7, we present and discuss our quantitative results. In Section 8, compare model output with reduced from exercises in the data. In Section 9, we present results from sensitivity exercises. Finally, in Section 10 we conclude.

2. Related Literature

Gains from New Transportation Infrastructure. We contribute to the literature that analyzes the income gains from new transportation infrastructure using general equilibrium models of trade. Papers in this area include Adamopoulos (2011), Donaldson (2018), Donaldson and Hornbeck (2016), Herrendorf, Schmitz, and Teixeira (2012), Gollin and Rogerson (2014), Redding and Turner (2015, chap. 20). There are contemporaneous works that also investigate the effects of internal trade barriers in India. Alder (2017) estimates the effect of the GQ on Indian districts using satellite data on night lights and finds significant increases in economic activity across regions. Van Leemput (2016) builds a multisector model in which both internal and international trade are present. She finds that reducing internal trade costs would generate welfare gains considerably larger than that of lifting all international trade barriers.

Our paper is the first to quantitatively study the effects of new transportation infrastructure on allocative efficiency. The existing work in this literature typically uses an Eaton and Kortum (2002) model. In that model, or in any of the other workhorse models considered by Arkolakis, Costinot, and Rodriguez-Clare (2012), there is no scope for gains from allocative efficiency.[2] Our results show that improvements in allocative efficiency can be an important channel of income gains.

2. A notable exception is the framework used in Caliendo et al. (forthcoming), where reductions in transportation costs can improve efficiency in the allocation of labor across sectors and regions.

Identification of Transportation Costs Within a Country. We extend the existing methodologies to identify transportation costs in the existing literature by relaxing the assumption of perfect competition. To do so, we apply the two-step procedure used by Donaldson (2018). He uses data of products produced in only one location to identify transportation costs and the parameter governing the trade elasticity in his model. This two-step procedure is useful since it is a way of disciplining parameters of the model in a setting in which aggregate trade flows across regions are not observed. We show that this procedure is consistent with a model of oligopolistic competition when applied to monopolistic producers. Thus, by exploiting our plant level data set, we can identify both transportation costs and the elasticity of substitution across sectors using a gravity approach.

Our identification of transportation costs is also methodologically related to Atkin and Donaldson (2015). In their paper, the authors highlight three challenges faced by the literature that uses price differences across space to identify transportation costs. First, price differences can reflect unobserved product characteristics across locations, such as quality. We attempt to control for this by using very narrowly defined products (around 5,000). Furthermore, we have specifications in which we attempt to control for destination characteristics that could influence unobserved product characteristics, such as average income. In contrast, Atkin and Donaldson (2015) rely on data at the bar code level, which provides them with information on products more narrowly defined. For instance, in our case, a product would be “Coffee bean, green (raw)”. In their case, a product would be “Ground And Whole Bean Coffee - Folgers Classic Roast”.

The second challenge is that, even in a setting with perfect competition, only price differences between two locations that trade a product are useful in identifying transportation costs. Thus, it is important to know which location pairs are trading, which is often hard to determine. We tackle this problem by using the production information in plant-level data to identify national monopolists using narrowly defined products. We complement this information with data on intermediate input usage to determine where the products are used. These two pieces of information allow us to pin down the origin and destination of the product. In contrast, Atkin and Donaldson (2015) carry out phone interviews with firms to determine the origin of products.

The third challenge is that, even if we know the origin and destination of a product, the price differences contain both transportation costs and markups. To overcome this challenge, we use a result from our model that implies that national monopolists have the same markup across destinations. Thus, the differences in prices charged by monopolists across destinations reveal transportation costs. On the other hand, Atkin and Donaldson (2015) focus on an environment in which markups may depend on transportation costs. They show that in a general oligopolistic model with very flexible preferences, pass-through rates across locations are a sufficient statistic of the reaction of markups to changes in transportation costs. They then estimate these pass-through rates and use them to “correct” for markups in the observed price differences.

Misallocation. Our paper also contributes to the recent literature that emphasizes misallocation of resources across firms as one of the main sources of TFP differences across countries. In their influential paper, Hsieh and Klenow (2009) show that wedges between the marginal products of factors may account for up to 60% of the TFP gap between India and the United States. Other papers in this literature include Restuccia and Rogerson (2008), Bartelsman, Haltiwanger, and Scarpetta (2013), and Peters (2013).

We quantitatively study the effects of a policy that took place instead of a counterfactual that removes all misallocation in the economy.[3] The construction of the GQ provides a quasi-natural experiment, which allows us to check that the main mechanisms of the model are present in the data.

Procompetitive Gains in International Trade. Lastly, this paper contributes to the active debate in international trade relating to the size of procompetitive gains. Gains in allocative efficiency are equivalent to procompetitive gains since they are due to changing markups. Prominent papers in this large literature include Arkolakis et al. (forthcoming), de Blas and Russ (2015), Dhingra and Morrow (forthcoming), Edmond, Midrigan, and Xu (2015), Epifani and Gancia (2011), Feenstra (2014), Feenstra and Weinstein (2017), Holmes et al. (2014).[4] The most closely related paper to ours is that of Edmond et al. (2015). The authors use an Atkeson and Burstein (2008) model to study the size of procompetitive gains in a context in which Taiwan trades with the rest of the world.

To the best of our knowledge, ours is the first paper to quantitatively study the size of procompetitive gains in a setting with many nonsymmetric economies. The fact that the economies are not symmetric plays a key role in determining both the size and the distribution of procompetitive gains. First, procompetitive gains are concentrated in states with low wages. Low wages in those states imply that firms located there will be able to charge high markups. Second, for some states, we find that changing wages can account for large fractions of the procompetitive gains.

Finally, we find that a setting with asymmetric economies plays an important role in another determinant of income, which is related to the aggregate markup charged on exported goods relative to those that are imported. This can be interpreted as the effect of markups on a state's terms of trade since it affects the price of exported versus imported goods. We find that income changes through this channel can be quantitatively important in some states.

3. Our paper is not the first in quantifying the income effects of a specific distortion. Some examples are Gourio and Roys (2014), Garicano, Lelarge, and Van-Reenen (2016), and Guner, Ventura, and Xu (2008). Although not studying the effects of an particular policy, David, Hopenhayn, and Venkateswaran (2016) link misallocation to a specific distortion, that is, informational frictions, and quantify its effects on aggregate income and productivity.

4. Workhorse international trade models with variable markups include: Bernard et al. (2003) and Melitz and Ottaviano (2008).

3. Roads in India and the Golden Quadrilateral

India has the second largest road network in the world, spanning approximately 3.3 million km. It comprises expressways, national highways (79,243 km), state highways (131,899 km), major district highways, and rural roads. Roads play an important role in facilitating trade in India: approximately 65% of freight in terms of weight and 80% of passenger traffic are transported on roads.[5] National highways are critical since they facilitate interstate traffic and carry about 40% of the total road traffic.

At the end of the 1990s, India's highway network left much to be desired. The major economic centers were not linked by expressways, and only 4% of roads had four lanes. In addition to the limited lane capacity, more than 25% of national highways were considered to be in poor surface condition. Congestion was also an important issue, with 25% of roads categorized as congested. This was due to poor road conditions, increased demand from growing traffic, and crowded urban crossings. Frequent stops at state or municipal checkpoints for government procedures such as tax collection or permit inspection also contributed to congestion (see World Bank 2002).

In order to improve this situation, the Indian government launched the National Highways Development Project (NHDP) in 2001. The goal of the initiative was to improve the performance of the national highway network. The first phase of the project involved the construction of the Golden Quadrilateral (GQ), a 5,800 km highway connecting the four major metropolitan areas via four and six-lane roads. The four metropolitan centers that were connected are Delhi, Mumbai, Chennai, and Calcutta. Apart from the increase in the number of lanes, additional features of a high-quality highway system were constructed. These features include grade separators, over-bridges, bypasses, and underpasses.

The cost was initially projected to be 600 billion rupees (equivalent to \$13.4 billion in 2006). As of October 2013, the total cost incurred by the Indian government was approximately half of the projected sum (250 billion rupees or \$5.6 billion). In Section 7, we compare this cost with the benefits predicted by our model.

The second phase of the NHDP consists of the construction of the North-South and East-West corridor, a highway that aims to connect Srinagar in the north to Kanyakumari in the south, and Silchar in the east to Porbandar in the west. Although this second phase was approved in 2003, there have been many delays for its construction, and less than 10% of the work was completed by the end of 2006. Thus, we will not consider that project in our analysis.

Geospatial Data. We have geospatial data for all the National Highways of India, which was supplied by ML Infomap. We complement this data using information provided by the National Highways Authority of India (NHAI) on the completion

5. The importance of railroads has declined in India over time. Although in 1950 more than 80% of freight traveled by rail, this figure has steadily been decreasing. At present, rail carries mostly bulk freight such as iron, steel, and cement. Nonbulk freight represents only around 3% of total rail freight in terms of ton km.

(a) GQ construction in 2001 (b) GQ construction in 2006

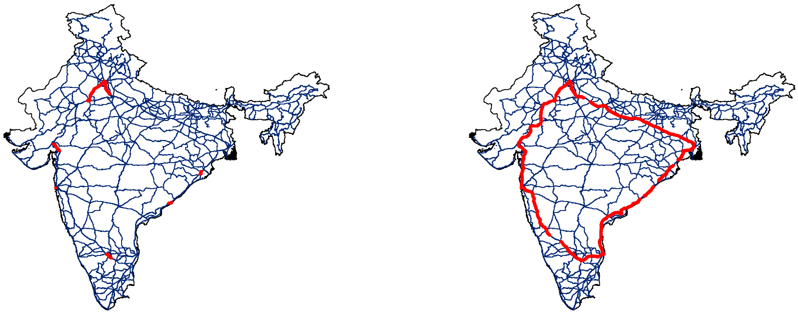


FIGURE 1. Road Network in India and the GQ. Panel (a) shows a map with the road network in India at the end of 2001, including the sections of the Golden Quadrilateral that were finished by then (approximately 10% of the total project). Panel (b) shows the same map but for 2006 (approximately 95% of the total project).

dates of various portions of the GQ. The GQ consisted of 127 stretches and we have detailed information about the start and end points.[6] Figure 1 shows the evolution of the GQ (in red) in 2001 and 2006. Although the GQ was finished in 2013, more than 90% of the project was completed by 2006. We will link this geospatial data to manufacturing data for 2001 and 2006.

4. Model

In this section, we present our static general equilibrium model of internal trade based on Atkeson and Burstein (2008). This model has been used to study firm pricing under strategic complementarities in international trade (see for instance Amiti, Itskhoki, and Konings (2016)). This model has CES demand while also generating variable markups by departing from monopolistic competition. This is particularly convenient for us since, as we will show in Section 6, the CES demand structure of the model gives convenient expressions for estimating transportation costs and the elasticity of substitution across sectors.

We consider N asymmetric states trading with each other. In each state, there is a measure 1 of sectors. Within each sector, there is a finite number of firms that compete in an oligopolistic manner. Labor is immobile across states.[7]

6. See nhai.org/completed.asp and the Annual Reports of NHAI.

7. We do not find evidence that the construction of the GQ induced movements of labor across states in India. See Section 9 for a full discussion of this topic.

4.1. *Consumers*

In each state n, there is a representative household with a utility function:

$$C_n = \left(\int_0^1 C_n(j)^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}}, \tag{1}$$

where $C_n(j)$ is the composite good of sector j and $\theta > 1$ is the elasticity of substitution across composite goods of different sectors. The sector-level composite good is defined as

$$C_n(j) = \left(\sum_{o=1}^{N} \sum_{k=1}^{K_{oj}} c_n^o(j,k)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}, \tag{2}$$

where $c_n^o(j,k)$ is the good consumed by state n and provided by firm k in sector j shipped from state o, N is the number of states, K_{oj} is the number of firms that operate in sector j in state o, and $\gamma > 1$ is the elasticity of substitution between goods produced by different firms in the same sector. We assume that $\gamma > \theta$, which means that goods are more substitutable *within* sectors than *between* sectors.

The budget constraint of the representative household in state n is given by

$$\int_0^1 \left(\sum_{o=1}^{N} \sum_{k=1}^{K_{oj}} p_n^o(j,k) c_n^o(j,k) \right) dj = W_n L_n + \Pi_n, \tag{3}$$

where W_n is the equilibrium wage, L_n is the labor endowment, and Π_n is the income derived from the profits of firms located in n.

4.2. *Firms*

In each sector j in state o, there is a finite number of K_{oj} firms. Firms draw their productivity from a distribution with CDF $G(a)$. A firm with a productivity level a has a constant labor requirement of $1/a$ to produce one unit of good. Because firms do not pay a fixed cost to operate in a market, they sell to all N states.

To determine the firm's pricing rule, we first find the demand it faces. Equations (1)–(3) generate the demand:

$$c_n^o(j,k) = \left(\frac{P_n}{P_n(j)} \right)^{\theta} \left(\frac{P_n(j)}{p_n^o(j,k)} \right)^{\gamma} C_n, \tag{4}$$

where

$$P_n(j) = \left(\sum_{o=1}^{N} \sum_{k=1}^{K_{oj}} p_n^o(j,k)^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \tag{5}$$

is the price index for sector j in state n and

$$P_n = \left(\int_0^1 P_n(j)^{1-\theta} dj \right)^{\frac{1}{1-\theta}} \tag{6}$$

is the aggregate price index in state n. Intuitively, the relative demand for a differentiated good within a sector depends on the price of the good relative to the price of the composite good of the sector, and also on the price of the composite good of the sector relative to the aggregate price index.

Firms within sectors compete à la Cournot. Firm k located in state o selling to state d takes the demand characterized by equation (4) and the quantity supplied by competitor firms in the sector as given and solves the following problem:

$$\pi_d^o(j,k) = \max_{c_d^o(j,k)} \; p_d^o(j,k)c_d^o(j,k) - \frac{W_o \tau_d^o}{a_o(j,k)} c_d^o(j,k), \tag{7}$$

where $a_o(j, k)$ is the productivity of firm k in sector j producing in state o, τ_d^o is the iceberg transportation cost to ship one unit of good from o to d. Note that, because of the constant returns to scale technology, the problem of a firm across all different destinations can be solved independently. The solution to this problem is

$$p_d^o(j,k) = \frac{\varepsilon_d^o(j,k)}{\varepsilon_d^o(j,k) - 1} \frac{W_o}{a_o(j,k)} \tau_d^o, \tag{8}$$

where

$$\varepsilon_d^o(j,k) = \left(\omega_d^o(j,k)\frac{1}{\theta} + (1 - \omega_d^o(j,k))\frac{1}{\gamma} \right)^{-1}, \tag{9}$$

and $\omega_d^o(k, j)$ is the market share of firm k producing in state o in sector j selling to state d:

$$\omega_d^o(j,k) = \frac{p_d^o(j,k)c_d^o(j,k)}{\sum_{o=1}^{N} \sum_{k=1}^{K_{oj}} p_d^o(j,k)c_d^o(j,k)}. \tag{10}$$

The price that firms set in equation (8) is similar to the markup over marginal cost that is found in a setup with monopolistic competition. The difference is that the markups are endogenous here, and depend on the market structure of the sector. For example, suppose that there is only one firm in a given sector, then that firm will compete only with firms operating in other sectors and its demand elasticity will be equal to θ. This means that the firm faces the sector-level elasticity of demand. At the other extreme, suppose that a firm's market share is close to zero, then the firm will compete only with firms in its own sector and its elasticity of demand will be equal to γ. Notice that a given firm will generally have different market shares and hence charge different markups across different destinations.

The aggregate profits of firms in state n are characterized by

$$\Pi_n = \int_0^1 \left(\sum_{d=1}^{N} \sum_{k=1}^{K_{nj}} \pi_d^n(j,k) \right) dj. \tag{11}$$

4.3. Balanced Trade and Labor-Clearing Condition

All states n must have balanced trade:

$$\int_0^1 \left(\sum_{o=1,\ o\neq n}^{N} \sum_{k=1}^{K_{oj}} p_n^o(j,k) c_n^o(j,k) \right) dj = \int_0^1 \left(\sum_{d=1,\ d\neq n}^{N} \sum_{k=1}^{K_{nj}} p_d^n(j,k) c_d^n(j,k) \right) dj. \tag{12}$$

The labor-clearing condition for state n is

$$\int_0^1 \left(\sum_{d=1}^{N} \sum_{k=1}^{K_{nj}} \frac{c_d^n(j,k)}{a_n(j,k)} \tau_d^n \right) dj = L_n. \tag{13}$$

4.4. Definition of Equilibrium

Equilibrium. For all states n and n', sectors j, and firms k_{nj}, an equilibrium is a set of allocations of consumption goods $\{c_{n'}^n(j,k),\ C_n(j)\}$, firm prices $\{p_{n'}^n(j,k)\}$, sector prices $\{P_n(j)\}$, and aggregate variables $\{W_n, P_n, \Pi_n\}$ such that

(1) Given firm prices, sector prices, and aggregate variables, $\{c_{n'}^n(j,k)\}$ is given by (4), $C_n(j)$ by (2), and they solve the consumer's problem in (1), and (3).
(2) Given aggregate variables, $p_{n'}^n(j,k)$ is given by (8), (9), and (10), and solves the problem of the firm in (7).
(3) Aggregate profits satisfy (11), aggregate prices satisfy (6), and sector prices satisfy (5).
(4) Trade flows satisfy (12).
(5) Labor markets satisfy (13).

4.5. Misallocation in the Model

Misallocation in this setting arises due to dispersion in markups across producers. We can show that the revenue productivity of a firm operating in state o and selling to destination d, defined as $TFPR_d^o(j,k) = p_d^o(j,k) a_o(j,k)$, is $W_o \tau_d^o \varepsilon_d^o(j,k)/(\varepsilon_d^o(j,k) - 1)$.[8] Thus, conditonal on transportation costs, firms with high productivity draws (and high markups) also have a high revenue productivity. Firms with high productivity draws are smaller in size than they would be in the case of perfect competition. Thus, India's welfare would increase by reallocating labor from firms with low productivity draws (low-markup firms) to firms with high productivity

8. Note that this is equivalent to the *TFPR* measure in Hsieh and Klenow (2009) since labor is the only factor of production.

draws (high-markup firms). This type of misallocation has already been emphasized by Peters (2013) and by Epifani and Gancia (2011) (at the level of industries).

Other papers in the literature often interpret this misallocation as resulting from government policies that create idiosyncratic distortions at the firm level, which affect the optimal decision of firms. In the particular case in which these idiosyncratic distortions are positively correlated with firm size, the misallocation studied in those papers is similar in nature to the one predicted by our model.

4.6. *A Framework to Decompose the Effects of the GQ*

We can apply the framework developed by Holmes et al. (2014) (HHL) to decompose the changes in real income in our model in a way that highlights the various mechanisms at work. The framework allows us in particular to distinguish between Ricardian, allocative efficiency, and markups terms of trade effects from lowering transportation costs.

We now introduce some notation for the purpose of the decomposition. First, we define the aggregate markups on the goods sold. This reflects how much market power firms producing in a state have when selling to other states. First, the revenue-weighted mean labor cost share for the products sold by state n is

$$c_n^{sell} = \int_0^1 \left(\sum_{d=1}^{N} \sum_{k=1}^{K_{nj}} c_{n,d}^{sell}(j,k) s_d^n(j,k) \right) dj,$$

where $c_{n,d}^{sell}(j,k)$ is the labor cost share of goods produced by firm k in sector j and sold in state d and $s_d^n(j,k)$ is the share of state n's revenue that comes from selling those goods. The aggregate markup on the goods sold can be expressed:

$$\mu_n^{sell} = \frac{R_n}{W_n L_n} = \frac{1}{c_n^{sell}},$$

where $R_n = W_n L_n + \Pi_n$, which is the state's total revenue. Note that there is an analogous expression at the firm level, which is that the firm's markup is equal to the reciprocal of the labor share.

We next define the aggregate markups on the goods purchased by state n, which reflect how much market power firms located in other states have when selling to state n. The revenue-weighted mean labor cost for the products purchased by state n is

$$c_n^{buy} = \int_0^1 \left(\sum_{o=1}^{N} \sum_{k=1}^{K_{oj}} c_{o,n}^{buy}(j,k) b_n^o(j,k) \right) dj.$$

where $c_{o,n}^{buy}(j,k)$ is the labor cost share of goods produced by firm k in sector j located in state o and $b_n^o(j,k)$ is the share of expenditures in state n on those goods. The aggregate markups on the goods purchased are

$$\mu_n^{buy} = \frac{1}{c_n^{buy}}.$$

Lastly, let P_n^{pc} be the aggregate price of state n if every firm engages in marginal cost pricing, which is the aggregate price index that would emerge in a context of perfect competition. This price index depends on the factors that determine the marginal cost of firms: the distribution of firm productivity, the wages paid by firms, and the transportation costs that these firms face.

Using this notation, the real income in state n can be rewritten into the following components:

$$Y_n = \underbrace{W_n L_n}_{\textit{Labor income}} * \underbrace{\frac{1}{P_n^{pc}}}_{\textit{Prod. efficiency}} * \underbrace{\frac{\mu_n^{sell}}{\mu_n^{buy}}}_{\textit{Markup ToT}} * \underbrace{\frac{P_n^{pc}}{P_n}\mu_n^{buy}}_{\textit{Allocative efficiency}}, \tag{14}$$

where $Y_n = (W_n L_n + \Pi_n)/P_n$. The first component is the aggregate *labor income*. The second component is the *productive efficiency* component of welfare. This component is simply the inverse of the price index if all firms charged their marginal cost. The third component is the *markups terms of trade*. This component compares the aggregate markups charged for the goods a state sells with those that it purchases. The last component is *allocative efficiency*. This term is related to the welfare loss that arises due to the dispersion in markups, which results in misallocation. In a situation in which there is no variations on markups, or when there is no misallocation, this index is equal to one. As misallocation increases, this index decreases.[9]

Combining the first two terms leads to an expression that is equal to real income if firms charge their marginal cost. This expression maps back to welfare in the large class of models considered by Arkolakis et al. (2012), in which the markups of firms remain unchanged. Thus, we consider changes in this component to be Ricardian effects.[10] Given the expression in equation (14), we decompose the changes in real income into the following terms:

$$\Delta \ln Y_n = \underbrace{\Delta \ln W_n L_n + \Delta \ln \frac{1}{P_n^{pc}}}_{\textit{Ricardian}} + \underbrace{\Delta \ln \frac{\mu_n^{sell}}{\mu_n^{buy}}}_{\textit{Markup ToT}} + \underbrace{\Delta \ln \frac{P_n^{pc}}{P_n}\mu_n^{buy}}_{\textit{Allocative efficiency}}.$$

9. It can be shown that this term is equal to the cost of one unit of utility under marginal cost pricing divided by the cost of acquiring one unit of utility with the equilibrium bundle under marginal cost pricing.

10. Caliendo et al. (forthcoming) also present a decomposition of real income for a model of internal trade that deviates from the formula presented by Arkolakis et al. (2012). Our decomposition allows for changes in real income in a given region being affected by changes in markups. Their decomposition allows for real income in a given region being affected by selection effects in intermediate goods production, the cost of labor relative to other inputs, and changes in the returns of land and structures at the aggregate level.

5. Manufacturing Plant-Level Data

We use plant-level data on the Indian manufacturing sector together with geospatial data to obtain information that allows us to discipline the main parameters of the model. In particular, as we explain in Section 6.1, we rely on goods that are produced by monopolists and used by other plants as intermediate goods. We do so for two snapshots in time (2001 and 2006). It is important to note that, to the best of our knowledge, interstate trade data on goods transported by road is not collected in India. Hence, throughout our analysis, we do not use any direct information on trade flows across Indian regions.

5.1. Annual Survey of Industries and National Sample Survey

We first construct a representative sample of the Indian manufacturing sector. To do so, we merge two separate sets of plant-level data: the Annual Survey of Industries (ASI) and the National Sample Survey (NSS). The ASI targets plants that are in the formal sector. It is the main source of manufacturing statistics in India and has been commonly used in the development literature.[11] It covers plants that have more than 10 workers if they have electricity and 20 if they do not. The information provided by the establishments is very rich, covering several operational characteristics such as sales, employment, wage bill, capital stock, and intermediate goods usage. The NSS covers all informal establishments in the Indian manufacturing sector. "Informal" refers to all manufacturing enterprises not included in the ASI. The process of merging the ASI and NSS data is straightforward since very similar questions are used to collect both sets of data. For the year 2005–2006 the final dataset contains 17 million manufacturing plants that employ 45 million workers once the observation weights are used. According to the Indian Labor Force Survey, 46 million workers were employed in the manufacturing sector that year.[12]

It is important to note the huge differences in productivity between formal and informal plants. Informal plants account for approximately 80% of employment and only 20% of value added. Thus, it is crucial to merge these data sets to have an accurate picture of the Indian manufacturing sector.

5.2. Prices and the Use of Intermediates in ASI-NSS

The ASI and NSS data contain detailed information about production and intermediate inputs usage. For each plant in our data, we observe the value and physical quantity of production and intermediate goods usage broken down by product. This means that we can compute the input prices paid by plants, which allows us to identify transportation

11. See for instance Aghion et al. (2005), Aghion et al. (2008), Chari (2011), Hsieh and Klenow (2009), and Bollard, Klenow, and Sharma (2013).

12. This is consistent with Hsieh and Klenow (2014), which is an example of another paper that jointly uses the ASI and NSS datasets.

costs.[13] To compute the price of inputs, we divide the expenditure on a particular good by physical units.

The product classification used in both the ASI and NSS is the Annual Survey of Industries Commodities Classification (ASICC). The ASICC contains approximately 5,400 different products, which are very narrowly defined. For instance, the ASICC distinguishes between different types of black tea such as leaf, raw, blended, unblended, and dust. In the processed mineral category, the ASICC distinguishes between 12 different types of coke.

6. Inferring Parameter Values

We calibrate our model to 2006, when the GQ was already in place. Our calibration strategy is as follows. Our model is characterized by (i) a set of bilateral iceberg costs between states (a 29 by 29 matrix of iceberg costs), (ii) the elasticity of substitution across sectors θ, (iii) the elasticity of substitution within sectors γ, (iv) the number of producers in state i and sector j K_{ij}, (v) the labor endowment of states, and (vi) the parameters governing the productivity distribution of firms.

Using structural equations from the model, we first estimate the transportation costs and the two elasticities (Sections 6.1, 6.3, 6.4, and 6.5). We next plug into the model the number of firms per state-sector that we observe in the data, and calibrate the labor endowment of the states and the productivity distribution to match the relevant statistics of the Indian manufacturing sector (Section 6.5).

6.1. Estimating Transportation Costs

The first step is to infer transportation costs. As mentioned before, the main limitation that we face is the lack of direct information on trade flows of manufacturing goods across Indian regions. To overcome this limitation, we use pricing data from intermediate inputs used across India as described in Section 5.2, together with theoretical results from the model. Equation (8) shows that the prices charged by firms depend both on transportation costs and on firms' market shares in the destination market. In order to identify transportation costs, we exploit one implication of the model: variations in prices for nation-wide monopolists are due solely to variations in transportation costs across destinations. To see this formally, equation (8) and the fact that a monopolist has a market share of one in all destinations imply that the firm will charge:

$$p_d^o(j,k) = \frac{\theta}{\theta - 1} \frac{W_o}{a_o(j,k)} \tau_d^o. \tag{15}$$

13. Although the ASI and NSS datasets have been previously used, not much attention has been paid to the pricing information. A notable exception is Kothari (2014).

Then, the relative price across destinations is

$$\frac{p_d^o(j,k)}{p_{d'}^o(j,k)} = \frac{\tau_d^o}{\tau_{d'}^o},$$

which only depends on the ratio of transportation costs. Hence, through the lens of our model, the prices charged by monopolists across destinations reveal differences in transportation costs.

Empirically, we define a monopolist as a plant selling at least 95% of the value of a given 5-digit ASICC product nationally. Using the ASI and NSS for the years 2001 and 2006, we identify 165 products that are manufactured by monopolists. The largest category is "Manufacture of chemicals and chemical products," which contains around 40% of the identified products. This is consistent with the nature of the chemical industry, in which production is often concentrated in one plant due to economies of scale, with the product then shipped to many locations.[14]

Once the products manufactured by monopolists are identified, we use the price paid for intermediate inputs in order to estimate equation (15). The strategy is similar to the one used by Donaldson (2018), except we work with plant-level data and with a framework that accommodates oligopolistic competition. In our empirical specification, we parametrize τ_d^o with effective distance. This measure computes the least cost path to travel from origin to destination, taking the road network and the variation in road quality into account.

In order to compute effective distance, we first convert the national highway network into a graph. The graph consists of a series of nodes that are connected by arcs. In our case, a node is the most populous city in each district and an arc is the road that connects these cities. An arc is referred to as being GQ or non-GQ depending on whether it was completed in a specific year. Each road segment is assigned a cost:

$$\begin{aligned} \text{Effective Distance}_{n_2}^{n_1} &= \text{Road Distance}_{n_2}^{n_1} \text{ if GQ} = 0, \\ \text{Effective Distance}_{n_2}^{n_1} &= \alpha \text{Road Distance}_{n_2}^{n_1} \text{ if GQ } = 1, \end{aligned} \tag{16}$$

where n_1 and n_2 are nodes, and α indicates the effective distance of the GQ relative to stretches of road that are not GQ. We use a value of $\alpha = 0.52$, which is based on average speeds calculated by the World Bank.[15] We then use Dijkstra's shortest-path algorithm to construct a matrix of lowest-cost routes between all the districts for the years 2001 and 2006. The sets of bilateral effective distances in these two years are different since the algorithm internalizes the fact that traveling on a better quality road, that is completed stretches of the Golden Quadrilateral, is less costly.

14. A description of the production structure of the chemical industry in India can be found at http://smallb.in/sites/default/files/knowledge_base/reports/IndianChemicalIndustry.pdf.

15. The value of α is based on the fact that the average speed on a national highway is between 30 and 40 km/h according to World Bank (2002). By contrast, the average speed on the GQ is estimated to be around 75 km/h. This can be computed by calculating the predicted average speed while traveling from a random sample of origins to a random sample of destinations over GQ roads using Google Maps (see Alder 2017).

We take equation (15) to the data by regressing prices on our measures of effective distance. We use a flexible specification of effective distance in order to capture nonlinearities in transportation costs. Such a flexible specification is commonly used to estimate the parameters of trade models using gravity equations, such as in Eaton and Kortum (2002). We estimate equation (15) as follows:

$$\log p^{o}_{d,t}(j) = \sum_{\ell=1}^{10} \beta_{\ell} \mathbb{I}\{\text{Effective Distance}^{o}_{d,t} \in \text{decile } \ell\} + \sum_{o,t} \delta_{o,t} + \sum_{j,t} \alpha_{j,t} + \varepsilon^{o}_{d,t}(j), \tag{17}$$

where $p^{o}_{d}(j)$ is the weighted average of the prices paid by plants in district d in year t for the intermediate input j produced by a monopolist located in district o, $\mathbb{I}$ is an indicator function that takes value 1 if the condition within brackets is satisfied, $\delta_{o,\,t}$ are district of origin fixed effects that vary by year, $\alpha_{j,\,t}$ are product fixed effects that vary by year, and $\varepsilon^{o}_{d,t}(j)$ is the error term. The origin fixed effects control for local wages and the product fixed effects control for firm productivity. Note that origin and product fixed effects are time dependent, which implies that the identification comes from the cross-sectional variation. We estimate equation (17) at the district level instead of the state level, in order to exploit all possible variation in the data.[16]

Table 1 presents the results from estimating equation (17). Column (1) uses data from 2001 and 2006, whereas column (2) only uses data from 2006. We use column (1) as our baseline specification. In both cases, we find that prices increase significantly over long distances. For example, prices are 51% higher in the 10th decile than in the 1st decile. The 10th decile includes districts located more than 1,800 km away in effective distance, which is approximately the road distance from New York City to Des Moines, Iowa.

Although the overall pattern is that prices increase over long distances, the estimates are nonmonotonic over shorter distances. For example, in column (1), the coefficient associated with the third decile is 7 percentage points lower than the coefficient in the second decile. In order to avoid having nonmonotonic transportation costs in the model, we assume that the relationship between iceberg costs and effective distance is given by a discrete monotonically increasing cubic function $g(\text{Decile}^{o}_{d})$, where Decile^{o}_{d} indicates the corresponding decile between o and d. We first normalize iceberg costs in the first decile to 1. The resulting iceberg costs from the regression are

$$\hat{\tau}^{o}_{d} = e^{\hat{\beta}_{\text{Decile}^{o}_{d}}}. \tag{18}$$

16. In order to avoid noisy estimates, we clean the data in several dimensions. First, we exclude input items whose description refers to "other" or "nonelsewhere classified" products. Second, we exclude goods that are not consumed in at least five districts. Finally, we identify unit misreporting in several goods, which generates large jumps in prices. See the Online Appendix for more details.

TABLE 1. Impact of road distance and infrastructure quality on prices.

	2001 and 2006 (1)	2006 (2)	State FE (3)	Transport prices (4)	2006 (5)	2001 (6)
Dep. variable: All columns except 4: Log price at district of destination. Column (4): Log price of transportation cost.						
Effective distance 2nd decile	0.2855**	0.2429*	0.2771**	0.2675***		
	(0.1196)	(0.1440)	(0.1217)	(0.0719)		
Effective distance 3rd decile	0.2120*	0.1797	0.1368	0.5394***		
	(0.1168)	(0.1442)	(0.1229)	(0.0714)		
Effective distance 4th decile	0.0981	0.0618	0.0070	0.9513***		
	(0.1206)	(0.1554)	(0.1298)	(0.0662)		
Effective distance 5th decile	0.1305	0.0114	0.0980	1.1635***		
	(0.1351)	(0.1582)	(0.1418)	(0.0658)		
Effective distance 6th decile	0.3538***	0.3784**	0.3163**	1.2869***		
	(0.1320)	(0.1731)	(0.1394)	(0.0663)		
Effective distance 7th decile	0.3009**	0.1835	0.2884**	1.3895***		
	(0.1390)	(0.1747)	(0.1456)	(0.0663)		
Effective distance 8th decile	0.3491**	0.2615	0.3045*	1.4892***		
	(0.1510)	(0.1814)	(0.1597)	(0.0676)		
Effective distance 9th decile	0.2476*	0.3279*	0.2674*	1.6771***		
	(0.1485)	(0.1914)	(0.1599)	(0.0680)		
Effective distance 10th decile	0.5107***	0.5770***	0.5282***	1.9164***		
	(0.1439)	(0.1990)	(0.1608)	(0.0698)		
Log effective distance					0.0765***	
					(0.0293)	
Predicted price in 2001						0.7952*
						(0.4594)
Origin-year fixed effects	YES	YES	YES	–	YES	–
Product-year fixed effects	YES	YES	YES	–	YES	–
State-year fixed effects	–	–	YES	–	–	–
Origin fixed effects	–	–	–	YES	–	YES
Product fixed effects	–	–	–	–	–	YES
Observations	1,999	1,460	1,999	1,372	1,460	539
R-squared	0.87	0.86	0.87	0.82	0.86	0.88
Number of products	165	119	165	–	119	53
Number of origins	86	63	86	75	63	38
Number of destinations	367	338	367	319	338	171

Notes: Table 1 shows the results of the estimation of equation (17). The dependent variable is the log price at a destination of a product manufactured by a monopolist. The variable of interest is the effective distance between the district where the product is manufactured and the destination district. Effective distance is defined as the least cost path between both districts, taking into account road distance and infrastructure quality. Specifically, using the Golden Quadrilateral reduces effective distance by 48% relative to roads that are not part of the Golden Quadrilateral. The least cost path is computed by converting the road network into a graph and applying Dijkstra's algorithm. Columns (1) and (2) use our ASI-NSS data for 2001 & 2006 and 2006, respectively. Column (3) adds destination state fixed effects to the specification of column (1). The dependent variable of column (4) is the log price of shipping a container from origin to destination, according to GIR Logistics. Column (5) introduces effective distance linearly and estimates the regression with data of 2006, and column (6) compares the estimated prices in 2001 from column (5) to the actual prices in 2001. All pooled specifications include origin-year and product-year fixed effects. Robust standard errors are in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%.

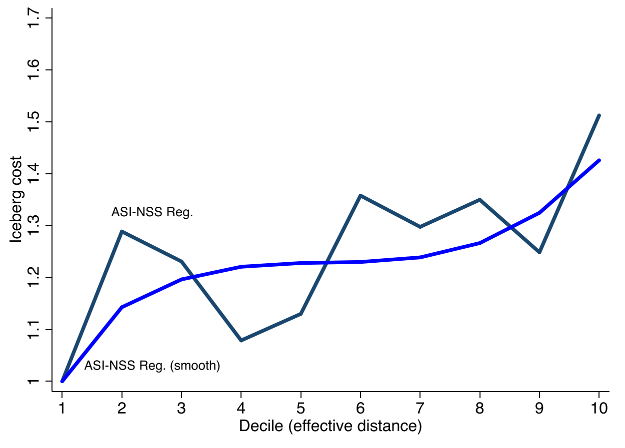


FIGURE 2. Smoothed iceberg costs using ASI-NSS. The figure shows the transportation costs implied by the estimated coefficients of column (1) of Table 1—"ASI-NSS Reg." and a monotonic cubic function that best fits the estimated coefficients—"ASI-NSS Reg. (smooth)". This is $g(x_d^o) = 0.9 + 0.176x_d^o - 0.0317(x_d^o)^2 + 0.002(x_d^o)^3$, where x_d^o is a discrete variable that indicates the decile of effective distance.

We then find the parameters of the cubic polynomial $g(\text{Decile}_d^o)$ that best fit the iceberg costs characterized by equation (18).

In Figure 2, we plot both sets of iceberg costs. The smoothed iceberg costs indicate that there are indeed significant nonconvexities with respect to effective distance. For example, we find that there is an initial sharp increase between deciles 1 and 2. Then, there is a subsequent flattening out starting in the third decile. Lastly, we see another large increase in deciles 9 and 10.

Panel (a) of Figure 3 shows a map of the transportation costs from the district of New Delhi (located in the National Capital Territory of Delhi). The legend on the map shows transportation costs divided into quartiles. The figure also shows that only a small portion of the GQ had been upgraded by this point (depicted in red). The first thing to notice is the concentric circles around New Delhi. This means that the further the destination, the higher the transportation costs. These circles also show that straight-line distances are highly correlated with the shortest path on the highway system. The reason is that the highway system is dense, as can be seen in Figure 1. Next, we look at transportation costs in the year 2006 (Panel (b) of Figure 3), after significant portions of the upgrade of the GQ had been completed. The color categories for the map have not changed compared to Panel (a), so that the colors are comparable across maps. The lighter colors reflect a general decrease in transportation costs.

6.2. *Possible Shortcomings and Additional Checks*

In this section, we discuss possible shortcomings of our methodology to measure transportation costs within India. In the cases in which it is feasible, we also assess whether these concerns may be empirically relevant in our case.

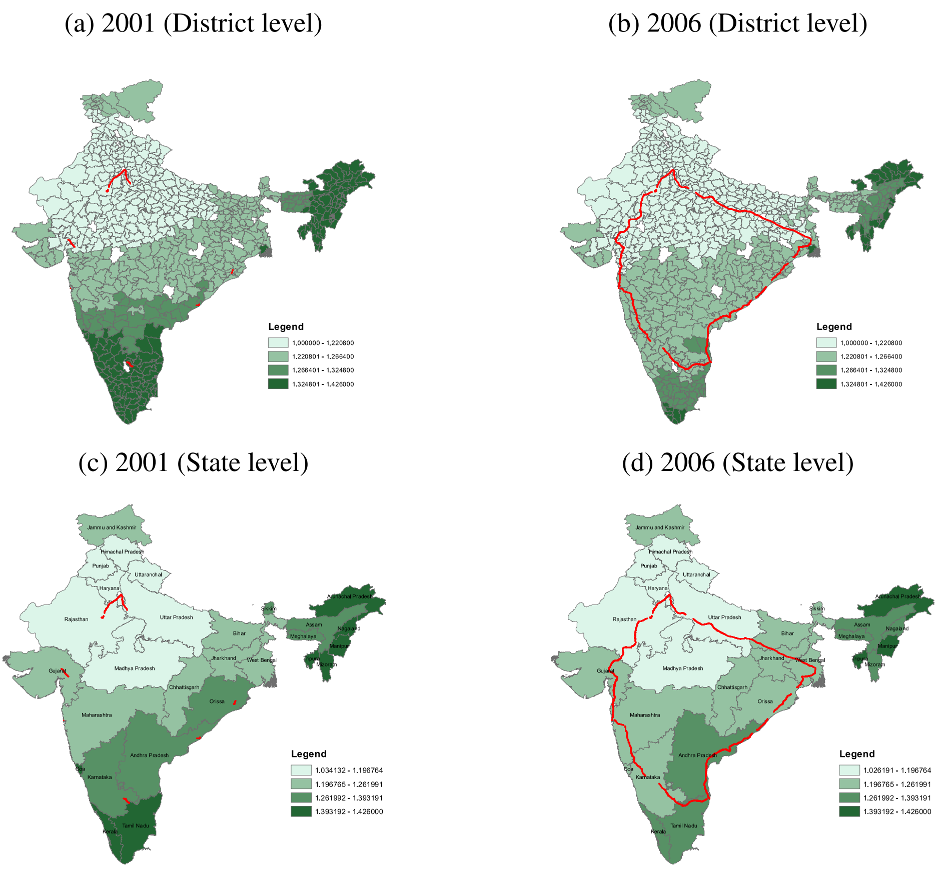


FIGURE 3. Estimated transportation costs from Delhi. Panel (a) shows the estimated transportation costs from Delhi at the district level for 2001; Panel (b) shows the estimated transportation costs from New Delhi at the district level for 2006; Panel (c) shows the estimated transportation costs from Delhi at the state level for 2001; Panel (d) shows the estimated transportation costs from Delhi at the state level for 2006. The transportation costs have been estimated as explained in Section 6.1.

Unobserved Variation in Product Quality. When estimating equation (17), it is important to consider whether there are unobserved factors that could be correlated with both distance and reported price. If monopolists in the data are concentrated in a few places, it could be the case that destination markets that are far away could have characteristics that generate higher/lower prices. For example, further destinations could be associated to higher quality products and hence higher prices that are unrelated to transportation costs.

For our specification, the ideal would be to have sellers (monopolist producers) and buyers (plants that report using a monopolist product) located in various parts of the country. Thus, the likelihood that there are unobservable characteristics systematically correlated with distance would be reduced. In Figure 4, we show a map of the location of all monopolist producers (Panel (a)) and the plants that utilize the products produced

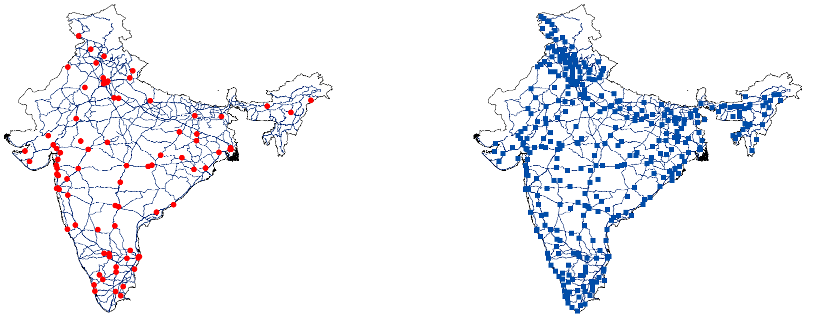


FIGURE 4. Road network in India and the GQ. Panel (a) shows the location of monopolist plants. Panel (b) shows the location of plants that report using a monopolist product.

by the monopolists (Panel (b)). Reassuringly, we find that they are highly spread out geographically. As an additional check, we estimate a specification in which we include per capita income and average compensation per employee as additional controls, none of which enter significantly into the estimation.

Spatial Price Gaps May Reflect Variation in Markups Even for Monopolists. A theoretical result that is crucial for our methodology is that markups charged by monopolists are constant across destinations. The CES preference structure implies that monopolists face the same demand elasticity across destinations independently on their marginal cost, which vary across destinations due to different transportation costs. However, it could be the case that markups depend on transportation costs. For example, consumers could have different elasticities at different levels of prices. In that case, our estimates would be biased. In particular, if monopolists charge higher markups in further destinations (the elasticity of demand is lower at higher prices), we would be overestimating the size of transportation costs. In contrast, if monopolists charge lower markups in more remote destinations (the elasticity of demand is higher at higher prices), we would be underestimating transportation costs. Atkin and Donaldson (2015) find evidence that is consistent with the latter in Ethiopia and Nigeria.

Lack of Direct Information on Origin-Destination. Given the structure of our model, we show that transportation costs are identified using monopolist price gaps across destinations. However, this result is only useful if we know the exact location of the seller (plant producing the product) and the buyer (plant using the product). Since we do not have plant-to-plant transaction data, we rely on the assumption that, once we identify that a product is produced by a monopolist in the data, it has necessarily to be the case that all plants using that product are buying it from the monopolist.

Imported Intermediate Inputs. A key consideration when estimating equation (8) is that we have identified plants that are monopolists. One potential source of competition is that of foreign plants. Thus, we check the robustness of our pricing regressions by excluding goods in districts where monopolist producers may face foreign competition. To do so, we use the fact that plants report domestic and foreign intermediate inputs separately. We exclude any observations in districts where imports account for more than 5% of total input usage. This corresponds to 11% of the good-district observations. Excluding these observations yields a very similar profile in the association between prices and effective distance. See Section C of the Online Appendix for more details.

Relying on a Few Set of Products. Our methodology crucially relies on goods that are produced by monopolists, which could be a problem if transportation costs are different for other goods in the economy. These differences may arise from differences in levels and differences in the elasticity of transportation costs with respect to distance. Since we include product fixed effects in equation (17), our estimates of β_ℓ inform us about the relationship between distance and transportation costs but do not reflect any differences in levels. As mentioned previously, we normalize all goods to have iceberg transportation costs of 1 in the first decile of effective distance, which means that we assume the lowest possible transportation cost when shipping to the closest location for all goods. A more problematic issue would be if the elasticity of transportation costs with respect to distance for goods produced by monopolists was different from that of other goods. If this slope is particularly steep for the goods we use in the estimation, we would be overestimating transportation costs at further distances. To the best of our knowledge, there is no evidence in the existing literature on across product/industry differences in how transportation costs increase with distance.

Internal Tariffs. A possible limitation of our methodology is the fact that we do not consider trade barriers across Indian regions that are different from transportation costs. If those additional trade barriers systematically correlate with our measures of effective distance then our estimates would be biased. There is indeed a number of regulations in India that make internal trade across regions costly. Perhaps the most striking ones are the entry taxes, which regulated at the state level and they act as internal trade tariffs. Crucially, these taxes do not have to be paid if goods only "transit" through the state.[17] However, it could still be the case that further destinations in our sample are systematically associated to states with higher/lower entry taxes. As we have shown in Figure 4, we use multiple origins and destinations in our analysis, which makes that possibility unlikely. To formally examine if this is the case, we have also estimated versions of equation (17) in which we control for state of destination fixed effects, which should capture any variation in prices paid at destination coming from differences in taxes across states. Column (3) in Table 1 shows the results, which

17. For instance, according to the *The West Bengal Tax on Entry of Goods into Local Areas Act, 2012*, "... no tax under this Act shall be levied, and accordingly the import value of goods shall not be included in turnover of imports of a dealer or an importer other than a dealer, in respect of entry of specified goods dispatched, at the time of entry into local area, directly to a place outside the State in the same form in which such goods have been entered into the local area".

confirm that our estimates remain virtually unchanged after controlling for state of destination fixed effects.

Comparison with Direct Measures of Transportation Prices. We have assembled an additional data set on transportation costs in India. The data contains prices charged by GIR Logistics, a large transportation logistics firm in India.[18] In particular, we have collected and digitized pricing quotes for transporting a shipping container of size 20 ft × 8 ft × 8.5 ft via truck for approximately 900,000 origin-destination city pairs in August 2014.

In order to compare the transportation costs implied by our estimates of equation (8) with those charged by GIR Logistics we proceed as follows. First, we construct prices at the district level by calculating the simple average across cities. We then select the same pairs of districts as those used in column (1) in order to make the two sets of transportation costs comparable. After that initial preparation of the data, we estimate the following regression:

$$\log p^{o}_{d,GIR} = \sum_{\ell=1}^{10} \beta_{\ell,GIR} \mathbb{I}\{\text{Effective Distance}^{o}_{d,2006} \in \text{decile } \ell\} + \sum_{o} \delta_{o,GIR} + \varepsilon^{o}_{d,GIR}, \tag{19}$$

where $p^{o}_{d,GIR}$ is the price charged by GIR Logistics to transport a container, $\delta_{o,GIR}$ is a set of origin fixed effects, and $\varepsilon^{o}_{d,GIR}$ is an error term. The results of this regression can be found in column (4) of Table 1.

Note that the estimates of $\beta_{\ell,GIR}$ cannot be compared to β_{ℓ} in columns (1)–(3). The coefficient $\beta_{\ell,GIR}$ measures changes in transportation prices, whereas β_{ℓ} measures changes in product prices at the destination. Thus, we convert the transportation costs estimated with the GIR Logistics data into iceberg costs. To do so, we use the following formula:

$$\tau^{o}_{d,GIR} = \frac{V + \hat{p}^{o}_{d,GIR}}{V}, \tag{20}$$

where $\tau^{o}_{d,GIR}$ is the implied iceberg cost using the GIR Logistics data, V is the value of shipments, and $\hat{p}^{o}_{d,GIR}$ is the transportation cost estimate from equation (19). It is important to note that V pins down the level of iceberg costs. For example, as the value of shipments increases, the level of implied iceberg costs declines.

We now want to find V in a way that makes it comparable to the ASI-NSS data. First, we pick a V and find $\tau^{o}_{d,GIR}$ for all deciles using equation (20). We then divide the iceberg costs of all deciles by the first one in order to normalize transportation costs. As mentioned previously, we have normalized the first decile of iceberg costs to one in our analysis. We then find V such that the average normalized iceberg costs across deciles is equal to that of the ASI-NSS data.

18. For details, see http://www.girlogistics.in/road-transportation.htm.

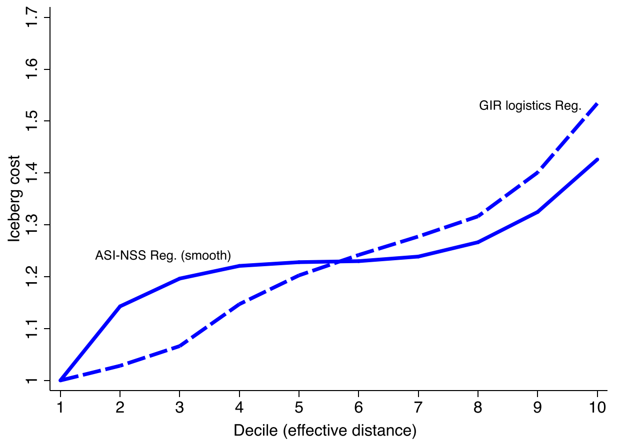


FIGURE 5. ASI-NSS versus GIR Logistics. Figure 5 compares the transportation costs estimated in our baseline case, "ASI-NSS Reg. (smooth)", with the ones estimated in column (3) of Table 1, which are labeled "GIR logistics Reg."

The results of this exercise can be found in Figure 5. In both cases, transportation costs increase more than linearly starting in deciles 7 and 8.

Predicted versus Actual Transportation Cost Estimates in 2001. We now investigate the ability of our empirical specification estimated using data from 2006 to predict transportation costs in 2001. We estimate equation (17) using log effective distance as the independent variable with data from the year 2006. The results of this estimation can be found in column (5) of Table 1. We then regress the observed prices in 2001 on the predicted prices from the previous regression. The results can be found in column (6). We find that the coefficient on the predicted price is 0.80, indicating that the empirical model has strong predictive powers.

State-Level Transportation Costs. It is necessary to aggregate the district-to-district transportation costs to the state level since the model that we simulate is based on interstate trade. We do so in two steps. In the first step, we choose a district and find the average transportation cost to a destination state. This process yields district-to-state transportation costs. In the second step, we obtain the state-to-state transportation costs by finding the average over districts in the origin state. All averages are weighted by population.

In Figure 3, we map transportation costs from the National Capital Territory of Delhi. Panel (c) shows transportation costs in 2001 where the legend colors reflect the quartile of each destination state. Panel (d) shows transportation costs in 2006. We hold the legend categories fixed so that the maps are comparable. The lighter colors in 2006 reflect declines in transportation costs from the GQ. Figure 6 shows the percentage

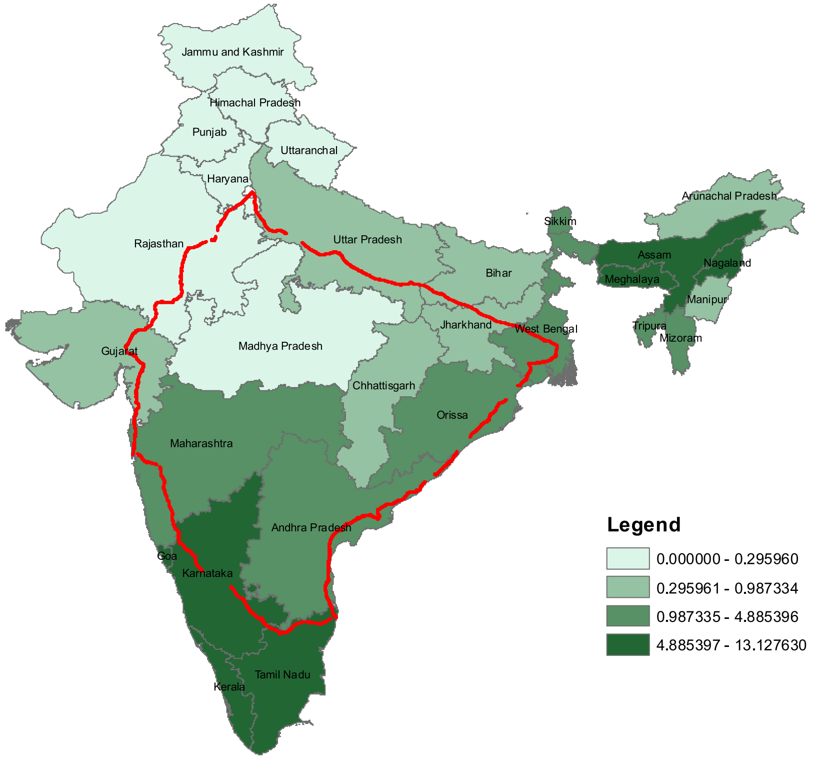


FIGURE 6. Percentage decline in transportation costs from Delhi. The figure shows the percentage decline in transportation costs from Delhi due to the construction of the GQ at the state level.

decline in these transportation costs. States in the quartile with the largest declines tend to be far from Delhi and in a location that can utilize the GQ for transportation between these locations. The states in the top quartile benefit from a decline of 4.9 to 13.1% in transportation costs. For the bottom quartile, this figure ranges from 0 to 0.3%.

6.3. Estimating the Across-Sector Elasticity of Substitution (θ)

The next step consists in estimating the elasticity of substitution across sectors. The identification strategy is to compare the differences in the transportation costs of the goods produced by monopolists across destinations with the trade flows across these destinations. This strategy is similar to that used by Donaldson (2018).

Formally, we derive a gravity equation implied by the model for the trade flows of monopolists. Combining equations (4) and (15), we derive the following condition for the trade flow values:

$$\log c_d^o(j,k)\,p_d^o(j,k) = (1-\theta)\log W_o + (\theta-1)\log a_o(j,k) + \log P_d^{\theta} Y_d + (1-\theta)\log \tau_d^o + (1-\theta)\log \frac{\theta-1}{\theta}. \quad (21)$$

The model predicts that higher transportation costs reduce trade flows, and the strength of this relationship depends on the value of θ. The intuition behind this identification strategy is that if small differences in transportation costs across destinations are associated with big differences in trade flows, then the value of θ must be high (and vice versa). It is also important to note that this straightforward relationship only holds when firms are monopolists.

We estimate equation (21) as follows:

$$\log \mathrm{Sales}_{d,t}^o(j,k) = \zeta \log \hat{\tau}_{d,t}^o + \sum_{o,t}\delta_{o,t} + \sum_{j,t}\alpha_{j,t} + \sum_{d,t}\lambda_{d,t} + \varepsilon_{d,t}^o(j,k) \quad (22)$$

where $\mathrm{Sales}_{d,t}^o(j,k)$ is the value of sales of product j in year t consumed in district d and produced by a monopolist located in district o, $\hat{\tau}_{d,t}^o$ is the predicted iceberg transportation cost found in Section 6.1, $\delta_{o,\,t}$ are district of origin dummies that vary by year, $\alpha_{j,\,t}$ are product dummies that vary by year, $\lambda_{d,\,t}$ are district of destination dummies that vary by year, and $\varepsilon_{d,t}^o(j,k)$ is the error term. The origin dummies control for local wages. The product dummies control for firm productivity. The destination dummies control for market size and aggregate prices at the destination. As in Section 6.1, this specification uses cross-sectional variation to identify parameters. Furthermore, we estimate it at the district level in order to fully exploit the variation in the data.

Table 2 presents the results of estimating equation (22). Columns (1)–(3) show the coefficient associated with the predicted transportation costs constructed from the coefficients of columns (1)–(3) of Table 1, respectively. We find that higher transportation costs are associated with lower trade flows at statistically significant levels. Our estimates range from 0.78 to 0.99. Thus, a 10% increase in transportation costs is associated to a 8%–10% decrease in trade flows. In column (4) we assume that all variation in transportation infrastructure are translated into prices, which means introducing effective distance directly into equation (22). We find that a 10% increase in transportation costs is associated to a 2% decrease in trade flows. Given these estimates, we take a value of 1.99 for θ as a benchmark, which is the most conservative one in terms of its implications for the size of allocative efficiency gains.[19]

19. We also assessed the sensitivity of the these results to different market share thresholds for the identification of monopolistic producers. We found that restricting to producers with market shares between 90% and 94% would yield an across-sector elasticity of substitution ranging from 1.86 to 1.99. Threshold levels above 95% produced lower elasticities (of around 1.35) and less precise estimates.

TABLE 2. Gravity equations for monopolists.

	ASI-NSS years 2001 and 2006 (1)	ASI-NSS year 2006 (2)	State FE in first stage (3)	Transport costs as effective distance (4)
Dep. variable: Log value of sales at district of destination				
$\log \tau_d^o$	−0.9917*	−0.8378	−0.7772	−0.2085***
	(0.5821)	(0.5588)	(0.5359)	(0.0647)
Origin-year fixed effects	YES	YES	YES	YES
Destination-year fixed effects	YES	YES	YES	YES
Product-year fixed effects	YES	YES	YES	YES
Observations	1,999	1,460	1,999	1,999
R-squared	0.58	0.54	0.59	0.59
Number of origins	86	63	86	86
Number of destinations	367	338	367	367
Number of products	165	119	165	165

Notes: Table 2 shows the estimates of equation (22). The dependent variable is the log value of sales at the destination of products manufactured by monopolists. The variable of interest is the predicted values of equation (17), namely, the predicted transportation costs across districts. In columns (1)–(3) the predicted transportation costs are those derived from columns (1)–(3) of Table 1, that is, $\log \hat{\tau}_{d,t}^o = \hat{\beta}_k$ if Effective Distance$_{d,t}^o \in$ decile k. In column (4) we assume the functional form $\log \hat{\tau}_{d,t}^o = \hat{\beta}$Effective Distance$_{d,t}^o$, and impose $\beta = 1$. Hence, we include effective distance directly as a covariate in equation (22). This amounts to assuming that the differences in effective distance (transportation infrastructure) fully translate into prices. All specifications include origin-year, destination-year, and product-year fixed effects. Robust standard errors are in parentheses. *Significant at 10%; ***significant at 1%.

6.4. *Estimating the Within-Sector Elasticity of Substitution (γ)*

We now estimate the within-sector elasticity of substitution. To do so, we derive the following condition from the model between a firm's labor share and its sectoral share for a given destination:

$$\frac{W_o l_d^o(j,k)}{\tilde{p}_d^o(j,k) c_d^o(j,k)} = 1 - \frac{1}{\gamma} - \left(\frac{1}{\theta} - \frac{1}{\gamma}\right) \omega_d^o(j,k), \tag{23}$$

where $\tilde{p}_d^o(j,k)$ is the factory gate price of the good. This condition implies that firms with a higher sectoral share at a destination have a lower labor share. The reason is that firms with higher sectoral shares charge higher markups, which result in lower labor shares. See the Online Appendix for more details.

In the data, we do not observe the market shares of firms by destination. However, a similar condition can be derived for goods that are only produced in one state. The reason is that in these sectors, the market shares of firms are constant across destinations. Empirically, we find that approximately 12% of goods are produced only in one state. Using data from these plants producing these products, we estimate

TABLE 3. Labor shares versus sectoral shares.

	2001–2006		2006	
	Labor (1)	Capital + labor (2)	Labor (3)	Capital + labor (4)
Dep. variable: Share in firm's value added				
Firm's sectoral share	−0.3407***	−0.4633***	−0.4088***	−0.4932***
	(0.076)	(0.0937)	(0.0941)	(0.1058)
State-year fixed effects	YES	YES	YES	YES
Product-year fixed effects	YES	YES	YES	YES
Observations	2,257	1,510	1,166	1,008
R-squared	0.86	0.88	0.87	0.89

Notes: Table 3 shows the estimates of an OLS regression of firms' labor shares against sectoral shares (equation (24)) for products (measured at the ASICC 5-digit level) that are operated only in one state. Column (1) shows the results including the pool of observations for the years 2001 and 2006. Column (2) shows the results for the same regression but includes capital remuneration on the left hand side. Columns (3) and (4) are the equivalent but include only observations for the year 2006. The implied γs in columns (1)–(4), which are given by $\gamma = \hat{\theta}/(1+\hat{\beta}\hat{\theta})$ (with $\hat{\theta} = 1.99$), are 6.17, 25.30, 10.67, 107.38, respectively. Robust standard errors are in parentheses. ***Significant at 1%.

equation (23) as follows:

$$LS_{o,t}(j,k) = \beta\omega_t^o(j,k) + \sum_{o,t}\delta_{o,t} + \sum_{j,t}\alpha_{j,t} + \varepsilon_t^o(j,k), \tag{24}$$

where $LS_{o,t}(j,k)$ and $\omega_t^o(j,k)$ are the labor and sectoral shares respectively in state o, $\delta_{o,t}$ are district of origin dummies that vary by year, $\alpha_{j,t}$ are product dummies that vary by year, and $\varepsilon_t^o(j,k)$ is the error term. Note that γ will be given by $\hat{\theta}/(1+\hat{\beta}\hat{\theta})$. In contrast to the estimation of transportation costs and the elasticity of substitution across sectors, we estimate equation (24) at the state level in order to maximize the number of products produced in one location.

We present the results in Table 3. Columns (1) and (3) show the results when we include only labor remuneration on the left-hand side of the equation, whereas in columns (2) and (4) we also include capital remuneration on the left-hand side of the equation. This second type of specification controls for across-firm variations in capital intensity. In columns (1) and (2), we include the pool of observations for the years 2001 and 2006, and control for time-variant state and product fixed effects. In columns (3) and (4), we only include observations for the year 2006.

We find a strong correlation between the labor shares and sectoral shares of firms in the data. The point estimates are similar in magnitude across the four specifications, ranging from −0.34 to −0.49. The implied values for γ in columns (1)–(4) are 6.17, 25.30, 10.67, and 107.38, respectively. Note that small changes in β can lead to large changes in γ, given the functional form that relates these two variables. We choose 10.67 as a benchmark, since it is the closest to the value used by Atkeson and Burstein (2008) and Edmond et al. (2015).

6.5. *Calibrating the Remaining Parameters*

Labor Endowment. In order to measure differences in economic size across states, we compute total value added in manufacturing for each state. To that end, we first compute value added for each plant in our sample by subtracting expenditure in intermediate goods and materials from sales. We then aggregate it up at the level of state using the provided sampling weights. We find large differences in economic size across states. For example, Maharashtra (the largest state) accounts for 23% of Indian manufacturing value added, whereas Arunachal Pradesh (the smallest state) accounts for only 0.01%. In order to capture these differences in the model, we first normalize the labor endowment of Arunachal Pradesh to 1. We then set the labor endowments of each state, L_n, so that the model matches the ratio of manufacturing value added observed in the data across states. Note that in the model the total value added of a state n is defined by $W_n L_n + \Pi_n$ and that the equilibrium value added of state n is positively related to L_n. Note also that in the baseline version of the model, we do not consider productivity differences across states. Thus, a large state could correspond to a state with a high L_n and low average productivity or, alternatively, a state with a low L_n but high average productivity. These productivity differences could be incorporated by assuming that there is a state-specific component in firms' productivity. In Section 9, we show that including a state-specific productivity component would affect the distribution of wages across states but would not affect our quantitative results given that the distribution of markups does not change.

Number of Producers by State and Sector. The number of firms that operate in each state is important to determine the nature of gains from lower transportation costs. To illustrate this idea, consider a two-state example in which these two states go from autarky to trading with each other. If firms in these two states produce in entirely different sectors, the effects from trade will be purely Ricardian since markups will remain unchanged. However, if the two states produce goods in the same sectors, then there may be effects on allocative efficiency.

We set the number of firms in sector j of state n, K_{nj}, to match the number of plants observed in the data. Since there are no fixed costs in the model, firms always choose to operate. Thus, there is no entry and exit of firms after changes in transportation costs. Abstracting from firm entry and exit in these kinds of models does not affect the final results quantitatively, as discussed by Atkeson and Burstein (2008) and Edmond et al. (2015). The reason is that a reduction in transportation costs leads to the entry and exit of low-productivity firms, which do not significantly affect the markups that large firms charge. Furthermore, the data does not show significant changes in the number of firms operating in each state. For example, the autocorrelation of the number of producers per sector-state between 2001 and 2006 is 0.98. We did not see large changes in the number of active sectors either (average change of 3%), or in the total number of firms (average change of 2%) by state over this period.

Finally, in order to reduce the computational burden, we limit the number of firms operating in each sector of a state to 50. This means that we set the maximum number of producers per sector to 1,450 (29 × 50). In the data, there are 129,514 sector-state combinations. There are more than 50 firms operating in approximately 5,000 of these combinations. This means that the restriction is binding in around 4% of the cases.

Productivity Distribution. We use a Pareto distribution for the productivity draws. The tail parameter, α, is calibrated in equilibrium to match the fact that the top 5% of firms in manufacturing value added account for 89% of value added. In the sensitivity analysis (Section 9), we discuss the inclusion of cross-state heterogeneity in productivity.

Within-Sector Productivity Across States. The correlation of firm productivity draws across states is important to determine the size of allocative efficiency gains. The reason is that if firms across states have a similar productivity, then there is a high degree of head-to-head competition. Thus, lowering transportation costs will have a larger impact on the distribution of markups.

We assume that firms across states have perfectly correlated productivity draws. To implement this, we first find the maximum number of plants present in any state for each sector. We make this number of draws from a Pareto distribution. We then sort the productivities in descending order. If a state has one firm, we select the first productivity on the sorted list. If a state has ten firms, we select the first ten productivities on the sorted list. This setup ensures that the firms with the highest productivity face head-to-head competition. Note that this does not imply that the sectors are symmetric across states. The reason is that states have a different number of operating firms. Furthermore, states have different wages and transportation costs, which affect their marginal cost.

It is important to determine whether the model generates reasonable levels of head-to-head competition given the assumption of perfectly correlated productivity draws. We create a "similarity" index that measures the similarity in size among the largest firms across states. We focus on the largest firms since they are the ones that drive most of the dispersion in markups as we will show in Section 7. To calculate the index, for each sector and state we identify the firm with the largest value added. Then, we regress the log of the value added of these firms on sector dummies. The R squared of that regression, which we use as our index, indicates the extent to which large firms in each sector are of similar size. For example, an R squared of one indicates that the largest firms across states are exactly the same size. We find an index of 0.45 in the data and 0.51 in the model. A similar picture emerges when we use employment as a measure of firm size. In that case, we find a similarity index of 0.43 in the data and 0.46 in the model. This exercise indicates that the model generates levels of head-to-head competition that are in line with the data.

Furthermore, we can check whether the trade elasticity implied by the model is consistent with other estimates in the literature. More head-to-head competition implies a larger trade elasticity. The reason is that when producers in different locations have similar levels of productivity, small changes in trade costs have larger effects on trade flows between states. We calculate the trade elasticity implied by our model by estimating the following regression:

$$S_d^o = \sigma \log \tau_d^o + \sum_o \delta_o + \sum_d \lambda_d + \varepsilon_d^o, \tag{25}$$

where S_d^o is the bilateral trade from state o to d, σ is the trade elasticity, δ_o is a set of state-origin fixed effects, and λ_d is a set of state-destination fixed effects. The trade elasticity implied by our model is 4.71, which is similar to recent estimates found in the literature. For example, Head and Mayer (2014, chap. 3) carry out a meta-analysis of empirical estimates of trade elasticity and find a median estimate of 5.03. We will show in the sensitivity analysis that the case of noncorrelated draws cannot match the data in the two dimensions listed previously.

6.6. Discussion of Markups

Distribution of Markups Faced by Consumers. Table 4 summarizes the distribution of markups charged to consumers in each state. We find an average markup of 1.11 in all destinations, which is very close to the lowest possible markup of $\gamma/(\gamma - 1)$. Furthermore, our results indicate that the bulk of firms do not have enough market shares to charge significantly higher markups. For example, even in the 95th percentile of the markup distribution, we do not see a large increase in the minimum markup. Markups become significantly larger in the 99th percentile, which ranges from 1.26 to 1.29 across states. There are two ingredients in the model that can explain this markup distribution. First, we use a Pareto distribution for productivity draws. Second, the model implies a convex relationship between sectoral shares and markups. Thus, the few firms with large market shares also have the high markups.

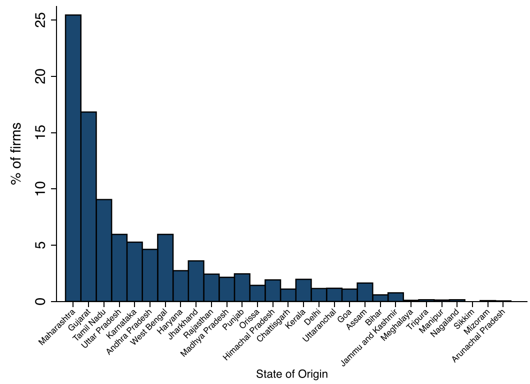
Markups Compared to Empirical Studies. Empirical studies in industrial organization find that the bulk of firms have modest markups and that a minority of firms have markups that are significantly higher. For example, De Loecker et al. (2016) estimate the median markup by sector. They use the Prowess data set that covers medium to large Indian firms. The authors find a median markup of 1.18 across sectors. They also find a mean markup of 2.24 across sectors indicating a skewness in the right tail of the markup distribution. De Loecker and Warzynski (2012) find similar results using data from Slovenian manufacturing. They find a median markup of 1.17–1.28 across sectors depending on the specification. Furthermore, they find a standard deviation of 0.50 across all specifications, also implying a skewness in the right tail of the distribution.

Our calibrated model matches the fact that most firms have small markups and that a few firms have very large markups. On the other hand, our model does not quantitatively capture the high end of the markup distribution found in these empirical studies. For example, the highest possible markup that firms can charge in the model is $\theta/(\theta - 1)$ or 2.01. In Section 9, we perform a sensitivity analysis by lowering θ to allow for higher markups.

TABLE 4. Markups in the model.

State	std			Mean			p95			p99			log p99/p50		
	Before	After	% Change	Before	After	% Change	Before	After	% Change	Before	After	% Change	Before	After	% Change
Maharashtra	0.0464	0.0459	−1.1639	1.1104	1.1104	−0.0028	1.125	1.126	0.080	1.295	1.288	−0.521	0.160	0.155	−3.310
Gujarat	0.0458	0.0453	−1.1025	1.1104	1.1104	−0.0026	1.126	1.127	0.070	1.289	1.283	−0.419	0.155	0.151	−2.736
Tamil Nadu	0.0457	0.0451	−1.2421	1.1104	1.1104	−0.0029	1.126	1.127	0.124	1.287	1.279	−0.587	0.154	0.148	−3.891
Uttar Pradesh	0.0442	0.0440	−0.5686	1.1103	1.1103	−0.0013	1.130	1.131	0.071	1.266	1.263	−0.305	0.138	0.135	−2.243
Karnataka	0.0451	0.0445	−1.3377	1.1104	1.1103	−0.0032	1.127	1.129	0.176	1.275	1.268	−0.564	0.145	0.139	−3.980
Andhra Pradesh	0.0444	0.0441	−0.5885	1.1103	1.1103	−0.0014	1.130	1.130	0.062	1.265	1.262	−0.248	0.137	0.135	−1.826
West Bengal	0.0441	0.0442	0.2096	1.1103	1.1103	0.0005	1.130	1.131	0.013	1.267	1.267	0.062	0.138	0.139	0.452
Haryana	0.0441	0.0438	−0.7157	1.1103	1.1103	−0.0016	1.131	1.132	0.093	1.263	1.259	−0.291	0.135	0.132	−2.185
Jharkhand	0.0440	0.0441	0.1581	1.1103	1.1103	0.0004	1.132	1.131	−0.083	1.263	1.265	0.150	0.135	0.137	1.102
Rajasthan	0.0440	0.0439	−0.3427	1.1103	1.1103	−0.0008	1.131	1.131	0.037	1.262	1.261	−0.077	0.134	0.133	−0.577
Madhya Pradesh	0.0438	0.0437	−0.2209	1.1103	1.1103	−0.0005	1.131	1.132	0.031	1.260	1.259	−0.087	0.133	0.132	−0.658
Punjab	0.0439	0.0438	−0.3358	1.1103	1.1103	−0.0008	1.131	1.132	0.049	1.260	1.258	−0.118	0.132	0.131	−0.897
Orissa	0.0439	0.0437	−0.4190	1.1103	1.1103	−0.0010	1.131	1.132	0.059	1.261	1.259	−0.212	0.134	0.132	−1.596
Himachal Pradesh	0.0440	0.0440	−0.1741	1.1103	1.1103	−0.0004	1.131	1.131	0.005	1.262	1.261	−0.108	0.134	0.133	−0.809
Chattisgarh	0.0439	0.0439	−0.1612	1.1103	1.1103	−0.0004	1.131	1.131	0.015	1.262	1.261	−0.053	0.134	0.134	−0.393
Kerala	0.0445	0.0443	−0.4644	1.1103	1.1103	−0.0011	1.129	1.129	0.073	1.267	1.265	−0.174	0.138	0.136	−1.266
Delhi	0.0440	0.0436	−0.7594	1.1103	1.1103	−0.0017	1.131	1.132	0.086	1.260	1.257	−0.249	0.133	0.130	−1.893
Uttaranchal	0.0439	0.0437	−0.3371	1.1103	1.1103	−0.0008	1.132	1.132	0.057	1.260	1.258	−0.132	0.132	0.131	−1.001
Goa	0.0447	0.0448	0.3791	1.1103	1.1103	0.0008	1.128	1.128	0.009	1.269	1.272	0.249	0.140	0.142	1.767
Assam	0.0437	0.0435	−0.3640	1.1103	1.1103	−0.0009	1.132	1.132	0.070	1.261	1.258	−0.223	0.133	0.131	−1.686
Bihar	0.0435	0.0439	0.9613	1.1103	1.1103	0.0022	1.133	1.132	−0.126	1.257	1.264	0.589	0.130	0.136	4.434
Jammu & Kashmir	0.0435	0.0436	0.2252	1.1103	1.1103	0.0005	1.133	1.133	−0.024	1.257	1.257	0.013	0.130	0.130	0.100
Meghalaya	0.0436	0.0434	−0.4313	1.1103	1.1103	−0.0010	1.132	1.133	0.087	1.259	1.256	−0.227	0.132	0.129	−1.742
Tripura	0.0435	0.0434	−0.1592	1.1103	1.1103	−0.0004	1.133	1.133	0.035	1.258	1.256	−0.095	0.131	0.130	−0.732
Manipur	0.0435	0.0434	−0.1399	1.1103	1.1103	−0.0003	1.133	1.133	0.027	1.258	1.256	−0.104	0.131	0.130	−0.801
Nagaland	0.0435	0.0434	−0.2546	1.1103	1.1103	−0.0006	1.132	1.133	0.040	1.258	1.256	−0.160	0.131	0.130	−1.231
Sikkim	0.0434	0.0435	0.0990	1.1103	1.1103	0.0002	1.133	1.133	0.012	1.256	1.256	−0.011	0.129	0.129	−0.089
Mizoram	0.0434	0.0434	−0.1368	1.1103	1.1103	−0.0003	1.133	1.133	0.028	1.257	1.256	−0.071	0.130	0.130	−0.543
Arunachal Pradesh	0.0435	0.0434	−0.1188	1.1103	1.1103	−0.0003	1.133	1.133	0.035	1.257	1.256	−0.086	0.131	0.130	−0.662

(a) Firms selling to Arunachal Pradesh



(b) Firms selling to Maharashtra

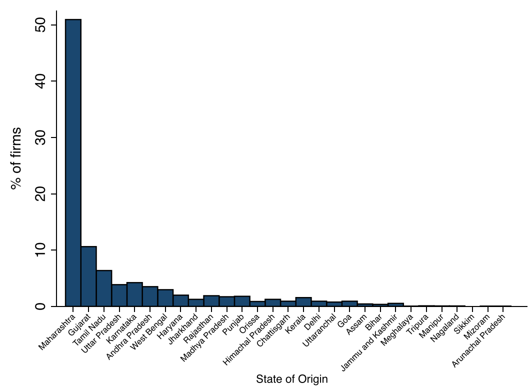


FIGURE 7. Spatial distribution of the top 1% firms in terms of markups (Model). The figure shows the distribution of states in which the top 1% of firms in terms of markups operate. Panel (a) refers to the markups charged on goods sold in Arunachal Pradesh. Panel (b) refers to the markups charged on goods sold in Maharashtra.

Where are the High Markup Firms Located? An important dimension of the markup distribution is related to the location of firms. In the model, firms located in large states have lower marginal costs because of lower wages. For example, the 5 largest states have an average wage of 0.45, where we have normalized the wage of the smallest state to 1. States ranked 10–20 and 25–29 in size have an average wage of 0.51 and 0.83, respectively. As a result, firms located in large states tend to have a cost advantage and thus charge higher markups. Another implication is that large states have lower levels of allocative efficiency. The reason is that, again, the local firms can charge relatively high markups. The allocative efficiency index from equation (14) indicates a loss in welfare of 2%–3% across states due to a dispersion in markups, with the low states having the highest losses due to poor allocative efficiency.

Figure 7 shows the location of the firms whose markups on goods purchased in Arunachal Pradesh (the smallest state) and Maharashtra (the largest state) are in the

TABLE 5. Parameter values (benchmark calibration).

Parameter	Definition	Value
(A) Parameters estimated with structural equations		
τ_d^o	Iceberg transportation costs between states	Varies by state pair
θ	Elasticity of substitution across sectors	1.99
γ	Elasticity of substitution within sector	10.67
(B) Parameters taken directly from data		
K_{ij}	Number of firms operating in sector j of country i	Varies by state/sector
(C) Parameters calibrated in equilibrium		
L_i	Labor endowment of the states	Varies by state
α	Shape parameter Pareto	2.28

Notes: Table 5 refers to a our benchmark calibration. We explain how we estimate the parameters τ_d^o, θ, and γ in Sections 6.1, 6.3, and 6.4, respectively. We set the value K_{ij} to match the number of plants observed in the data. We calibrate L_n to the relative manufacturing value added across states. We calibrate α to match the fact that the top 5% of plants in manufacturing accounted for 89% of value added in 2006 (see Section 6.5 for details).

top 1%. Note that the state of origin is ranked from largest to smallest. We see that, in both cases, firms with the highest markups are primarily located in Maharashtra and other big states where wages tend to be lower. For instance, around 50% of the firms charging the markups in the top 1% in the market of Maharashtra are local firms.

7. Quantifying the Impact of the GQ

In this section, we quantify the aggregate and state-level effects of the construction of the GQ on the Indian manufacturing sector. To this end, we compare the outcomes from our calibrated model in 2006 with the outcomes when we remove the GQ. To remove the GQ, we use the estimates from Section 6.1 to determine the changes in transportation costs. For illustrative purposes, we present all the results as changes from before to after the construction of the GQ (2001–2006).

In order to quantify the effects of the GQ, we begin with our baseline calibration described in Table 5. We then feed the iceberg transportation costs in 2001 into the calibrated model. To estimate these transportation costs, we first find the new effective distance between districts in 2001 by recomputing the shortest path between them taking into account the road network at the time. We use these effective distances, along with estimates from equation (17), to find the new iceberg transportation costs. Finally, we re-aggregate the district-to-district transportation costs to state-to-state transportation costs as described in Section 6.3.

7.1. Welfare Changes

First, we consider the aggregate change in real income resulting from the GQ. We find that real income increased by 2.72% as shown in Table 6. In our quantitative exercise,

TABLE 6. Changes in real income resulting from the GQ.

State	Size	Income change	Decomposition			
			η_w	$\eta_{P_{pc}}$	η_{ToT}	η_{ae}
India		2.72	2.10	0.44	0.00	0.20
Maharashtra	100.00	1.78	1.67	−0.36	0.15	0.32
Gujarat	64.58	3.05	2.34	0.30	0.05	0.37
Tamil Nadu	40.74	2.43	2.07	−0.02	0.06	0.31
Uttar Pradesh	28.81	2.11	1.81	0.25	−0.08	0.12
Karnataka	25.99	4.07	2.76	0.96	0.11	0.23
Andhra Pradesh	20.20	1.92	1.64	0.19	−0.01	0.10
Haryana	18.04	1.27	1.43	−0.18	−0.07	0.10
West Bengal	17.80	6.88	4.15	3.29	−0.50	−0.06
Jharkhand	16.21	8.28	4.36	3.75	0.03	0.14
Rajasthan	11.96	3.62	2.49	1.26	−0.16	0.02
Madhya Pradesh	10.68	0.54	0.94	−0.42	−0.02	0.04
Orissa	10.02	3.36	2.30	0.94	0.01	0.11
Punjab	9.61	1.49	1.40	0.11	−0.06	0.04
Himachal Pradesh	8.97	1.44	1.50	0.12	−0.22	0.03
Chattisgarh	8.74	0.00	0.76	−0.70	−0.07	0.02
Kerala	6.98	1.81	1.48	0.22	0.01	0.10
Delhi	4.32	1.05	1.08	−0.25	0.12	0.09
Uttaranchal	4.32	1.67	1.48	0.20	−0.05	0.03
Assam	3.42	1.57	1.40	0.04	0.04	0.09
Goa	3.26	11.22	6.06	5.85	−0.44	−0.26
Bihar	2.47	7.25	4.23	3.98	−0.66	−0.30
Jammu & Kashmir	2.38	0.47	0.87	−0.18	−0.18	−0.04
Meghalaya	0.55	2.13	1.65	0.29	0.11	0.09
Tripura	0.24	−1.54	−0.19	−1.54	0.15	0.04
Manipur	0.11	−1.49	−0.21	−1.56	0.24	0.03
Nagaland	0.07	−0.62	0.21	−1.10	0.21	0.05
Sikkim	0.03	6.00	3.28	2.46	0.25	0.01
Mizoram	0.02	−1.11	0.16	−1.52	0.22	0.03
Arunachal Pradesh	0.01	−1.35	0.00	−1.68	0.31	0.02

Notes: Table 6 shows the percentage change in real income and the decomposition of the Holmes et al. (2014) index for the 29 Indian states; η_w represents the % change in labor income component of the index; $\eta_{P_{pc}}$ represents the % change in the *marginal cost price* component; η_{ToT} represents the % change in the *markups terms of trade* component; and η_{ae} represents the % change in the *allocative efficiency* component.

we only consider the manufacturing sector that had a value added of \$152.8 billion in 2006 (around 16% of Indian GDP). Thus, the static benefit from the GQ project is \$4.2 billion. Note that these static benefits accrue to the economy *each year*. At the same time, estimates indicate that the government spent approximately \$5.6 billion on this project. Thus, we find that the benefits over a two-year period exceed the initial construction costs. For context of the size of the gains in relation to the size of the national economy, we find that the gains comprise 0.44% (2.72% × 16%) of national income.

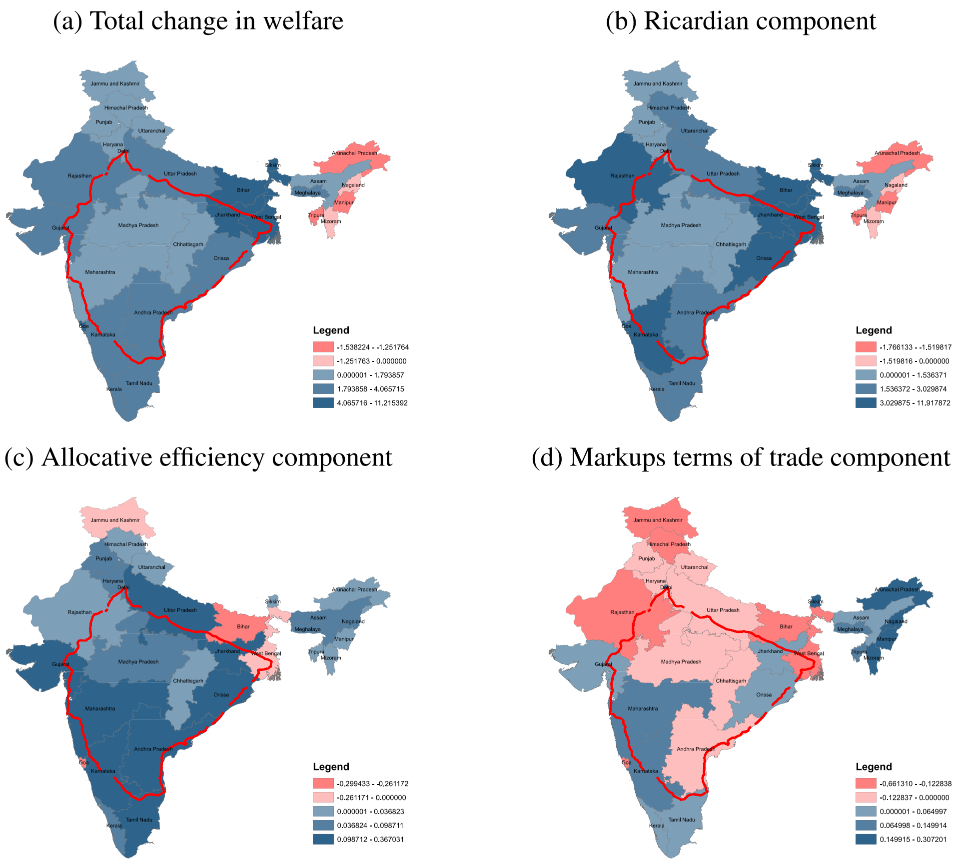


FIGURE 8. Percentage change in real income after GQ with HHL components. Panel (a) shows the percentage change in real income after the decrease in transportation costs due to the construction of the GQ; Panel (b) shows the Ricardian component of the change in welfare; Panel (c) shows the allocative efficiency component of the change in welfare; Panel (d) shows the markups terms of trade component of the change in welfare. The numbers represented in this map correspond to the ones presented in columns (2)–(6) of Table 6.

The welfare effects of the GQ are heterogeneous across states. Table 6 lists the welfare effects across states in descending order of size. Overall, large states have gained more from the reduction in transportation costs. Small states have seen modest gains and, in some cases, have even lost. This is driven by the fact that, due to its placement, the GQ has lowered transportation costs primarily for large states. Panel (a) of Figure 8 shows a map of the welfare effects across states. The map shows that most of the states that have lost are located in the Northeast, which are the states located farthest from the GQ. The states in the Northeast that have experienced losses include: Arunachal Pradesh, Manipur, Mizoram, Nagaland, and Tripura. Finally, the state of Chattisgarh has experienced a loss that is very close to zero.

TABLE 7. Quantitative results.

State	w_n		$\frac{1}{P_n^{pc}}$		$\frac{\mu_n^{sell}}{\mu_n^{buy}}$		$\frac{P_n^{pc}}{P_n}\mu_n^{buy}$	
	Before	After	Before	After	Before	After	Before	After
Maharashtra	0.4218	0.4289	0.0124	0.0123	1.0272	1.0288	0.9635	0.9666
Gujarat	0.4234	0.4334	0.0120	0.0120	1.0160	1.0165	0.9669	0.9705
Tamil Nadu	0.4414	0.4506	0.0117	0.0117	0.9986	0.9993	0.9698	0.9728
Uttar Pradesh	0.4740	0.4827	0.0116	0.0116	0.9986	0.9978	0.9770	0.9782
Karnataka	0.4664	0.4795	0.0116	0.0117	0.9847	0.9858	0.9750	0.9773
Andhra Pradesh	0.4946	0.5028	0.0115	0.0115	0.9892	0.9891	0.9783	0.9793
Haryana	0.4801	0.4870	0.0116	0.0116	0.9805	0.9798	0.9788	0.9798
West Bengal	0.4859	0.5065	0.0111	0.0115	0.9864	0.9815	0.9772	0.9766
Jharkhand	0.4038	0.4218	0.0113	0.0117	0.9957	0.9960	0.9764	0.9778
Rajasthan	0.5022	0.5149	0.0115	0.0116	0.9864	0.9849	0.9791	0.9793
Madhya Pradesh	0.5020	0.5068	0.0115	0.0115	0.9736	0.9734	0.9797	0.9801
Orissa	0.4702	0.4811	0.0113	0.0114	0.9756	0.9757	0.9792	0.9803
Punjab	0.5210	0.5284	0.0113	0.0113	0.9899	0.9893	0.9797	0.9801
Himachal Pradesh	0.4740	0.4812	0.0112	0.0112	0.9803	0.9782	0.9787	0.9790
Chattisgarh	0.4486	0.4520	0.0114	0.0113	0.9702	0.9695	0.9788	0.9790
Kerala	0.5346	0.5425	0.0111	0.0111	0.9855	0.9856	0.9778	0.9787
Delhi	0.5646	0.5708	0.0116	0.0116	0.9662	0.9674	0.9797	0.9806
Uttaranchal	0.5136	0.5213	0.0112	0.0112	0.9830	0.9826	0.9797	0.9801
Assam	0.5056	0.5127	0.0104	0.0104	0.9785	0.9789	0.9793	0.9801
Goa	0.5198	0.5523	0.0112	0.0119	0.9592	0.9549	0.9773	0.9748
Bihar	0.5318	0.5547	0.0110	0.0115	0.9708	0.9644	0.9806	0.9777
Jammu & Kashmir	0.5474	0.5521	0.0107	0.0107	0.9922	0.9904	0.9809	0.9805
Meghalaya	0.5229	0.5316	0.0104	0.0104	0.9274	0.9285	0.9803	0.9812
Tripura	0.6336	0.6324	0.0102	0.0100	0.9912	0.9927	0.9808	0.9812
Manipur	0.6954	0.6939	0.0102	0.0100	1.0202	1.0227	0.9808	0.9811
Nagaland	0.7332	0.7348	0.0102	0.0101	1.0130	1.0152	0.9807	0.9812
Sikkim	0.7562	0.7814	0.0106	0.0109	1.0078	1.0103	0.9810	0.9811
Mizoram	0.9670	0.9685	0.0101	0.0100	1.0892	1.0916	0.9808	0.9811
Arunachal Pradesh	1.0000	1.0000	0.0101	0.0099	1.1766	1.1803	0.9808	0.9811

Notes: Table 7 shows the level of the four different components of the Holmes et al. (2014) index for the 29 Indian states before and after the construction of the GQ; w_n is the wage (note that we have excluded labor endowment, which is constant); P_n^{pc} is the aggregate price index in state n if all firms charged marginal cost; μ_n^{buy} represents the aggregate markup charged on goods purchased in state n; μ_n^{sell} represents the aggregate markup charged on goods produced in state n; P_n is the aggregate price index in state n.

7.2. *Decomposition of Welfare Changes*

We use the Holmes et al. (2014) decomposition to break down the effect of the GQ on changes in real income into Ricardian, markups terms of trade, and allocative efficiency effects. Table 6 shows these components at the aggregate and state level. Table 7 shows the change in these three components and Figure 8 shows the geographical distribution across India.

7.2.1. Allocative Efficiency. We find that, for the manufacturing sector as a whole, the allocative efficiency component accounts for 7.4% of the gains (0.20% of the

2.72% total gains). Lower transportation costs have generally led to welfare-enhancing changes in markups since the allocative efficiency effects are positive in all but four states. This quantitative result is informative since theory is ambiguous as to whether declines in transportation costs lead to these types of gains. We find that these gains are concentrated in the largest states. The average gain in allocative efficiency is 0.27% for the five largest states and this number subsequently declines. The reason is that large states have low levels of allocative efficiency since local firms tend to have the highest markups.

We report the results from two sets of exercises that serve to disentangle whether improvements in allocative efficiency come from: (1) changing transportation costs, which are a direct effect of the GQ, or (2) changing wages, which are the result of general equilibrium effects. In the first exercise, we calculate the allocative efficiency index when we change transportation costs for only one bilateral pair of states, while holding all other transportation costs and wages fixed. Given the new transportation costs, we re-solve for the distribution of prices for all firms across destinations. This information allows us to recalculate the allocative efficiency index. Note that when we do this exercise, we do not re-solve all of the aggregate variables in the model, which would result in changing wages. Although this recomputed allocative efficiency index is not an equilibrium outcome, it is useful in order to disentangle the direct effect of changing transportation costs from the general equilibrium effects. The changes in allocative efficiency in this exercise are reported in Table 8. Each column indicates the state for which we report the percentage change in allocative efficiency and each row indicates the state for which we change the transportation costs. Consider the case of Chattisgarh, which is the median state in terms of size. The column for that state indicates positive effects from reducing transportation costs to all but four states. Thus, we find that transportation costs tend to have a positive effect. The reason is that local firms, which have relatively high markups, must lower their markups when transportation costs decline. One notable exception is the direct effect of Chattisgarh reducing transportation costs with Maharashtra. In this case, this direct effect of lowering transportation costs is negative. The reason is that firms located in Maharashtra have relatively high markups since wages in that state are low enough to compensate for transportation costs.

In the second exercise, we change wages in one state and hold all other wages and transportation costs fixed. The changes in allocative efficiency are reported in Table 9. Each row indicates the state for which we change wages and each column indicates the state for which we report the percentage change in allocative efficiency. It is important to note that wages rose for states close to the GQ. The reason is that the exports of these states became more competitive relative to other states. Thus, wages must rise in order to satisfy the balanced trade condition. As before, consider the case of Chattisgarh. Allocative efficiency rises if we let wages only in Chattisgarh rise since local firms, which have relatively high markups, lower their markups. If we inspect the rest of that column, we find that rising wages in other states negatively affects allocative efficiency in Chattisgarh. One exception is the increase in wages in Maharashtra, which improves allocative efficiency in Chattisgarh.

TABLE 8. Effects of a partial change in transportation costs.

	Arunachal Pradesh	Mizoram	Sikkim	Nagaland	Manipur	Tripura	Meghalaya	Jammu & Kashmir	Bihar	Assam	Goa	Uttaranchal	Delhi	Kerala
Arunachal Pradesh	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mizoram	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sikkim	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000	0.0000	0.0001	0.0006	0.0003	0.0000
Nagaland	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Manipur	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0000	0.0000	0.0000	0.0000	−0.0000	0.0000
Tripura	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
Meghalaya	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0004	0.0000
Jammu & Kashmir	0.0000	0.0000	0.0014	0.0000	0.0000	0.0000	0.0000	0.0000	0.0023	0.0002	0.0008	0.0000	0.0000	0.0000
Bihar	0.0001	0.0002	0.0001	0.0001	0.0002	0.0001	0.0001	0.0016	0.0000	0.0001	0.0023	0.0005	0.0003	0.0008
Assam	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0002	0.0000	0.0000	0.0026	0.0033	0.0000
Goa	0.0000	0.0000	0.0009	0.0000	0.0000	0.0000	0.0000	0.0018	0.0056	0.0000	0.0000	0.0079	0.0091	0.0003
Uttaranchal	0.0003	0.0000	0.0050	0.0006	0.0000	0.0002	0.0056	0.0000	0.0011	0.0039	0.0075	0.0000	0.0000	0.0008
Delhi	0.0010	0.0025	0.0040	0.0072	0.0009	0.0020	0.0087	0.0000	0.0011	0.0091	0.0089	0.0000	0.0000	0.0030
Kerala	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0057	0.0000	0.0008	0.0024	0.0093	0.0000
Chattisgarh	0.0005	0.0007	−0.0010	0.0011	0.0008	0.0007	−0.0003	0.0022	0.0013	0.0017	0.0075	0.0015	0.0004	0.0036
Himachal Pradesh	0.0000	0.0000	0.0115	0.0000	0.0000	0.0000	0.0054	0.0000	0.0053	0.0053	0.0141	0.0000	0.0000	0.0006
Orissa	0.0026	0.0044	0.0009	0.0040	0.0052	0.0046	0.0025	0.0051	0.0020	0.0040	0.0176	0.0074	0.0034	0.0163
Punjab	0.0000	0.0000	0.0146	0.0000	0.0000	0.0000	0.0129	0.0000	0.0051	0.0089	0.0164	0.0000	0.0000	0.0013
Madhya P.	0.0043	0.0063	0.0152	0.0100	0.0073	0.0065	0.0181	0.0013	0.0084	0.0164	0.0119	0.0007	0.0007	0.0066
Rajasthan	0.0012	0.0006	0.0146	0.0039	0.0006	0.0007	0.0178	0.0000	0.0044	0.0139	0.0225	0.0000	0.0000	0.0133
Jharkhand	−0.0090	−0.0205	−0.0032	−0.0206	−0.0152	−0.0142	−0.0087	−0.0091	−0.2947	−0.0096	0.0165	−0.0052	−0.0014	0.0070
Haryana	0.0028	0.0022	0.0134	0.0114	0.0012	0.0032	0.0224	0.0000	0.0038	0.0222	0.0532	0.0000	0.0000	0.0141
West Bengal	0.0007	0.0022	0.0003	0.0025	0.0011	0.0007	0.0007	0.0259	0.0165	0.0014	0.0255	0.0186	0.0055	0.0238
Andhra Pradesh	0.0005	0.0001	0.0282	0.0018	0.0000	0.0002	0.0109	0.0018	0.0232	0.0112	0.0110	0.0225	0.0193	0.0060
Karnataka	0.0000	0.0000	0.0214	0.0000	0.0000	0.0000	0.0000	0.0045	0.0408	0.0002	0.0462	0.0362	0.0423	0.0008
Uttar Pradesh	0.0114	0.0130	0.0028	0.0120	0.0133	0.0134	0.0000	0.0005	0.0093	0.0094	0.0706	0.0003	0.0002	0.0163
Tamil Nadu	0.0000	0.0000	0.0185	0.0000	0.0000	0.0000	0.0000	0.0000	0.0479	0.0017	0.0073	0.0174	0.0391	−0.0014
Gujarat	0.0000	0.0000	−0.0090	0.0000	0.0000	0.0000	−0.0076	−0.0323	0.0031	−0.0039	0.0523	−0.0089	−0.0080	0.0335
Maharashtra	−0.0029	−0.0004	−0.0623	−0.0050	0.0000	−0.0010	−0.0127	−0.0196	−0.0305	−0.0119	−0.4336	−0.0668	−0.0249	−0.0323
All states	0.0129	0.0105	−0.0226	0.0271	0.0148	0.0166	0.0617	−0.0318	−0.3333	0.0749	−0.2537	0.0296	0.0991	0.1152

	Chattisgarh	Himachal Pradesh	Orissa	Punjab	Madhya Pradesh	Rajasthan	Jharkhand	Haryana	West Bengal	Andhra Pradesh	Karnataka	Uttar Pradesh	Tamil Nadu	Gujarat	Maharashtra
Arunachal Pradesh	0.0000	0.0000	−0.0000	0.0000	−0.0000	0.0000	−0.0000	0.0000	0.0000	0.0000	0.0000	−0.0000	0.0000	0.0000	−0.0000
Mizoram	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
Sikkim	0.0002	0.0007	0.0001	0.0006	0.0006	0.0005	0.0000	0.0004	0.0000	0.0006	0.0004	0.0002	0.0003	0.0007	0.0006
Nagaland	0.0001	0.0000	0.0001	0.0000	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000
Manipur	−0.0000	0.0000	−0.0000	0.0000	−0.0001	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000	−0.0001	0.0000	0.0000	0.0000
Tripura	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
Meghalaya	0.0005	0.0002	0.0003	0.0002	0.0005	0.0003	0.0001	0.0004	0.0000	0.0001	0.0000	0.0005	0.0000	0.0002	0.0001
Jammu & Kashmir	0.0013	0.0000	0.0010	0.0000	0.0003	0.0000	0.0025	0.0000	0.0030	0.0001	0.0003	0.0003	0.0000	0.0015	0.0018
Bihar	0.0005	0.0012	0.0004	0.0008	0.0011	0.0006	0.0203	0.0004	0.0020	0.0013	0.0021	0.0038	0.0024	0.0022	0.0029
Assam	0.0034	0.0015	0.0021	0.0017	0.0041	0.0022	0.0012	0.0028	0.0004	0.0008	0.0000	0.0041	0.0002	0.0010	0.0008
Goa	0.0036	0.0063	0.0064	0.0073	0.0046	0.0078	0.0048	0.0090	0.0048	0.0014	0.0198	0.0076	0.0009	0.0047	0.0177
Uttaranchal	0.0024	0.0000	0.0036	0.0000	0.0002	0.0000	0.0015	0.0000	0.0037	0.0033	0.0050	0.0002	0.0017	0.0010	0.0048
Delhi	0.0009	0.0000	0.0024	0.0000	0.0004	0.0000	0.0009	0.0000	0.0015	0.0037	0.0064	0.0008	0.0044	0.0014	0.0026
Kerala	0.0067	0.0007	0.0166	0.0016	0.0074	0.0137	0.0120	0.0076	0.0126	0.0025	0.0007	0.0050	0.0005	0.0163	0.0046
Chattisgarh	0.0000	0.0029	−0.0000	0.0018	0.0001	0.0016	0.0008	0.0009	0.0016	0.0004	0.0026	0.0014	0.0069	0.0041	0.0032
Himachal Pradesh	0.0058	0.0000	0.0078	0.0000	0.0005	0.0000	0.0064	0.0000	0.0107	0.0055	0.0103	0.0002	0.0019	0.0025	0.0133
Orissa	0.0003	0.0080	0.0000	0.0068	0.0014	0.0069	0.0042	0.0050	0.0170	0.0055	0.0087	0.0036	0.0149	0.0083	0.0087
Punjab	0.0057	0.0000	0.0082	0.0000	0.0004	0.0000	0.0059	0.0000	0.0116	0.0071	0.0117	0.0003	0.0034	0.0022	0.0113
Madhya P.	0.0004	0.0008	0.0019	0.0004	0.0000	0.0028	0.0066	0.0006	0.0095	0.0032	0.0054	0.0151	0.0068	0.0042	0.0033
Rajasthan	0.0045	0.0000	0.0091	0.0000	0.0030	0.0000	0.0049	0.0001	0.0105	0.0123	0.0192	0.0029	0.0169	0.0294	0.0087
Jharkhand	−0.0013	−0.0035	−0.0098	−0.0049	−0.0052	−0.0013	0.0000	−0.0014	−0.3533	−0.0006	0.0102	−0.0140	0.0195	0.0212	0.0274
Haryana	0.0045	0.0000	0.0115	0.0000	0.0009	0.0001	0.0043	0.0000	0.0104	0.0187	0.0358	0.0016	0.0226	0.0051	0.0200
West Bengal	0.0044	0.0242	0.0362	0.0221	0.0164	0.0174	−0.0254	0.0103	0.0000	0.0148	0.0260	0.0115	0.0314	0.0303	0.0254
Andhra Pradesh	0.0023	0.0138	0.0110	0.0180	0.0071	0.0272	0.0125	0.0202	0.0167	0.0000	0.0064	0.0215	0.0289	0.0294	0.0084
Karnataka	0.0084	0.0303	0.0160	0.0344	0.0121	0.0447	0.0336	0.0426	0.0341	0.0043	0.0000	0.0388	0.0112	0.0353	0.0338
Uttar Pradesh	0.0054	0.0004	0.0087	0.0004	0.0156	0.0044	0.0246	0.0011	0.0129	0.0284	0.0481	0.0000	0.0376	0.0115	0.0330
Tamil Nadu	0.0147	0.0074	0.0130	0.0134	0.0166	0.0530	0.0444	0.0366	0.0444	−0.0007	0.0009	0.0405	0.0000	0.0640	0.0143
Gujarat	−0.0000	−0.0090	0.0152	−0.0079	−0.0088	−0.1185	0.0239	−0.0050	0.0382	0.0285	0.0369	0.0002	0.0792	0.0000	0.0923
Maharashtra	−0.0238	−0.0404	−0.0393	−0.0483	−0.0198	−0.0201	0.0214	−0.0228	0.0222	−0.0169	−0.0573	−0.0162	0.0022	0.0300	0.0000
All states	0.0473	0.0392	0.0992	0.0438	0.0560	0.0124	0.0598	0.1098	−0.1844	0.1251	0.2171	0.1322	0.3252	0.3399	0.3771

Notes: Table 8 shows the effect of partial changes in transportation costs on allocative efficiency across the different Indian states. In particular, the element shows the effect on allocative efficiency of state *j* of decreasing transportation costs between state *i* and *j* (according to the counterfactual transportation the GQ) and keeping the rest of transportation costs in the network unchanged.

TABLE 9. Effects of a partial change in wages costs.

	Aruchanal Pradesh	Mizoram	Sikkim	Nagaland	Manipur	Tripura	Meghalaya	Jammu & Kashmir	Bihar	Assam	Goa	Uttaranchal	Delhi	Kerala	Chattisgarh	Himachal Pradesh	Orissa	Punjab	Madhya Pradesh	Rajasthan	Jharkhand	Haryana	West Bengal	Andhra Pradesh	Karnataka	Uttar Pradesh	Tamil Nadu	Gujarat	Maharashtra	India
Arunachal Pradesh	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mizoram	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
Sikkim	−0.0004	−0.0004	−0.0004	−0.0004	−0.0004	−0.0004	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
Nagaland	−0.0000	−0.0000	−0.0000	−0.0001	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
Manipur	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	−0.0000	−0.0000	0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
Tripura	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Meghalaya	−0.0004	−0.0004	−0.0004	−0.0004	−0.0004	−0.0004	0.0035	−0.0001	−0.0004	−0.0007	−0.0001	−0.0001	−0.0001	−0.0001	−0.0003	−0.0001	−0.0002	−0.0001	−0.0002	−0.0001	−0.0003	−0.0001	−0.0004	−0.0001	−0.0001	−0.0002	−0.0001	−0.0001	−0.0001	−0.0002
Jammu & Kashmir	−0.0006	−0.0006	−0.0004	−0.0005	−0.0006	−0.0006	−0.0005	0.0040	−0.0006	−0.0005	−0.0003	−0.0009	−0.0006	−0.0003	−0.0005	−0.0013	−0.0003	−0.0011	−0.0006	−0.0007	−0.0005	−0.0007	−0.0005	−0.0003	−0.0003	−0.0007	−0.0003	−0.0007	−0.0004	−0.0005
Bihar	−0.0026	−0.0029	−0.0027	−0.0030	−0.0029	−0.0028	−0.0029	−0.0023	−0.0067	−0.0032	−0.0015	−0.0021	−0.0019	−0.0013	−0.0025	−0.0025	−0.0022	−0.0021	−0.0020	−0.0021	−0.0079	−0.0020	−0.0039	−0.0015	−0.0014	−0.0037	−0.0018	−0.0023	−0.0023	−0.0025
Assam	0.0029	0.0020	−0.0015	0.0041	0.0028	0.0016	0.0040	−0.0008	−0.0019	0.0257	−0.0005	−0.0010	−0.0010	−0.0007	−0.0014	−0.0009	−0.0012	−0.0009	−0.0012	−0.0008	−0.0018	−0.0010	−0.0020	−0.0006	−0.0005	−0.0015	−0.0007	−0.0008	−0.0007	−0.0007
Goa	−0.0059	−0.0058	−0.0044	−0.0054	−0.0057	−0.0057	−0.0048	−0.0055	−0.0057	−0.0049	−0.0166	−0.0067	−0.0064	−0.0080	−0.0062	−0.0065	−0.0060	−0.0065	−0.0066	−0.0068	−0.0049	−0.0067	−0.0052	−0.0064	−0.0120	−0.0063	−0.0085	−0.0085	−0.0183	−0.0101
Uttaranchal	−0.0012	−0.0012	−0.0012	−0.0011	−0.0012	−0.0012	−0.0011	−0.0020	−0.0015	−0.0012	−0.0013	0.0067	−0.0014	−0.0009	−0.0015	−0.0022	−0.0012	−0.0022	−0.0013	−0.0016	−0.0014	−0.0017	−0.0015	−0.0009	−0.0011	−0.0017	−0.0009	−0.0021	−0.0018	−0.0015
Delhi	−0.0012	−0.0013	−0.0017	−0.0016	−0.0012	−0.0012	−0.0017	−0.0020	−0.0015	−0.0018	−0.0013	−0.0024	−0.0027	−0.0007	−0.0016	−0.0023	−0.0013	−0.0022	−0.0017	−0.0025	−0.0013	−0.0034	−0.0013	−0.0010	−0.0011	−0.0023	−0.0009	−0.0017	−0.0014	−0.0016
Kerala	−0.0041	−0.0041	−0.0031	−0.0039	−0.0040	−0.0040	−0.0036	−0.0033	−0.0030	−0.0037	−0.0050	−0.0029	−0.0029	0.0068	−0.0037	−0.0029	−0.0041	−0.0028	−0.0034	−0.0033	−0.0033	−0.0029	−0.0035	−0.0045	−0.0052	−0.0028	−0.0068	−0.0040	−0.0044	−0.0040
Chattisgarh	−0.0001	−0.0002	0.0007	−0.0000	−0.0002	−0.0001	0.0006	−0.0005	−0.0009	0.0001	−0.0014	−0.0002	−0.0004	−0.0009	0.0150	−0.0006	0.0001	−0.0005	−0.0004	−0.0007	−0.0012	−0.0006	−0.0014	−0.0008	−0.0012	−0.0009	−0.0017	−0.0018	−0.0024	−0.0011
Himachal Pradesh	−0.0023	−0.0024	−0.0020	−0.0024	−0.0024	−0.0023	−0.0023	0.0038	−0.0032	−0.0025	−0.0032	−0.0011	−0.0015	−0.0024	−0.0029	0.0299	−0.0027	0.0042	−0.0027	−0.0026	−0.0031	−0.0014	−0.0034	−0.0024	−0.0028	−0.0031	−0.0024	−0.0045	−0.0045	−0.0025
Orissa	−0.0032	−0.0029	−0.0007	−0.0021	−0.0026	−0.0029	0.0001	−0.0039	−0.0045	−0.0019	−0.0061	−0.0033	−0.0033	−0.0058	−0.0036	−0.0041	0.0411	−0.0037	−0.0038	−0.0043	−0.0043	−0.0036	−0.0022	−0.0059	−0.0060	−0.0043	−0.0092	−0.0058	−0.0078	−0.0047
Punjab	−0.0034	−0.0034	−0.0039	−0.0032	−0.0033	−0.0034	−0.0036	−0.0038	−0.0041	−0.0035	−0.0032	−0.0049	−0.0043	−0.0021	−0.0037	−0.0039	−0.0031	0.0111	−0.0036	−0.0038	−0.0037	−0.0047	−0.0038	−0.0023	−0.0026	−0.0045	−0.0022	−0.0043	−0.0039	−0.0033
Madhya Pradesh	−0.0022	−0.0022	−0.0022	−0.0022	−0.0022	−0.0022	−0.0020	−0.0023	−0.0029	−0.0023	−0.0025	−0.0025	−0.0024	−0.0020	−0.0027	−0.0028	−0.0023	−0.0024	0.0088	−0.0026	−0.0027	−0.0025	−0.0027	−0.0022	−0.0022	−0.0033	−0.0024	−0.0035	−0.0035	−0.0026
Rajasthan	−0.0065	−0.0064	−0.0065	−0.0064	−0.0064	−0.0063	−0.0065	−0.0063	−0.0081	−0.0070	−0.0083	−0.0074	−0.0057	−0.0062	−0.0077	−0.0078	−0.0066	−0.0069	−0.0074	0.0171	−0.0073	−0.0073	−0.0074	−0.0061	−0.0075	−0.0088	−0.0074	−0.0149	−0.0094	−0.0082
Jharkhand	0.0463	0.0573	0.0482	0.0629	0.0578	0.0564	0.0621	0.0220	0.1427	0.0521	−0.0080	0.0241	0.0157	0.0014	0.0203	0.0153	0.0352	0.0192	0.0196	0.0108	0.1269	0.0135	0.1496	0.0092	−0.0017	0.0297	−0.0091	−0.0134	−0.0204	0.0113
Haryana	−0.0048	−0.0047	−0.0028	−0.0043	−0.0048	−0.0045	−0.0027	−0.0011	−0.0061	−0.0045	−0.0088	−0.0012	0.0208	−0.0055	−0.0060	−0.0022	−0.0052	0.0003	−0.0055	−0.0036	−0.0063	0.0359	−0.0064	−0.0060	−0.0070	−0.0063	−0.0063	−0.0100	−0.0109	−0.0053
West Bengal	−0.0135	−0.0097	−0.0120	−0.0067	−0.0095	−0.0092	−0.0075	−0.0191	−0.0228	−0.0144	−0.0192	−0.0207	−0.0186	−0.0201	−0.0226	−0.0221	−0.0053	−0.0205	−0.0210	−0.0201	0.0927	−0.0198	0.0823	−0.0218	−0.0207	−0.0236	−0.0247	−0.0227	−0.0232	−0.0132
Andhra Pradesh	−0.0075	−0.0073	−0.0069	−0.0071	−0.0073	−0.0071	−0.0066	−0.0062	−0.0083	−0.0073	−0.0122	−0.0071	−0.0070	−0.0114	−0.0091	−0.0066	−0.0083	−0.0066	−0.0082	−0.0078	−0.0084	−0.0072	−0.0090	0.0338	−0.0119	−0.0081	−0.0156	−0.0107	−0.0136	−0.0086
Karnataka	−0.0100	−0.0101	−0.0118	−0.0106	−0.0102	−0.0100	−0.0113	−0.0117	−0.0141	−0.0122	0.0198	−0.0125	−0.0118	−0.0079	−0.0127	−0.0131	−0.0095	−0.0126	−0.0121	−0.0133	−0.0137	−0.0126	−0.0138	−0.0107	0.0870	−0.0152	−0.0230	−0.0218	−0.0309	−0.0127
Uttar Pradesh	−0.0032	−0.0015	0.0011	0.0019	−0.0009	−0.0011	0.0076	−0.0002	0.0056	0.0026	−0.0147	−0.0005	0.0014	−0.0111	−0.0071	−0.0068	−0.0070	−0.0070	−0.0016	−0.0083	−0.0055	−0.0043	−0.0097	−0.0107	−0.0130	0.0717	−0.0129	−0.0162	−0.0176	−0.0060
Tamil Nadu	0.0023	0.0016	−0.0081	−0.0006	0.0011	0.0013	−0.0060	−0.0097	−0.0105	−0.0064	−0.0170	−0.0117	−0.0102	0.0341	−0.0047	−0.0120	0.0011	−0.0110	−0.0092	−0.0114	−0.0097	−0.0111	−0.0096	0.0103	0.0046	−0.0138	0.1545	−0.0225	−0.0297	0.0015
Gujarat	0.0245	0.0227	0.0270	0.0175	0.0220	0.0222	0.0171	0.0501	0.0148	0.0131	−0.0173	0.0360	0.0284	0.0078	0.0086	0.0333	−0.0000	0.0329	0.0270	0.0782	0.0041	0.0235	0.0009	0.0005	−0.0056	0.0072	−0.0225	0.1926	−0.0456	0.0232
Maharashtra	0.0376	0.0340	0.0370	0.0293	0.0328	0.0331	0.0190	0.0209	0.0268	0.0175	0.1132	0.0414	0.0276	0.0430	0.0454	0.0293	0.0333	0.0331	0.0427	0.0228	0.0082	0.0238	0.0067	0.0339	0.0425	0.0187	0.0008	−0.0023	0.1800	0.0573
All wages	0.0134	0.0216	0.0150	0.0248	0.0218	0.0215	0.0231	−0.0004	0.0615	0.0088	−0.0301	−0.0022	−0.0086	−0.0153	−0.0278	−0.0109	0.0145	−0.0077	−0.0131	0.0089	0.1071	−0.0149	0.1195	−0.0175	0.0061	−0.0025	−0.0131	0.0147	−0.0646	−0.0073

Notes: Table 9 shows the effect of partial changes in wages on allocative efficiency across the different Indian states. In particular, the element in row i and column j shows the effect on allocative efficiency of state j of changing the equilibrium wage in state i (according to the new equilibrium under the presence of the GQ) and keeping the rest of wages unchanged.

The last row of Table 8 shows the change in allocative efficiency in each state if we change all transportation costs and hold wages fixed. The last row of Table 9 indicates the change in allocative efficiency if we change all wages and hold transportation costs fixed. Let's come back to the case of Chattisgarh. The change in allocative efficiency that comes from the direct effect of changes in transportation costs is positive (0.047%). In contrast, the indirect effect implies a negative change (−0.028%). This means that for the particular case of Chattisgarh, ignoring the general equilibrium effects through wages would lead to overestimating the size of allocative efficiency gains.

We find that the relative importance of the direct effect versus indirect effect in explaining allocative efficiency gains varies across states. In particular, we find that the direct effect accounts for the bulk of changes in allocative efficiency in big states. Consider the case of Maharashtra, which as mentioned before is the largest state. In this case, the gains from changes in relative wages are −0.065%, whose absolute value represents around 17% of the gains that come from the direct effect. For the case of small states, however, the importance of the indirect effect is bigger. Take for instance the case of Aruchanal Pradesh, which as mentioned before is the smallest state. In this state, we find that the gain from the indirect effect (0.013%) is larger than the gain from the direct effect.

7.2.2. Markups Terms of Trade. We find that welfare gains from changes in markups terms of trade are quantitatively important. There is a significant reshuffling of income across states due to the markups terms of trade component. We use the term reshuffling since this term is zero in the aggregate. For example in the case of Mizoram, welfare gains from the improvement in its markups terms of trade are 0.22%. This implies that, had this effect not been present, welfare losses would have been around 20% bigger in absolute value. This effect is due to the fact that the increase in wages for states close to the GQ forced firms located in those states to lower their markups in Mizoram. Thus, the aggregate markup on the goods imported by Mizoram declined.

7.2.3. Change in the Distribution of Markups. Figure 9 shows the percentage change in markups that firms charge in Arunachal Pradesh and Maharashtra, the smallest and the largest states. To construct the figure, we first find the markups of firms in the various percentiles of the markup distribution before the construction of the GQ. For each of these percentiles, we then find the average percentage change in markups after the construction of the GQ. As mentioned before, most firms charge markups that are very close to the lowest possible one. That is why we only see quantitatively relevant changes starting in the 90th percentile. We also find that the largest decline is in the 99th percentile of the distribution. This result is consistent with other works which find that, after trade reforms, declines in markups are more pronounced among firms with initially high markups. For instance, De Loecker et al. (2016) find that, for high-markup products (above the 90th percentile), the same reduction in tariffs results in an additional 3.14% decline in markups. Lastly, we find that the markups in the 90th and 95th percentiles of the distribution increase. On the other hand, in both cases, we find that this increase is smaller than the decline among the firms in the 99th percentile.

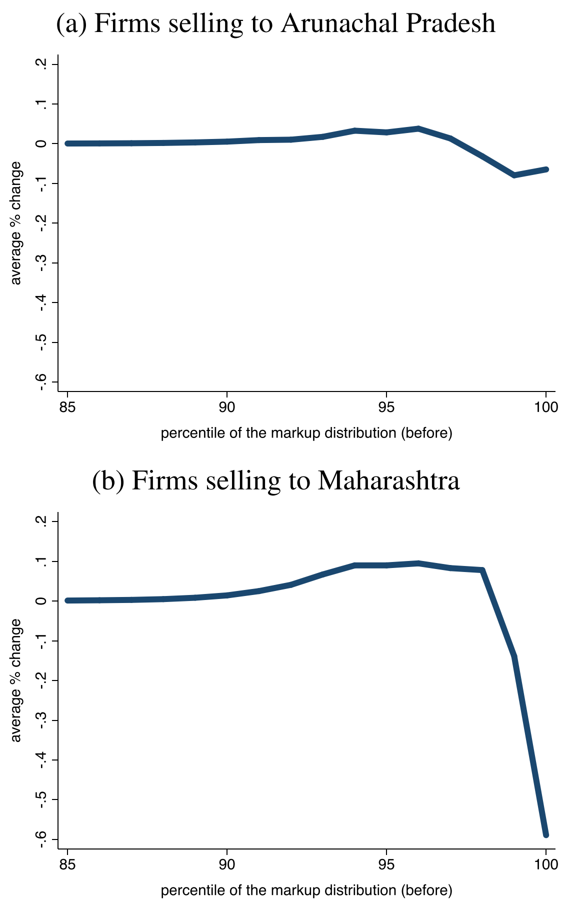


FIGURE 9. Distribution of the change in markups (Model). The figure shows the average percentage change in markups across firms across different percentiles of the distribution of markups before the construction of the GQ in the model. Panel (a) refers to the markups charged on goods sold in Arunachal Pradesh. Panel (b) refers to the markups charged on goods sold in Maharashtra. Average % changes in percentiles lower than 85 are virtually zero and are not reported.

The model also indicates that the largest declines in markups are in Maharashtra. This finding is consistent with the fact that Maharashtra experienced the largest gains in allocative efficiency.

7.2.4. Ricardian. We now turn to the Ricardian component of welfare across states, which is generally positive and large across states. It also explains the negative effects for the states in the Northeast. The fact that the Ricardian term is negative for Northeastern states comes from the fact that the price index under marginal cost pricing increases. The reason is that it becomes more expensive to purchase goods at marginal cost from states close to the GQ. The only two factors that affect a firm's

TABLE 10. % Change in total trade between i and j (model).

		Mean	Median	sd/mean	N
	Both i and j in GQ	5.11	4.33	3.21	78
(A)	Either i or j in GQ	1.40	−1.11	10.00	208
	Neither i nor j in GQ	1.88	0.39	7.37	120

Notes: Table 10 shows the mean, median, and coefficient of variation of the % change in total trade between states i and j after the construction of the GQ; "both i and j in GQ" refer to state pairs in which both of them are crossed by the GQ; "either i or j in GQ" refers to state pairs in which only one of them is crossed by the GQ; "neither i nor j in GQ" refers to state pairs in which none of them are crossed by the GQ. The states crossed by the GQ are Delhi, Bihar, Orissa, Rajasthan, Jharkhand, Haryana, West Bengal, Andhra Pradesh, Karnataka, Uttar Pradesh, Tamil Nadu, Gujarat, and Maharashtra. N is the number of state pairs that fall into the different categories.

marginal cost to serve a destination are the transportation costs that it faces and wages. First, we know that the GQ lowers transportation costs for some destinations and leaves those for others unchanged. Second, states close to the GQ trade more intensively with each other. The result is that they become more open and their wages increase. Thus, the increase in wages in the states close to the GQ outweighs the benefits of the GQ in terms of lower transportation costs.

For states in the Northeast, we find that the negative Ricardian effect induced by changing trade patterns is mitigated by the markups terms of trade term. The average state in the Northeast that lost due to the construction of the GQ had an average gain of 0.23% in markups terms of trade.

Predictions of the Model About Trade Diversion and Creation. We now study the changes in state-to-state trade patterns induced by the construction of the GQ. The fact that reductions in transportation costs are not uniformly distributed across states leaves room for trade diversion and creation. To study this possibility, we compute bilateral trade flows across all Indian state pairs implied by the model before and after the GQ. We define the total trade between state i and state j as

$$\text{Total Trade}_{i,j} = \text{exports}^i_j + \text{exports}^j_i,$$

where exports^i_j and exports^j_i are the total exports from state i to state j and the total exports from state j to state i, respectively.

Table 10 shows summary statistics of the change in trade patterns for state pairs according to their access to the GQ.[20] In the first row, we include state pairs in which both states are crossed by the GQ. In the second row, we include state pairs in which only one of the states is crossed by the GQ. In the third row, we include state pairs in which neither state is crossed by the GQ.

We find that on average trade increases considerably more between state pairs in which both states are either crossed by the GQ or not crossed by the GQ. We also find evidence of trade diversion. For instance, for the median trade relationship, trade flows between state pairs crossed by the GQ increase by 4.33%. For state pairs in which

20. This analysis is similar in spirit to papers that study trade diversion such as Krueger (1999) and Bayoumi and Eichengreen (1998).

neither state is crossed by the GQ, the median increase in trade is 0.39%. On the other hand, the median change in trade between state pairs in which only one of the states is crossed by the GQ is −1.11%.

8. Reduced-Form Evidence on the Effects of the GQ

In this section, we use reduced-form approaches to estimate the effect of the GQ regarding two important economic outcomes: prices and the Olley and Pakes (1996) (OP) covariance between size and productivity. In Section 8.1, we show evidence at the state level, which is the geographical level at which we have calibrated our model. This allows us to compare our estimates with model outcomes. In Section 8.2, we show additional evidence at the district level, which is the maximum level of geographical disaggregation that we have in the data. This allows us to fully exploit the richness of our data and apply a more convincing identification strategy.

8.1. Evidence at the State Level and Data versus Model Comparison

Our goal is to compare the results of regressions estimated using model-simulated data and regressions estimated using actual data at the state-level. In particular, we study whether the differential evolution of prices and the OP covariance term across states in the model is similar to that in the data.

Prices. We estimate the following difference-in-differences regression:

$$\Delta \log P_{js} = \beta_1 \Delta \mathrm{GQ}_s + \sum_j \alpha_j + \varepsilon_{js}, \tag{26}$$

where $\Delta \log P_{js}$ is the change in log price of input j in state s between 2001 and 2006, GQ_s is a dummy variable taking value 1 if state s has been crossed by the GQ, α_j are product fixed effects, and ε_{js} is an error term. Thus, $\Delta \mathrm{GQ}_s$ takes value 1 if the state was crossed by the GQ in 2006 but not in 2001.

The results for prices are shown in Panel (a) of Table 11. We find that prices in states crossed by the GQ fell on average 39 percentage points more than in states not crossed by the GQ. The average change in prices in our data is 82%. Thus, relative to the sample mean, there is an additional decline in prices of 48% (39/82) in states treated by the GQ. In the model, prices went down 1.30 percentage points more in GQ states than in non-GQ states. Given the average fall in prices of 0.74% predicted by our model, prices declined by 176% (1.30/0.74) more in GQ states relative to the average change in prices. We thus find that our model predicts differential changes that are qualitatively consistent but quantitatively higher than in the data.

OP Covariance Term Between Size and Productivity. In order to explore the implications of the GQ on allocative efficiency, we analyze the changes in the OP within-industry covariance term between size and value added per worker. We show

TABLE 11. Prices, allocative efficiency, and the gq: State-level differences-in-differences. Data versus model.

	(A) Change in prices		(B) Change in OP covariance	
	Data	Model	Data	Model
	(1)	(2)	(3)	(4)
Mean dep. variable	−0.8162	−0.0074	0.0749	0.0029
Estimated coefficient	−0.3889***	−0.0130***	0.0367	0.0031***
	(0.1182)	(0.0001)	(0.0303)	(0.0001)
Relative effect of the GQ	1.48	2.75	1.49	2.04
Fixed effects	YES	YES	YES	YES
Observations	6,658	129,514	1,930	24,669
R-squared	0.58	0.11	0.09	0.37

Notes: Table 11 shows the estimation of the state-level differences-in-differences regressions of prices and allocative efficiency in the data and in the model-simulated data (equations (26) and (27), respectively). The dependent variables are the log change in the price of input j between 2001 and 2006 in state s (columns (1) and (2)) and the change in the Olley and Pakes covariance term between 2001 and 2006 (columns (3) and (4)). The variable of interest is the connectivity of the state, defined as a dummy variable taking value 1 if the state is crossed by the GQ in 2006 but not in 2001. Input fixed effects are included in the specifications in columns (1), (2), and (4). Industry fixed effects are included in the specification in column (3). The effect over the average state is computed as the ratio between the estimated coefficient over the unconditional sample mean. Robust standard errors are in parentheses, clustered at the state level. ***Significant at 1%.

that in both the model and data, the OP covariance term increased significantly more in regions crossed by the GQ.

To do this exercise, we first compute the OP covariance term for each industry-state in both 2001 and 2006. Let ω_{ij} be the log of value added per worker of firm i in industry j. Let θ_{ij} be firm i's share in industry j, which we measure as the fraction of employment accounted for by the firm in the industry. Given these variables, we define industry j's log labor productivity ω_j as

$$\omega_j = \sum_{i}^{K_j} \theta_{ij}\omega_{ij},$$

where K_j is the number of firms in the industry. We can decompose this expression in the following manner:

$$\omega_j = \bar{\omega}_j + \sum_{i=1}^{K_j} \left(\theta_{ij} - \bar{\theta}_j\right)\left(\omega_{ij} - \bar{\omega}_j\right),$$

where $\bar{\omega}_j$ is the unweighted average firms' log value added per worker, and $\bar{\theta}_j$ is the unweighted average firm's industry share. We refer to the second term on the right-hand side of the expression as the OP covariance term.

In standard trade models, like Melitz (2003), markups are constant and hence there is no dispersion in value added per worker across firms. Thus, the covariance between size and value added per worker is zero by construction. This would also be the case in our model in the particular situation in which all firms charged the same markup. In general, however, whenever there is a dispersion in markups, the OP covariance term is positive. This comes from the fact that bigger firms charge higher markups and hence have a higher measured labor productivity. It is important to note that a higher OP covariance term does hence not necessarily imply higher levels of allocative efficiency. For instance, the economy attains its first-best when there is no dispersion in markups. Hence, any other allocation in which markups are heterogeneous would be associated with a higher OP covariance term and a lower level of allocative efficiency.

In our model, the sector-state OP covariance term between size and value added per worker is on average 0.0179 in 2001 (before the construction of the GQ) and 0.0209 in 2006 (after the construction of the GQ). Why does the OP covariance term increase after the construction of the GQ according to our model? On the one hand, θ_{ij} (firm's labor share in the industry) will increase for the largest firms in a given region due to the decline in their average markup. On the other hand, this decline in markups will also result in these large firms having a lower measured labor productivity. The former effect dominates in our calibrated economy, and hence the OP covariance term is positively associated with the increase in allocative efficiency implied by our model after the construction of the GQ.

In the data, we find an average sector-state OP covariance term of 0.4056 in 2001 and 0.4804 in 2006. It is not surprising that the covariance between size and productivity is higher in the data than in the model. In our model, there is only one channel that generates the positive covariance, which is the presence of endogenous markups. In the data, however, there may be other reasons that higher value added per worker firms operate at higher scales. Nevertheless, our main goal is to check whether there was a differential evolution of the OP covariance across states in a way that is consistent with the model. To this end, we estimate the following regression:

$$\Delta \mathrm{OP}_{js} = \beta \Delta \mathrm{GQ}_s + \sum_j \alpha_j + \varepsilon_{js}, \tag{27}$$

where $\Delta\mathrm{OP}_{js}$ is the change in the OP covariance term in industry j in state s between 2001 and 2006, GQ_s is a dummy variable taking value 1 if state s has been crossed by the GQ, α_j are product fixed effects, and ε_{js} is an error term.[21]

The results of the estimation of equation (27) are shown in Panel (b) of Table 11. In the data, the covariance between size and value added per worker in states crossed by the GQ increased 3.67 percentage points more than states not crossed by the GQ.

21. Each industry is a four-digit National Industrial Classification (NIC), which follows the procedures of the United Nations' International Standard Industrial Classification (ISIC). We map the 2006 codes, expressed in NIC 2004, to the 2001 codes, expressed in NIC 1998. Note that in this exercise, we consider industries (NIC) instead of products (ASICC). This allows us to use a level of aggregation that is sufficiently coarse to compute the covariance terms with a large number of observations and, at the same time, provide enough variation. This aggregation procedure is not possible with 5-digit ASICC data. Moreover, using ASICC entails the problem of dealing with multiproduct plants. We restrict the sample to cells containing at least 10 plants. We also trim the 1% tails of the distribution of covariance changes in order to reduce the influence of outliers.

This coefficient is imprecisely estimated and is associated with a p-value of 0.23. The average change in the covariance was 7.49%. Thus, our estimates implies an additional 49% (3.67/7.49) increase in allocative efficiency in states treated by the GQ relative to the average. In the model, states crossed by the GQ had an increase that was 0.31 percentage points higher than in non-GQ states. Given an average change of 0.29%, the change in allocative efficiency was 107% (0.31/0.29) higher in GQ states relative to the average change.

Discussion. Whereas the model does relatively well in predicting the differential change in prices and allocative efficiency between GQ states and non-GQ states, it clearly underpredicts the average changes. In particular, the average fall (increase) in prices (allocative efficiency) that we measure in the data is at least an order of magnitude bigger than the one predicted by our model. There were significant policy changes in Indian manufacturing between 2001 and 2006 that might have affected prices and allocative efficiency. For example, the removal of large portions of the existing reservation laws occurred precisely between 2000 and 2009.[22] However, our exercise only captures the effects from the construction of the GQ on economic outcomes. Nevertheless, it is worth noting that the empirical evidence is consistent with the relative evolution in prices and allocative efficiency predicted by model.

8.2. Evidence at the District Level

One of the challenges in identifying the causal impact of transportation infrastructure is its nonrandom placement. For example, transportation infrastructure may be placed in areas with characteristics that are correlated to economic outcomes of interest. For example, infrastructure may be placed in areas that are expected to have high future growth. An identification strategy used in the latest empirical literature has exploited the fact that infrastructure projects often aim to connect historical cities or large economic centers.[23] In our particular case, the stated goal of the GQ was to connect the major urban centers (Delhi, Kolkata, Chennai, and Mumbai). In this section, we estimate a difference-in-differences specification at the district level in which we compare economic outcomes for districts close to the GQ with those that are far away. We exclude the major urban centers or nodal districts since these areas were explicitly targeted by policymakers.

22. Reservation laws prevented large firms from producing manufacturing goods in a set of goods dictated by the government. The number of reserved goods declined from approximately 800 in early 2000 to around 90 in 2008. For more information, see Bollard et al. (2013), Garcia-Santana and Pijoan-Mas (2014), Tewari and Wilde (2014), or Galle (2018).

23. See Banerjee, Duflo, and Qian (2012) for an early example of this empirical strategy. This strategy has also been applied to the GQ by Alder (2017), Datta (2012), and Ghani, Goswami, and Kerr (2016). Our differences-in-differences strategy mimics that of these papers and we follow this literature in excluding nodal districts. Note that Alder (2017) studies the effect on economic activity; Datta (2012) on inventories, supplier relationships and perceptions of transport quality; and Ghani et al. (2016) on the organization and efficiency of the formal manufacturing activity.

Prices. We estimate the following differences-in-differences regression:

$$\Delta \log P_{jd} = \beta_1 \Delta \mathrm{GQ}_d + \sum_j \alpha_j + \varepsilon_{jd}, \tag{28}$$

where $\Delta \log P_{jd}$ is the change in log price of input j in district d between 2001 and 2006, GQ_d is a dummy variable taking value 1 if district d has been "treated" by the GQ, α_j are product fixed effects, and ε_{jd} is an error term.[24] Thus, $\Delta \mathrm{GQ}_d$ takes value 1 if a district was within the specified distance of the GQ in 2006 but not in 2001. Distance is calculated as the shortest straight-line distance between the district and a treated portion of the GQ. We use categories of distance ranging from 25 to 300 km. Standard errors are clustered at the district level in order to account for the possible serial correlation of price shocks within districts.

The estimates of equation (28) can be found in columns (1) and (2) of Table 12. The results in column (1) include nodal districts. Column (2), which is our baseline specification, excludes nodal districts. Each column shows the estimate of β_1 under different specifications of the treatment distance.

We find that prices declined significantly for areas close to the GQ relative to those farther away. For example, we find that for districts located within 25 km of the GQ, input prices declined by almost 60 percentage points more than in districts located farther away. Furthermore, we find that this effect dissipates as we increase the treatment distance. This trend toward zero can be seen in Panel (a) of Figure 10, in which we plot the coefficients in column (2) in steps of 25 km. Finally, we find that the exclusion of the nodal cities does not significantly change the estimates.

Recent empirical work, such as the work by Faber (2014), has emphasized the nonrandom placement of infrastructure even outside of non-nodal areas. Thus, we check the robustness of our results by instrumenting the distance to the GQ that we use in estimating equation (28). In particular, we instrument it with the straight lines that connect the four nodal cities, shown in Panel (a) of Figure 11. These straight lines resemble the lowest-cost path connecting the nodal cities. The identifying assumption is that the distance to the straight line affects districts only through how likely they are to be close to the GQ network. We add a second IV specification with a straight line connecting the city of Bangalore, shown in Panel (b) of Figure 11. These set straight-line IVs were used by Ghani et al. (2016). Columns (3) and (4) of Table 12 show the results of these IV specifications. We find that the effects of the GQ on prices follow a similar pattern and are somewhat higher in absolute value. In Panel (b) of Figure 10, we show that the overall pattern remains the same as in the baseline case.

24. We compute a weighted average of the prices paid by plants consuming the input in the district, excluding products with evidence of unit misreporting. We have data for 920 inputs consumed in 325 districts. See the Online Appendix for more details.

TABLE 12. Prices and the Golden Quadrilateral: District-level differences-in-differences.

	OLS (1)	OLS (2)	IV (3)	IV (4)
Dep. variable: Log change input prices 2001–2006				
District within 25 km from GQ	−0.5932***	−0.6011***	−0.6737***	−0.6178***
	(0.1489)	(0.1544)	(0.1970)	(0.1876)
District within 50 km from GQ	−0.5588***	−0.5649***	−0.5122**	−0.4727**
	(0.1358)	(0.1391)	(0.2104)	(0.1986)
District within 100 km from GQ	−0.4139***	−0.4184***	−0.8373***	−0.7383***
	(0.1499)	(0.1542)	(0.2371)	(0.2128)
District within 150 km from GQ	0.0217	0.0349	−0.5550	−0.3210
	(0.1476)	(0.1517)	(0.3740)	(0.2231)
District within 200 km from GQ	−0.0137	−0.0040	−0.2593	−0.2448
	(0.1612)	(0.1683)	(0.2244)	(0.2050)
District within 300 km from GQ	−0.1113	−0.1061	0.1445	−0.0874
	(0.1583)	(0.1646)	(0.2007)	(0.1893)
Input fixed-effects	YES	YES	YES	YES
Nodal districts	YES	NO	NO	NO
Instrument	–	–	Straight-line	Straight-line with Bangalore
Observations	5,123	5,037	5,037	5,037
Average R-squared	0.42	0.42	–	–
Number of products	920	912	912	912

Notes: Table 12 shows the results of the estimation of equation (28). The dependent variable is the log change in the price of input j between 2001 and 2006 in district d. The variable of interest is the connectivity of the district, defined as whether the district is within a certain distance from the GQ in 2006 and 2001. Each row corresponds to a different regression, where different distances are considered. Columns (1) includes all districts whereas column (2) excludes nodal districts. Column (3) instruments the distance to the GQ with the distance to the straight line connecting the four vertices of the GQ (Delhi, Chennai, Mumbai, and Calcutta). Column (4) instruments with the distance to the straight line connecting the five vertices of the GQ (adding Bangalore). Input fixed effects are included in all specifications. Robust standard errors are in parentheses, clustered at the district level. **Significant at 5%; ***significant at 1%.

OP Covariance Term between Size and Productivity. We estimate the following regression:

$$\Delta \mathrm{OP}_{jd} = \beta \Delta \mathrm{GQ}_d + \sum_j \alpha_j + \varepsilon_{jd}, \tag{29}$$

where $\Delta\mathrm{OP}_{jd}$ is the change between 2001 and 2006 in the OP covariance term in industry j in district d, GQ_d is a dummy variable taking value 1 if district d has been "treated" by the GQ, α_j are product fixed effects, and ε_{jd} is an error term. As before, distance is calculated as the shortest straight-line distance between the district and a treated portion of the GQ.

Table 13 shows the results of estimating equation (29). As before, column (1) includes nodal cities in the estimation and column (2) excludes them. We find improvements in allocative efficiency in the districts that became treated by the GQ

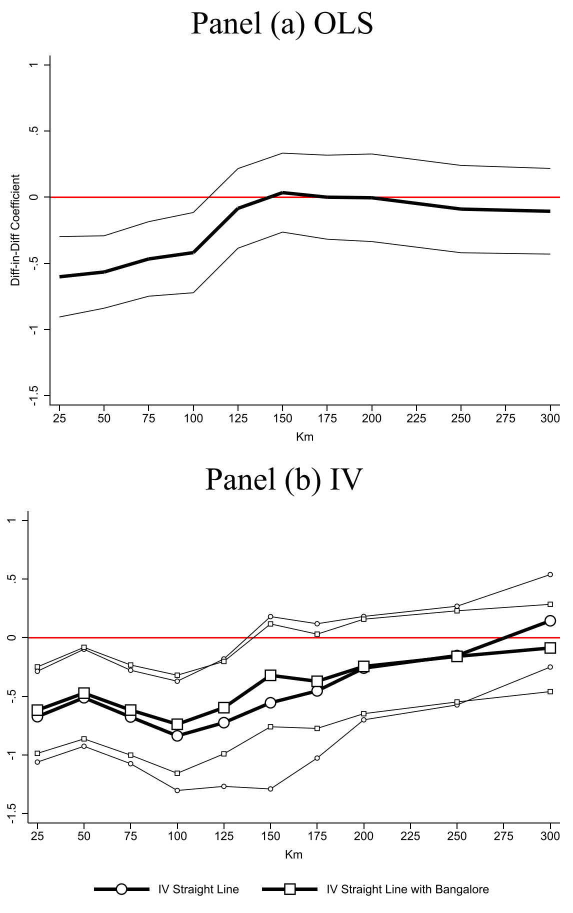


FIGURE 10. Prices and the Golden Quadrilateral: Differences-in-differences. The figure shows the estimates of equation (28) at each category of distance. The dependent variable is the log change in the price of input *j* between 2001 and 2006 in district *d*. The coefficients depicted are those associated to the connectivity of the district, defined as whether the district is within a certain distance from the GQ in 2006 and 2001. Nodal districts are excluded. Panel (a) displays OLS coefficients and Panel (b) IV estimates. The instruments are the distance to the straight line connecting the four and five vertices of the GQ (Delhi, Chennai, Mumbai, Calcutta, and Bangalore). 95% confidence intervals stemming from robust standard errors clustered at the district level are drawn in thinner lines.

compared with districts further away. The improvement in the covariance term is a decreasing function of distance, and converges rapidly toward zero. This pattern can be seen in Panel (a) of Figure 12, which shows the coefficient of β found in column (2).

For robustness, we estimate the specification using the straight-line IVs described previously. We find that the results do not change as shown in columns (3) and (4) of Table 13. The confidence intervals increase in size due to the use of the IV. However,

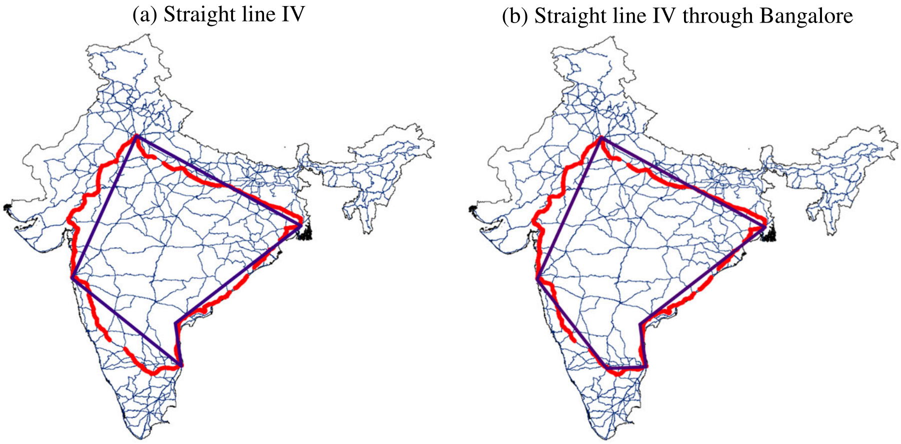


FIGURE 11. Road Network in India, the GQ and the straight line GQ. Panel (a) shows a map with the road network in India in 2006, including the sections of the Golden Quadrilateral that were finished by then (around 95% of the total project) and the IV straight line. Panel (b) shows the same map but making the straight line going through Bangalore.

the results preserve the relationship that allocative efficiency increased more in districts close to the GQ. The coefficients of column (4) are plotted in Panel (b) of Figure 12.

9. Sensitivity Analysis and Additional Discussions

9.1. Sensitivity Analysis of Parameters

We now examine the sensitivity of our results by considering versions of our model in which we change the value of some of the crucial parameters. We first examine the implications of setting a lower value for the elasticity of substitution across sectors, θ. Second, we study a version of the model in which productivity shocks are uncorrelated across states.

For all these cases, we keep the rest of the parameters that we estimated outside the model constant, and recalibrate the labor endowment for each state i, L_i, and the shape parameter of the Pareto distribution, α. To match the fact that the top 5% of plants in manufacturing account for 89% of total value added. The model requires a shape parameter of 1.61 in the case of $\theta = 1.24$, and 4.42 in the case of uncorrelated draws (vs. 2.28 in our benchmark calibration).

We find that the aggregate gains are remarkably stable across specifications. The share of allocative efficiency gains is similar to the benchmark calibration in the case of the lower θ. However, allocative efficiency gains disappear in the case of uncorrelated productivity draws across states.

TABLE 13. Allocative efficiency and the Golden Quadrilateral: District-level differences-in-differences.

	OLS (1)	OLS (2)	IV (3)	IV (4)
Dep. variable: Change in covariance term 2001–2006				
District within 25 km from GQ	0.0143	0.0196	0.0247	0.0231
	(0.0123)	(0.0122)	(0.0174)	(0.0163)
District within 50 km from GQ	0.0139	0.0180	0.0192	0.0164
	(0.0111)	(0.0111)	(0.0159)	(0.0149)
District within 100 km from GQ	0.0249**	0.0291***	0.0138	0.0158
	(0.0110)	(0.0109)	(0.0162)	(0.0148)
District within 150 km from GQ	0.0131	0.0168	0.0266	0.0238*
	(0.0111)	(0.0111)	(0.0163)	(0.0141)
District within 200 km from GQ	0.0161	0.0201*	0.0210	0.0233*
	(0.0107)	(0.0107)	(0.0149)	(0.0130)
District within 300 km from GQ	0.0023	0.0057	−0.0087	0.0013
	(0.0112)	(0.0111)	(0.0146)	(0.0130)
Input fixed-effects	YES	YES	YES	YES
Nodal districts	YES	NO	NO	NO
Instrument	–	–	Straight-line	Straight-line with Bangalore
Observations	6,832	6,721	6,721	6,721
Average R-squared	0.02	0.02	–	–
Number of industries	117	117	117	117

Notes: The table shows the estimation of equation (29). The dependent variable is the change between 2001 and 2006 of the Olley and Pakes (1996) within-industry cross-sectional covariance between the fraction of industry labor used by the plant and labor productivity in industry (NIC) j and district d. The variable of interest is the connectivity of the district, which takes value one if the district was within a certain distance of the Golden Quadrilateral in 2006 but not in 2001, and zero otherwise. Each row corresponds to a different regression, where different distances are considered. Columns (1) includes all districts whereas column (2) excludes nodal districts. Column (3) instruments the distance to the GQ with the distance to the straight line connecting the four vertices of the GQ (Delhi, Chennai, Mumbai, and Calcutta) and excludes nodal districts. Column (4) instruments with the distance to the straight line connecting the five vertices of the GQ (adding Bangalore) and excludes nodal districts. Industry fixed effects are included in all specifications. Robust standard errors are in parentheses, clustered at the district level. *Significant at 10%; **significant at 5%; ***significant at 1%.

A Lower Elasticity of Substitution Across Sectors. We set $\theta = 1.24$, which is the value estimated by Edmond et al. (2015) using Taiwanese data. In this economy, the maximum markup a firm can charge is 5.17 (vs. 2.01). There is more misallocation than in the benchmark economy: the allocative efficiency index ranges from 0.89 to 0.92 across states, whereas in the benchmark calibration it ranges from 0.96 to 0.98. The reason is that the lower θ implies that firms with large market shares charge higher markups, increasing the dispersion of markups.

It is interesting to note that the results do not change significantly relative to our baseline case. In this specification, allocative efficiency gains increase to 0.24% (vs. 0.20%). The share of allocative efficiency gains increases to 8.1% of the gains (vs. 7.4%). At the state level, allocative efficiency gains represent up to 20% of the overall gains (vs. 18%).

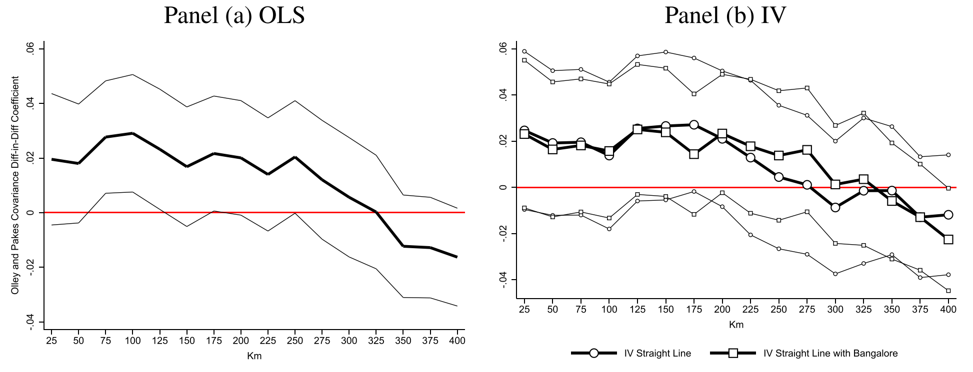


FIGURE 12. Allocative efficiency and the Golden Quadrilateral: Differences-in-differences. The figure shows the estimates of equation (29) at each category of distance. The dependent variable is the change between 2001 and 2006 of the Olley and Pakes (1996) within-industry cross-sectional covariance between the fraction of industry labor used by the plant and labor productivity in industry (NIC) j and district d. The coefficients depicted are those associated to the connectivity of the district, which takes value one if the district was within a certain distance of the Golden Quadrilateral in 2006 but not in 2001, and zero otherwise. Nodal districts are excluded. Panel (a) displays OLS coefficients and Panel (b) IV estimates. The instruments are the distance to the straight line connecting the four and five vertices of the GQ (Delhi, Chennai, Mumbai, Calcutta, and Bangalore). 95% confidence intervals stemming from robust standard errors clustered at the district level are drawn in thinner lines.

A value of 1.24 for θ would imply a trade elasticity for monopolists that is too low compared to the one we estimate using Indian data.

Uncorrelated Productivity Draws. We next examine how our results change if we have uncorrelated productivity draws across locations. We find that aggregate gains increase to 3.09% (vs. 2.72%). Furthermore, allocative efficiency gains do not account for any of the aggregate gains. However, the case of uncorrelated productivity draws does not match the data along two important dimensions. First, when we calculate our similarity index for this economy, we find a value of 0.26. This is lower than 0.46, which we obtained in our baseline calibration, and lower than 0.43, which we measure in the data. Thus, the degree of head-to-head competition that firms are confronted with is too low in the case of uncorrelated draws. Furthermore, the trade elasticity is 2.84 in the case of uncorrelated productivity draws, which is too low relative to those estimated in the literature. On the other hand, the trade elasticity of 4.74 implied by the baseline calibration is consistent with estimates from the literature.

9.2. Additional Discussions

We now study the implications of various changes to our baseline specification. First, we study how our results would change if we accounted for differences in state-level productivity. Second, we examine whether the construction of the GQ induced more migration across states and the implications of allowing for migration within the context of our model. Next, we consider the decomposition used by Edmond et al. (2015) to the one used in our baseline results. Finally, we compare our results with those implied by a model of monopolistic competition.

State-Specific Productivity Levels. We now study the implications of including a state-specific productivity term in the calibration of the model to account for cross-state heterogeneity in productivity.

PROPOSITION 1. *Consider the calibrated economy in Section 6. Now consider an alternative calibration in which we raise the productivities of all firms in one economy by a common factor and recalibrate the labor endowments of all economies to match the total income of each state. In the new calibration, the equilibrium distribution of prices, markups, market shares, value of sales, and quantities sold across destinations remain the same for all firms. Furthermore, the price index and aggregate output for each state remain the same. Finally, total labor income and profits for each state also remain unchanged.*

Proof. See Section F of the Online Appendix for full proof. □

In Proposition 1, we consider an alternative calibration from the one in Section 6. In the alternative calibration, we include a state-specific constant term on the productivity of firms located in a particular state and recalibrate the labor endowments. We find that the state-specific constant term will not affect the distribution of markups in the new calibrated economy. What we find is that the marginal cost of firms remains unchanged since both equilibrium wages and productivity change by the same factor. Since the marginal cost of firms does not change, the distribution of markups also remains unchanged. Likewise, we show that other key variables do not change in the new calibration. Thus, we conclude that cross-state heterogeneity in productivity will not affect our calibration.

Labor Migration. Most of the internal migration in India corresponds to short-distance movements within the same state. According to the 2001 Indian Population Census, around 96% of people report to be living in the state where they were born, making interstate migration flows in India among the lowest in the world.[25] These low levels of migration are often attributed to factors other than transportation costs, such as cultural differences across regions and the importance of social networks in providing insurance, as emphasized by Munshi and Rosenzweig (2016). Yet it could be the case that the construction of the GQ resulted in increased interstate migration. In that sense, a possible shortcoming of our model is the fact that we are not allowing for labor mobility across states, which could change our estimates of the effects of the GQ. To better understand whether this is empirically relevant, we estimated a differences-in-differences regression of states' net internal migration rate changes between 1999/2000

25. Additional evidence is provided by Mahapatro (2012), who shows that around 75% and close to 90% of male and female internal migration happens within the state boundaries, respectively.

and 2007/2008 against a dummy capturing whether the state is crossed by the GQ. We do not find a significant effect of being crossed by the GQ on state internal migration rates (see Online Appendix G for details).[26] This evidence is consistent with high migration costs across states, which in this case prevent workers from moving to areas that enjoy higher wages due to improved transportation infrastructure.

Although we do not see evidence that the GQ induced migration across states, we can hypothesize about how migration could affect allocative efficiency within the context of our model. It seems reasonable to think that a model with limited migration would predict some migration from states far from the GQ, to states close to the GQ, for which our model predicts a significant increase in wages. If that is the case, the implied increase in wages would be lower in such states, since labor supply would be higher. In this situation, firms located in those state would decrease their markups by less due to the lower increase in their marginal cost. These effects would imply an increase in allocative efficiency that would be lower than the one predicted by our current model.

Decomposition of Changes in Real Income Used by Edmond et al. (2015). We consider the decomposition used by Edmond et al. (2015), which allows us to decompose changes in real income into those attributed to the Ricardian and allocative efficiency components. Note that these authors consider a model in which symmetric economies trade with each other and thus do not consider the terms of trade component. For that reason, we only decompose changes in national real income, which does not have any terms of trade. At the national-level, the HHL decomposition is similar to the decomposition used by Edmond et al. (2015) as we find that the terms of trade term is zero in the HHL decomposition.

We decompose changes in the real income of India to be

$$\Delta \ln Y = \underbrace{\Delta \ln Y^{FB}}_{\textit{Ricardian}} + \underbrace{\Delta \ln Y - \Delta \ln Y^{FB}}_{\textit{Allocative efficiency}},$$

where Y is the Indian real income and Y^{FB} is the Indian first-best real income. To find the Indian real income, we sum the real income of all states. To calculate the first-best real income, we hold fixed the calibrated parameters and we resolve the model in the case in which all firms charge marginal cost. When we lower transportation costs, there will be an increase in the first-best real income. Thus, the allocative efficiency component captures the changes in real income that cannot be attributed to this increase in the first-best real income.

26. Donaldson and Hornbeck (2016) develop a model based on Eaton and Kortum (2002), which is suited to analyze the impact of improved infrastructure in settings in which labor is mobile across regions. Their theory predicts that areas with improved access to transportation infrastructure (market access) should see increases in population. Using this type of model within the Indian context, Alder (2017) estimates the relationship between changes in market access at the district-level due to the GQ and district-level population between 2001 and 2011. He did not find statistically significant changes in population as a response to changes in market access due to upgrades in transportation infrastructure. These results suggest that there are high migration costs even between districts of the same state in India.

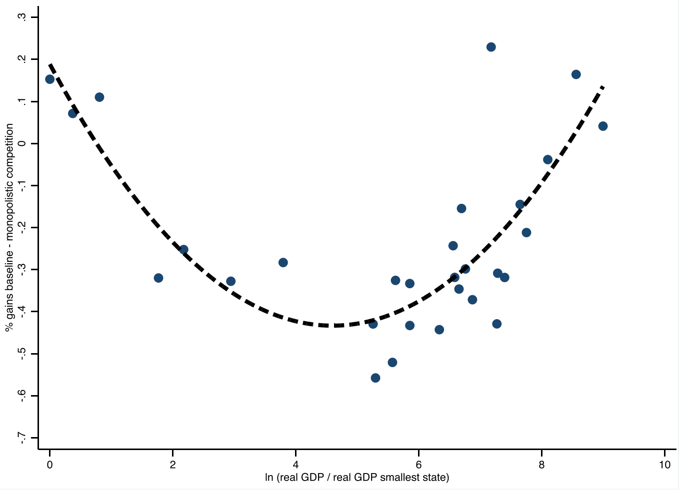


FIGURE 13. Baseline model versus Monopolistic competition model. The figure shows the gains in real income for each state predicted by our baseline model minus those of a recalibrated model of monopolistic competition. We plot this difference against the relative size of the state.

We find that there is an increase in real income of 2.72%. Of that increase, 2.51% is accounted for by the Ricardian component and 0.21% by allocative efficiency. This implies that 7.7% of the total aggregate gains are accounted for by allocative efficiency. Note that this is comparable to the allocative efficiency component reported in Table 6.

Comparison with Monopolistic Competition. How much different would the estimated effects be if we use a more standard model of trade? And second, is there a way to discriminate between the two models? To answer the first question, we re-do our quantitative exercise using a model of monopolistic competition. To conduct this exercise, we use our model and set $\theta = \gamma$. Note that in this case, all firms have the same markup and hence only the standard gains from trade operate. To make the exercise comparable to our baseline, we set the elasticity of substitution to 5.71, so that the model generates the trade elasticity of 4.71 as in the baseline (see Section 6.5). We recalibrate the labor endowments and tail parameter of the Pareto distribution to match the same statistics as in the benchmark case.

We find that the model of monopolistic competition generates aggregate gains of 2.83% (vs. 2.72% for our benchmark case). Thus, the aggregate gains are 4% higher in the model of monopolistic competition. This means that, if a policy maker wants to learn about the aggregate effects of the GQ, a standard model of trade and our richer model will provide approximately the same answer.

However, the distribution of gains across states is quite different. Figure 13 shows a scatterplot of the percentage point difference in the gains from the benchmark model and that of monopolistic competition. We plot this against the log of the ratio of the real income of the state and that of the smallest state. We find that the smallest and largest states gain more in the benchmark case. The states with the higher gains are precisely those which see larger effects from allocative efficiency and markups terms of trade in the baseline case. The percentage point differences range from −0.6% to 0.2%.

The answer to the second question is more difficult. In Section 8.1, we find that states crossed by the GQ were associated with larger declines in prices. We also find that those states experienced larger increases in the covariance between size and productivity. The first piece of evidence is consistent with a standard model that has constant markups across firms, so it does not help us to discriminate between the two models. As discussed in Section 8.1, the standard model with constant markups would fail to predict the second piece. The reason is that the OP covariance term is zero in that model and hence it implies no changes by construction. In our model, however, variable markups imply a positive OP covariance term whose level is affected by changes in competition. In particular, our model predicts that the OP covariance term increases after the construction of the GQ, and relatively more so in states affected by the fall in transportation costs. Importantly, in the case of our calibrated economy, that increase in the OP covariance term is associated with an improvement in allocative efficiency.

10. Conclusion

Construction of new transportation infrastructure is an important policy tool for international organizations and policymakers. Hence, understanding the economic effects of building new infrastructure is a matter of great importance in development. Not surprisingly, there has been much attention to this question. In fact, several different methodologies have been used to study this issue. First, there is an extensive empirical literature that uses a differences-in-differences approach to provide causal estimates of the effects of different types of infrastructure on economic outcomes. Second, there has been a recent emphasis on using a more structural approach, which consists of exploiting the structure of the Eaton and Kortum (2002) model to discipline the empirical specifications, known as the "market access" approach. This approach is quite useful because it allows the empirical specifications to capture the general equilibrium effects present in the Eaton and Kortum (2002) model.

The current paper aims to contribute to the literature by investigating the gains from improved infrastructure using a framework in which "firms matter." Our motivation for this approach is driven by the existence of a prominent literature that emphasizes misallocation of resources across firms as an important determinant of productivity and income in developing countries. We use the case of the GQ in India, which is an important road infrastructure project in the early 2000s. First, we quantify the aggregate gains and the gains across states from the GQ. Then, we decompose these gains to determine the relative importance of allocative efficiency.

More generally, our paper also contributes to the debate about the distributional consequences across regions of investing in infrastructure. Our model predicts, for instance, that using frameworks that consider variable markups can have implications for the distribution of gains. Our model also predicts that states that were initially poor became even less integrated as measured by their degree of trade openness with respect to the rest of the country. As emphasized by Alder (2017), the choice of the location of infrastructure and which cities are connected can have implications for income convergence across regions. Investigating possible mechanisms such as the creation of an interstate revenue sharing program that could help reduce regional inequality is an interesting avenue for future research.

Our analysis admittedly abstracts from additional channels through which transportation infrastructure may affect real income. For example, our framework ignores the importance of input-output linkages. Lower transportation costs would allow firms to have access to cheaper intermediate goods. Hence, improvements in transportation infrastructure in a particular region could act as a productivity shock and propagate to other regions through the production network (Caliendo et al. forthcoming). Another limitation of our framework is the lack of firm dynamics. Hsieh and Klenow (2014) show that differences in firms' life cycle dynamics may explain the low productivity in the Indian manufacturing sector. Changes in transportation costs could potentially affect firms' expectations about business opportunities and hence their incentives to innovate and grow. Analyzing these additional channels is left for future research.

References

Adamopoulos, Tasso (2011). "Transportation Costs, Agricultural Productivity, and Cross-Country Income Differences." *International Economic Review*, 52, 489–521.

Aghion, Philippe, Robin Burgess, Stephen Redding, and Fabrizio Zilibotti (2005). "Entry Liberalization and Inequality in Industrial Performance." *Journal of the European Economic Association*, 3, 291–302.

Aghion, Philippe, Robin Burgess, Stephen J. Redding, and Fabrizio Zilibotti (2008). "The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India." *American Economic Review*, 98(4), 1397–1412.

Alder, Simon (2017). "Chinese Roads in India: The Effect of Transport Infrastructure on Economic Development." Working paper, University of North Carolina at Chapel Hill.

Amiti, Mary, Oleg Itskhoki, and Jozef Konings (2016). "International Shocks and Domestic Prices: How Large Are Strategic Complementarities?" Working Paper 22119, National Bureau of Economic Research, http://www.nber.org/papers/w22119.

Arkolakis, Costas, Arnaud Costinot, Dave Donaldson, and Andrés Rodríguez-Clare (forthcoming). "The Elusive Pro-Competitive Effects of Trade." *Review of Economic Studies*.

Arkolakis, Costas, Arnaud Costinot, and Andres Rodriguez-Clare (2012). "New Trade Models, Same Old Gains?" *American Economic Review*, 102(1), 94–130.

Atkeson, Andrew and Ariel Burstein (2008). "Pricing-to-Market, Trade Costs, and International Relative Prices." *American Economic Review*, 98(5), 1998–2031.

Atkin, David and Dave Donaldson (2015). "Who's Getting Globalized? The Size and Implications of Intra-National Trade Costs." Working paper, MIT, Stanford, and NBER.

Banerjee, Abhijit Vinayak, Esther Duflo, and Nancy Qian (2012). "On the Road: Access to Transportation Infrastructure and Economic Growth in China." Working paper, MIT, Yale, J-PAL, BREAD, NBER, and CEPR.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta (2013). "Cross-Country Differences in Productivity: The Role of Allocation and Selection." *American Economic Review*, 103(1), 305–334.

Bayoumi, Tamim Barry Eichengreen (1998). "Is Regionalism Simply a Diversion? Evidence from the Evolution of the EC and EFTA." In *Regionalism Versus Multilateral Trade Arrangements*, edited by Takatoshi Ito and Anne Kruger. University of Chicago Press.

Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum (2003). "Plants and Productivity in International Trade." *American Economic Review*, 93(4), 1268–1290.

Bollard, Albert, Peter Klenow, and Gunjan Sharma (2013). "India's Mysterious Manufacturing Miracle." *Review of Economic Dynamics*, 16, 59–85.

Caliendo, Lorenzo, Fernando Parro, Esteban Rossi-Hansberg, and Pierre-Daniel Sarte (forthcoming). "The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy." *Review of Economic Studies*.

Chari, A. V. (2011). "Identifying the Aggregate Productivity Effects of Entry and Size Restrictions: An Empirical Analysis of License Reform in India." *American Economic Journal: Economic Policy*, 3, 66–96.

Datta, Saugato (2012). "The Impact of Improved Highways on Indian Firms." *Journal of Development Economics*, 99, 46–57.

David, Joel M., Hugo A. Hopenhayn, and Venky Venkateswaran (2016). "Information, Misallocation and Aggregate Productivity." *Quarterly Journal of Economics*, 131, 943–1005.

de Blas, Beatriz and Katheryn N. Russ (2015). "Understanding Markups in the Open Economy." *American Economic Journal: Macroeconomics*, 7, 157–180.

De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik (2016). "Prices, Markups, and Trade Reform." *Econometrica*, 84, 445–510.

De Loecker, Jan and Frederic Warzynski (2012). "Markups and Firm-Level Export Status." *American Economic Review*, 102(6), 2437–2471.

Dhingra, Swati and John Morrow (forthcoming). "Monopolistic Competition and Optimum Product Diversity Under Firm Heterogeneity." *Journal of Political Economy*.

Donaldson, David (2018). "Railroads of the Raj: The Economic Impact of Transportation Infrastructure." *American Economic Review*, 108, 899–934.

Donaldson, Dave and Richard Hornbeck (2016). "Railroads and American Economic Growth: A "Market Access" Approach." *Quarterly Journal of Economics*, 131, 799–858.

Eaton, Jonathan and Samuel Kortum (2002). "Technology, Geography, and Trade." *Econometrica*, 70, 1741–1779.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu (2015). "Competition, Markups, and the Gains from International Trade." *American Economic Review*, 105(10), 3183–3221.

Epifani, Paolo and Gino Gancia (2011). "Trade, Markup Heterogeneity and Misallocations." *Journal of International Economics*, 83, 1–13.

Faber, Benjamin (2014). "Trade Integration, Market Size, and Industrialization: Evidence from China's National Trunk Highway System." *Review of Economic Studies*, 81, 1043–1070.

Feenstra, Robert C. (2014). "Restoring the Product Variety and Pro-competitive Gains from Trade with Heterogeneous Firms and Bounded Productivity." NBER Working Paper No. 19833.

Feenstra, Robert C. and David E. Weinstein (2017). "Globalization, Competition, and U.S. Welfare." *Journal of Political Economy*, 125, 1041–1074.

Galle, Simon (2018). "Competition, Financial Constraints and Misallocation: Plant-Level Evidence from Indian Manufacturing." Working paper, BI Norwegian Business School.

Garcia-Santana, Manuel and Josep Pijoan-Mas (2014). "The Reservation Laws in India and the Misallocation of Production Factors." *Journal of Monetary Economics*, 66, 193–209.

Garicano, Luis, Claire Lelarge, and John Van-Reenen (2016). "Firm Size Distortions and the Productivity Distribution: Evidence from France." *American Economic Review*, 106(11), 3439–3479.

Ghani, Ejaz, Arti Grover Goswami, and William R. Kerr (2016). "Highway to Success: The Impact of the Golden Quadrilateral Project for the Location and Performance of Indian Manufacturing." *The Economic Journal*, 126, 317–357.

Gollin, Douglas and Richard Rogerson (2014). "Productivity, Transport Costs, and Subsistence Agriculture." *Journal of Development Economics*, 107, 38–48.

Gourio, Francois and Nicolas Roys (2014). "Size-Dependent Regulations, Firm Size Distribution, and Reallocation." *Quantitative Economics*, 5, 377–416.

Guner, Nezih, Gustavo Ventura, and Yi Xu (2008). "Macroeconomic Implications of Size-Dependent Policies." *Review of Economic Dynamics*, 11, 721–744.
Head, Keith and Thierry Mayer (2014). "Gravity Equations: Workhorse, Toolkit, Cookbook." In *Handbook of International Economics*, Vol. 4, edited by Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, pp. 131–195.
Herrendorf, Berthold, James A. Schmitz, Jr, and Arilton Teixeira (2012). "The Role of Transportation in U.S. Economic Development: 1840–1860." *International Economic Review*, 53, 693–716.
Holmes, Thomas J., Wen-Tai Hsu, and Sanghoon Lee (2014). "Allocative Efficiency, Mark-ups, and the Welfare Gains from Trade." *Journal of International Economics*, 94, 195–206.
Hsieh, Chang-Tai and Peter Klenow (2009). "Misallocation and Manufacuring TFP in China and India." *Quaterly Journal of Economics*, 124, 1403–1448.
Hsieh, Chang-Tai and Peter Klenow (2014). "The Life Cycle of Plants in India and Mexico." *Quaterly Journal of Economics*, 129, 1035–1084.
Kothari, Siddharth (2014). "The Size Distribution of Manufacturing Plants and Development." IMF Working Paper No. 14/236.
Krueger, Anne O. (1999). "Trade Creation and Trade Diversion Under NAFTA." NBER Working Paper 7429.
Mahapatro, Sandhya Rani (2012). "The Changing Pattern of Internal Migration in India." Working paper, http://epc2012.princeton.edu/papers/121017, Institute for Social and Economic Change (ISEC), Bangalore, India.
Melitz, Marc J. (2003). "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica*, 71, 1695–1725.
Melitz, Marc J. and Gianmarco I. P. Ottaviano (2008). "Market Size, Trade, and Productivity." *The Review of Economic Studies*, 75, 295–316.
Munshi, Kaivan and Mark Rosenzweig (2016). "Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap." *American Economic Review*, 106(1), 46–98.
Olley, S. and A. Pakes (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64, 1263–1297.
Peters, Michael (2013). "Heterogeneous Mark-Ups, Growth, and Endogenous Misallocation." Working paper, The London School of Economics and Political Science, London, UK.
Redding, Stephen and Matthew A. Turner (2015). "Transportation Costs and the Spatial Organization of Economic Activity." In *Handbook of Urban and Regional Economics*, Vol. 5, edited by Gilles Duranton, J. Vernon Henderson, and William Strange, pp. 1339–1398.
Restuccia, Diego and Richard Rogerson (2008). "Policy Distorsions and Aggregate Productivity with Heterogeneous Establishments." *Review of Economic Dynamics*, 11, 707–720.
Tewari, Ishani and Joshua Wilde (2014). "Multiproduc Firms, Product Scope and Productivity: Evidence from India's Product Reservation Policy." Working paper0214, University of South Florida, Department of Economics.
Van Leemput, Eva (2016). "A Passage to India: Quantifying Internal and External Barriers to Trade." International Finance Discussion Papers 1185, Board of Governors of the Federal Reserve System.
World Bank (2002). "India's Transport Sector: The Challenges Ahead." *World Bank Reports Series*, 1, 1–65.

Supplementary Data

Supplementary data are available at *JEEA* online.