

Geographic Distribution of Firm Productivity and Production: A “Market Access” Approach *

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Abstract

In a firm heterogeneity and trade framework, this paper develops a “market access” approach to studying the distribution of firm productivity and production in a network of geographic locations. We distinguish between two competing effects of trade cost changes, namely import competition and export access, and derive consumer market access (CMA) and firm market access (FMA) measures respectively to capture each effect. This approach allows us to investigate the effect of trade cost changes in general equilibrium, taking into account inter-location spillovers. Empirically, this paper examines how China’s dramatic expansion of its highway system from 1998 to 2007 shaped the geographic distribution of domestic manufacturing firms. We show that this highway expansion reduced inter-regional trade costs and affected the selection of firms and resource allocation among firms. For the manufacturing sector on aggregate, the highway expansion contributed to 24% of the observed productivity growth, 40% of the decline in productivity dispersion, and 16% of the output growth, but these effects differ substantially across industries and locations, highlighting the distributional impact of trade cost changes.

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1 Introduction

This paper studies the distribution of firm productivity and production in the network of geographic locations in an economy. It is well documented that there exists substantial dispersion of firm productivity within narrowly defined industries (see [Bernard *et al.* \(2007, 2012\)](#) for reviews). Despite attempts to investigate the causes underlying such dispersion, research work to date is far from exhaustive. Meanwhile, a vast literature in economic geography explores the spatial distribution of production activities, and frequently links firms' location choices to their productivity (see [Rosenthal & Strange \(2004\)](#) and [Puga \(2010\)](#) for reviews).

This paper highlights the under-studied role of geography from an inter-regional trade perspective: trade costs between locations affect where firms are located, influence the selection of firms that enter and produce in each location, and hence shape the geographic distribution of firm productivity and production in an economy. Formally, we further develop the “market access” approach of [Donaldson & Hornbeck \(2016\)](#) in a [Melitz \(2003\)](#) framework to capture the effects of trade cost changes in general equilibrium. We first derive simple expressions of two types of market access: consumer market access (CMA), which measures competition from rival firms, and firm market access (FMA), which measures market size available to local firms. We then use the dramatic expansion of highway networks in China from 1998 to 2007 as a source of variation in Chinese prefectures' market access, and examine how the geographic distribution of manufacturing firms' productivity and production evolved accordingly.

We start by establishing two empirical patterns related to how firm productivity and production are distributed across geographic locations. Our empirical setting is the Chinese manufacturing sector from 1998 to 2007, and “geographic locations” refer to prefectures.¹ First, geographic locations explain a significant fraction of between-firm productivity variation. On average across industries, a firm's prefecture location accounts for approximately 14% of the variation in firm productivity, yet this fraction ranges from below 2% for some industries to above 20% for some others. Second, while firms tend to be geographically concentrated, the degree of concentration again differs substantially by industry. Some industries have over 50% of total sales from firms in fewer than 5 locations, some have their sales spread out among firms in more than 200 locations, with no location accounting for more than 2% of industry aggregate.

¹ A prefecture usually consists of 2 – 4 core urban districts and 4 – 8 surrounding counties, similar to a commuting zone in the U.S.A.

These stylized facts provoke inquiry into the underlying mechanisms through which geographic locations matter. This paper tackles this question from an inter-regional trade perspective. Changes in inter-location trade costs induce two competing effects on firm productivity distribution and production in each location. On the one hand, as trade costs decline, local consumers will find it less expensive to buy from rival firms in other locations, or equivalently, local firms will face stronger competition from elsewhere (“import competition”). For each location, stronger import competition only allows the more productive firms to enter and produce, raises local average productivity, and shrinks each surviving firm’s output. On the other hand, local firms can also more easily sell to markets elsewhere (“export access”). For each location, better export access allows less productive firms to survive, lowers local average productivity, and increases each surviving firm’s output. Despite their countervailing effects, import competition and export access are also inter-related via an income-expenditure link: the more productive firms there are in a location, the higher competitive pressure these firms exert on firms in other locations; meanwhile, more productive firms bring in more revenue for local consumers, who can thus spend more on purchases from firms elsewhere.

This paper formalizes the intuition above by extending the “market access” approach of [Donaldson & Hornbeck \(2016\)](#) in the firm heterogeneity and trade framework of [Melitz \(2003\)](#). We derive two distinct market access measures: consumer market access (CMA) to capture import competition, and firm market access (FMA) to capture export access. For a location, both market access measures increase in another location’s economic mass, for example the number of competing firms or the total purchasing power of consumers, and decrease in the trade cost between the two locations. A location’s market access affects its local productivity distribution and production via firm selection and resource allocation among firms: as trade costs decline, better CMA makes it more difficult for less productive firms to survive and compresses the output of surviving firms, while better FMA works in the opposite direction simultaneously.

As local firms respond to trade cost shocks, the general equilibrium effect of these shocks becomes particularly salient. In an inter-connected network of locations, a trade cost shock between some locations not only influences local firms, but also generates spillovers on firms in other locations that do not experience trade cost changes directly. Moreover, such spillovers can feed back to locations directly affected by trade cost changes. For example, consider 3 locations o , m , and d that trade with one another. If many new firms enter o after a trade cost shock between o and d , firms in o will exert higher competitive pressure on rival firms in m (an increase in m ’s CMA),

even if the $o - d$ shock does not hit m directly. As less productive firms exit from m and surviving firms in m become smaller, workers in m live with lower income and hence spend less on goods imported from o and d (a decrease in FMA for o and d), discouraging potential entrants in both locations. Clearly, for location o , which market access force dominates depends on not only o 's initial productivity distribution, but also the initial productivity distributions in other locations connected to o via trade, and the relative changes in trade costs across location pairs. Given such inter-location interaction, one may want to be cautious about giving causal interpretation to treatment vs. control comparison between locations experiencing stronger trade cost shocks and those experiencing weaker shocks. This necessitates our “market access” approach, examining the effect of trade cost shocks in general equilibrium.

To implement our “market access” approach empirically, this paper exploits a common and important source of variation in trade costs: construction of transportation infrastructure. Specifically, in the decade from 1998 to 2007, along with a 5-fold increase in aggregate manufacturing output, China witnessed dramatic expansion of its highway networks, with only sporadic regional highways at the beginning but a well connected nationwide highway system in the end. We treat each prefecture as a local economy, and approximate the trade costs between them using road travel time, which highway networks reduced by over 40% on average across prefecture pairs in this period. Market access measures are then defined at industry-prefecture level. The historic expansion of China's manufacturing sector and highway networks resulted in substantial changes in both CMA and FMA, with sizable variation in such changes across industry-prefecture's.

We collect firm-level data and inter-prefecture travel time data for model calibration, allowing the empirical relationship between trade cost and travel time to differ across industries. The resulting parameter estimates make intuitive sense and the model provides a good fit of the actual data. For example, we find that trade cost increases in travel time, with a steeper slope for industries whose products have higher weight-to-value ratios, a proxy for the per-unit-value price of road transport, and industries for which expenses on road transport account for a larger fraction of total input. We then use the parameter estimates to compute market access measures and investigate how they are correlated with firm productivity distribution and production at industry-prefecture level. Due to the general equilibrium dynamics associated with trade cost shocks as described earlier, such regressions do not capture average treatment effects, but may still provide empirical support to our model.

We find 3 sets of reduced-form evidence consistent with the theoretical predictions above. First, holding FMA constant, CMA exhibits a strong positive correlation with local average productivity, with an increase of 1 standard deviation (s.d.) in CMA associated with about 0.24 s.d increase in local mean productivity. In contrast, holding CMA constant, an increase of 1 s.d. in FMA is associated with 0.18 s.d. decrease in local mean productivity. The correlations between market access and local average productivity are higher for high weight-to-value industries. Second, conditional on an individual firm’s own productivity, FMA exhibits a strong positive correlation with the firm’s output: 1 s.d. increase in FMA is associated with 0.32 s.d. increase in firm output, and this effect comes mostly from highly productive firms. Third, an increase in CMA or a decrease in FMA is related to a higher probability of exit among less productive firms and a smaller number of entrants. These findings reassure us that our structural model captures important variation in the data and can likely generate meaningful counterfactuals.

To estimate the general equilibrium effect of the highway expansion, we rely on our structural model to recover counterfactual scenarios, incorporating interaction among locations in the network. For our main counterfactual, we assume that the 2007 highway networks were put in place in 1998, and examine how the 1998 geographic distribution of firm productivity and production would have responded. As we restrict local underlying productivity distributions to the 1998 baseline, changes in local firm productivity and production outcomes come only from trade cost shocks and the resulting market access dynamics. In this scenario, the dispersion of firm productivity across locations is significantly reduced, production is concentrated in slightly fewer locations, and aggregate productivity and output levels are much higher. This overall trend masks considerable heterogeneity across industries and locations. For instance, productivity dispersion decreases more for industries with a higher share of output in (often inefficient) state-owned enterprises, and locations where firms are highly productive initially tend to see a larger increase in total output. We then compare this counterfactual, where only market access forces have been at work, with the actual 2007 firm-level data. We find that, for the manufacturing sector overall, the highway-induced market access dynamics alone accounts for a significant fraction of the observed changes between 1998 and 2007: around 24% of productivity growth, 40% of the decline in productivity dispersion, and 16% of output growth. These estimates are approximately 30 – 40% higher than reduced-form estimates, consistent with the earlier argument that the treatment vs. control method misses important general equilibrium effects.

Emphasizing import competition and export access effects, we are missing some potentially important impacts of highway construction that we can't measure due to data limitations. For example, highway networks can encourage firms to cluster in certain regions and create more benefits of agglomeration, improve access to locations from which firms source intermediate inputs,² raise individual firms' productivity levels by making it more convenient for experienced technicians to travel between locations and exchange ideas, etc. We focus on import competition and export access to keep our theoretical framework simple, tractable, and easy to estimate given our data. In fact, this seemingly narrow focus can explain a significant fraction of the observed productivity and production evolution, as shown in the counterfactual analysis above.

This paper connects two vast fields of active research: economic geography and firm heterogeneity. The spatial distribution of firms has long been an active area in economic geography, and has been frequently linked to firms' productivity. In firm heterogeneity literature, the sizable dispersion of firm productivity has been repeatedly highlighted, and remains prominent in research on international trade.

A voluminous literature on economic geography has proposed various theories of firms' location decisions, and many theories suggest that firms choose to locate where they can be most productive. [Puga \(2010\)](#) comprehensively reviews studies on the magnitude and causes of the geographic concentration of production activities. This paper stresses that, by determining where to locate, firms choose how close they are to their competitors and product markets, and affect other firms' location choices. A location where firms can be highly productive may seem less ideal if many competitors are nearby or product markets are distant. In other words, a location attracts firms not only because of its (immobile) endowment, but also because of its connection with other locations, and better connection often means lower trade costs. [Redding & Turner \(2015\)](#) offers a detailed review of transportation costs and the spatial organization of economic activity.

Directly contributing to the extensive research on firm heterogeneity (see [Bernard *et al.* \(2012\)](#) for an overview), this paper documents the important yet understudied role of geography in shaping firm productivity distribution. Many papers offer explanations of the enormous difference in productivity between firms, such as technology ([Eaton & Kortum, 2002](#)), policy distortions ([Hsieh & Klenow, 2009](#)), management practice ([Bloom *et al.*, 2013](#)), labor mobility ([Tombe & Zhu, 2015](#)), etc.

² In Appendix A.1.2, we supplement our main model by adding an input channel, and derive an expression for input market access (IMA) that captures the effect of input price changes in response to trade cost shocks. We also discuss what data we need to empirically estimate this more comprehensive model.

This paper focuses on an unexplored factor, namely geography-based market access, distinguishes between CMA and FMA, and discusses the respective implications for productivity distribution.

Using highway connection as an important source of variation in market access, this paper is also related to a large volume of research on the economic impact of transportation infrastructure. Many economists have explored how transportation infrastructure affects regional economic growth (Duranton & Turner (2012), Banerjee *et al.* (2012), Faber (2014), Lin (2017), Qin (2017)); inter-regional trade (Donaldson (forthcoming), Duranton *et al.* (2014), Allen & Arkolakis (2017)), labor market (Michaels, 2008), manufacturing activity (Ghani *et al.*, 2016), urban formation and development (Baum-Snow (2007), Baum-Snow *et al.* (forthcoming), Nagy (2017)), among others. We take a novel angle by examining the effect of highway networks on the geographic distribution of firm productivity and production, highlighting the market access dynamics in general equilibrium. By distinguishing between CMA and FMA, we formally model the distributional impact of trade cost shocks on heterogeneous firms, and hence rationalize earlier findings that some locations gain, while others lose, from improved transportation infrastructure.

This paper is closely related to a few recent ones in terms of the “market access” approach. Since Donaldson & Hornbeck (2016) and Baum-Snow *et al.* (2017) examine macro-level outcomes of local economies like total land value and GDP growth, for simplicity, they only specify one traded sector and one type of market access for each location, and find that better market access improves macro-level outcomes. A similar definition of market access is adopted by Yang (2017), which evaluates the heterogeneous effects of market access across industries. Looking at the distribution of individual firms’ productivity, this paper considers multiple industries with heterogeneous firms and the counteracting effects of two types of market access.³ Although a decrease in trade cost enhances both CMA and FMA for a location, total local firm revenue will not increase if import competition dominates export access. As the geographic distribution of firms varies by industry, so will the overall effect of trade cost shocks on a given location. While all three papers focus on reduced-form evidence, this paper estimates a fully specified structural model using detailed firm-level data and recovers counterfactuals related to trade cost shocks. In particular, we highlight how changes in location o ’s market access can influence the market access of other locations, and changes in other locations’ market access can in return affect o ’s market access.

The rest of this paper proceeds as follows. Section 2 briefly introduces the empirical setting,

³ As we will show in Sec.3.2, the two types of market access, CMA and FMA, are proportional in a one-sector setting.

and establishes two sets of stylized facts in order to motivate our model in Section 3. Section 4 describes how to measure historical road travel time between prefectures and link it to trade cost. Section 5 estimates the structural model and shows how well the model fits the data. Section 6 conducts reduced-form tests of the model’s key predictions, together with robustness checks and discussion of alternative hypotheses. Section 7 uses the model to recover counterfactual scenarios related to trade cost changes. Section 8 concludes.

2 Empirical Patterns: Geographic Distribution of Firm Productivity and Production

In this section, we briefly introduce our empirical setting, and establish two stylized facts about the geographic distribution of firm productivity and production. First, a firm’s location explains a significant fraction of the substantial variation in productivity, and the fraction of variation explained depends on the industry in question. Second, the degree of firms’ geographic agglomeration also varies dramatically by industry. These results point to the importance of understanding the distribution of firm productivity and production in an economy from a geographic perspective, with particular attention to industry-specific patterns, and motivate subsequent work on how productivity and production distributions are affected by trade costs that separate geographic locations.

2.1 Empirical Setting: Chinese Industrial Firms Database

Detailed firm-level data, based on which we calculate individual firms productivity, come from the Chinese Industrial Firms Database (CIFD). An annual firm-level survey conducted by China’s National Bureau of Statistics, the database covers mining, manufacturing, and public utility industries. In this paper, we will focus on manufacturing firms, and the decade between 1998 and 2007 in which the surveys contain necessary variables for standard productivity measurements.

Firms present in this dataset are relatively large. According to the official documentation, the surveys include all state-owned enterprises (SOEs), and non-state firms with sales greater than 5 million CNY (“above-scale” firms).⁴ Yet in fact, a significant number of below-5-million non-state firms, accounting for about 5% of the unbalanced panel, are also included. In comparison with the 2004 Economic Census that covers the universe of firms, the CIFD excludes 80% of firms, yet these “below-scale” firms only accounted for 28.8% of industrial workforce, 9.9% of output, and 2.5% of

⁴ 1 U.S. dollar \approx 8.3 Chinese yuan from 1998 to 2004, and gradually depreciated to 7.2 CNY at the end of 2007.

exports (Brandt *et al.*, 2012).⁵ Appendix A.(1.1.1) provides details about this database and how the final sample is constructed.

Table 1(A) provides key summary statistics from firm balance sheets. From 1998 to 2007, aggregate real industrial output experienced an impressive 4-fold increase, value added and export increased by even more, while total employment grew by 40%, suggesting considerable productivity gains. Though the total number of firms more than doubled from 129k to 288k, there was massive entry and exit simultaneously, as shown in Table 1(B). Approximately 10 – 15% of firms enter and exit every year, and only 30k firms remained throughout the sample period.

Table 1(C) summarizes firm productivity distributions across industries. For each of the 29 2-digit industries, we calculate the Levinsohn-Petrin output productivity for individual firms. The well documented firm heterogeneity is confirmed: if we rank firms by their productivity in a year, firms at the 90th percentile are about 0.7 log points, or 100% more productive than firms at the 10th percentile. The 1998-2007 decade saw a substantial increase in aggregate productivity level, and a slight decline in productivity dispersion. Productivity dispersion quantified using value-added productivity measures like Olley-Pakes and Akerberg-Caves-Frazer is an order of magnitude greater, echoing findings in Gandhi *et al.* (2016), but the overall rise in aggregate productivity and decline in productivity dispersion remain.

2.2 Geographic Location and Productivity Dispersion

We now show that a firm's geographic location explains a significant fraction of between-firm productivity dispersion. If we assume that a prefecture's contribution to local firms' productivity is the same across industries, then where firms are located accounts for about 2 – 3% of the variation in firm productivity (Table 2). This is already a sizable fraction in comparison with other common factors, such as ownership type (state-owned, private, etc.) and firm age, which explain less than 0.1%. Yet the effect of geographic locations likely varies by industry: while Boston can be a good fit for pharmaceutical firms, it does not seem an ideal environment for oil refineries. Allowing the effect of geographic locations to vary by industry boosts the fraction of variation explained by 5 times to 12 – 14% (Table 2). One may think of the first 2 – 3% of the variation explained as the common contribution of geographic locations to firm productivity, and the next 10 – 11% as the

⁵ Thus in this paper, the entry and exit of very small non-state firms are about when they first appear in and disappear from the CIFD. We discuss how this will affect our results in Sec.6.3.

industry-specific contribution. For example, a well-educated labor pool in a city supports local firms regardless of industry, yet industries that demand more skilled labor likely benefit more.

While geography seems to matter for firm productivity overall, Figure 1(A) documents that the importance of geography varies across industries. In 2006, the fraction of variance explained by firms' geographic locations ranges from less than 2% for industries like oil refining and coking to more than 20% for industries like ferrous metal smelting and rolling.

2.2.1 Geographic Agglomeration of Firms

Our second empirical pattern is about how firm production is distributed geographically. While we have documented that geography matters for firm productivity across industries, firms do not always agglomerate in highly productive locations. Figure 1(B) shows the Ellison-Glaeser agglomeration index for the 29 2-digit industries. Recall that, when [Ellison & Glaeser \(1997\)](#) introduce this index to the 1987 U.S. Census of Manufactures data, the authors designate an industry with an index value above 0.05 as “highly agglomerated”, and an industry with a negative index value as the opposite. Overall, Chinese manufacturing firms in 2006 were not highly agglomerated, with an average index of 0.017 across industries. Again, industry heterogeneity is evident: the index ranges from negative for industries like tobacco products to above 0.06 for industries like electronic equipment. ⁶ Together, results in this section invite questions about what determines the distribution of firm productivity and production across space.

3 Theoretical Framework

To understand the geographic patterns about firm productivity and production distributions, we further develop the “market access” approach per [Donaldson & Hornbeck \(2016\)](#) in a [Melitz \(2003\)](#) framework of firm heterogeneity and trade. As inter-location trade costs decline, firms in a location face more import competition on the one hand, but also have greater export access on the other. We derive expressions of consumer market access (CMA) to capture import competition, and firm market access (FMA) to capture export access. Both types of market access shapes the geographic distribution of firm productivity and production via firm selection: for a location, higher CMA, or more intense import competition, only allows the more productive firms to survive, raising local average productivity and shrinking the output of every surviving firm; higher FMA, or greater

⁶ Both the percent of variation explained by prefecture and the agglomeration index have much higher averages and greater dispersion at 4-digit industry level (about 420 4-digit industries), see [Glaeser & Xiong \(2017\)](#).

markets for export, works in the opposite direction.

The general equilibrium effect of trade cost changes becomes particularly salient in our setting and necessitates the “market access” approach. Many papers on the effect of transportation infrastructure strives to identify the partial equilibrium effect of trade cost shocks. For this purpose, the ideal experiment is to randomly assign highway connection, and compare locations that get connected with those that do not. However, in a network of locations, each location is affected by the global matrix of location-to-location trade costs. A change in trade cost between two locations not only directly affects trade between the two, but also generates spillovers on other locations. Consider two neighbor locations o_1 and o_2 and another distant location d with trade connections among them. A highway that connects o_1 and d reduces the travel time, and hence trade cost, between o_1 and d , changing the CMA and FMA of, and thus the set of firms in, both o_1 and d . As the sets of firms in o_1 and d are now different, so are CMA and FMA of o_2 . In addition, the o_1 - d highway can reduce the travel cost between o_2 and d , for instance, if it saves time for an o_2 - d trip to go through o_1 to take advantage of the o_1 - d highway. This will also change the market access of, and hence the set of producing firms in, o_2 . A change in the set of firms in o_2 feeds back to the market access of o_1 and d , and this loop continues in the network of locations until a new equilibrium is reached. A simple treatment-control (highway connection or not) comparison will miss such indirect effects of trade cost shocks, and thus we rely on our structural model to recover counterfactual scenarios.

3.1 Setup

We adopt the [Melitz \(2003\)](#) framework, derive explicit expressions of CMA and FMA, and show their respective implications for local firm productivity and production distributions. We begin by outlining the setup. ⁷

3.1.1 Notations

Representative consumers’ preferences are defined over the consumption of goods produced by J industries indexed by $j, k \in \{0, 1, 2, \dots, J\}$. Industry $j = 0$ produces a homogeneous good. Each industry $j \geq 1$ has a continuum of horizontally differentiated varieties, and each firm produces one of the varieties. There are N locations indexed by o (origin) or d (destination) $\in \{1, 2, \dots, N\}$, and

⁷ Readers interested in the details of the Melitz setup may refer to [Melitz & Redding \(2014\)](#).

a symmetric iceberg trade cost τ_{od} between o and d .

In industry j and location o , the unit cost of production (or composite input price) is c_{jo} , and there is an underlying distribution of firm productivity $G_{jo}(\varphi)$ and potential mass of firms S_{jo} . The mass of firms that produce (and we observe in data) is a fraction h_{jo} of S_{jo} . Individual firms are indexed by $\omega \in \Omega_{jo}$, with each firm's productivity draw $\varphi_{jo\omega}$.

3.1.2 Preferences

Representative consumers have Cobb-Douglas upper-tier utility over industries,

$$U = \sum_j \beta_j \ln Q_j, \quad \sum_j \beta_j = 1, \beta_j \in (0, 1)$$

In location o , total expenditure on industry j 's good is thus $X_{jo} = \beta_j I_o$, where I_o denotes the total income of o .

Within each differentiated industry $j \geq 1$, the aggregator over these varieties takes the Constant Elasticity of Substitution (CES) form:

$$Q_j = \left[\int_{\omega \in \Omega_j} q(\omega)^{(\sigma_j-1)/\sigma_j} d\omega \right]^{\sigma_j/(\sigma_j-1)}$$

where $\sigma_j > 1$ denotes the within-industry CES elasticity.

The price index of industry j 's good is then

$$P_j = \left[\int_{\omega \in \Omega_j} p(\omega)^{1-\sigma_j} d\omega \right]^{1/(1-\sigma_j)}$$

3.1.3 Production and Pricing

Industry $j = 0$ produces a homogeneous good with a unit input, and the price of this homogeneous good is chosen as the numeraire. In industry-location $j - o$, a potential entrant firm can pay fixed cost $c_{jo}e_{jo}$ for a productivity draw $\varphi_{jo\omega}$, and can then choose to produce at unit cost $\frac{c_{jo}}{\varphi_{jo\omega}}$ (so production features constant returns to scale). A firm will only start producing if it expects the revenue to at least cover the fixed cost of production $c_{jo}f_{jo}$.

Under CES demand and monopolistic competition, firms charge a constant mark-up $\frac{\sigma_j}{\sigma_j-1}$ above

their unit cost of production. Given the trade cost τ_{od} between locations o and d , the price of firm jow 's product in location d is

$$p_{j,od}(\varphi_{jow}) = \frac{\sigma_j}{\sigma_j - 1} \frac{c_{jo}}{\varphi_{jow}} \tau_{od}$$

3.2 Market Access

As we will characterize equilibrium in an industry, we now drop the industry subscript j to streamline notation.

While the Melitz model specifies a fixed cost of export for each pair of locations, we make a key simplifying assumption: inter-location trade is only subject to iceberg trade cost, not fixed cost of export. In other words, as long as a firm chooses to produce, it sells its variety to all locations in the economy. This assumption allows us to derive clean expressions for market access measures, and is less stringent in intra-national trade, as in our empirical setting, than in international trade. In addition, since our data do not cover the “export” (selling to other prefectures in China) status of individual firms, it is quite challenging to estimate the fixed cost of export as many papers on international trade do.

3.2.1 Firm Market Access (FMA)

A destination d 's demand for the variety produced by a firm with productivity φ in origin o is

$$\begin{aligned} r_{od}(\varphi) &= q_{od}(\varphi)p_{od}(\varphi) = \frac{X_d}{P_d^{1-\sigma}} p_{od}(\varphi)^{1-\sigma} \\ &= \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \tau_{od}^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}} \left(\frac{c_o}{\varphi} \right)^{1-\sigma} \end{aligned}$$

Total demand is the sum of demand over all destinations,

$$r_o(\varphi) = \left(\frac{c_o}{\varphi} \right)^{1-\sigma} FMA_o \quad (1)$$

where

$$FMA_o \equiv \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \sum_d \tau_{od}^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}}$$

A location has high FMA, or access to a large market, if (1) it is well connected to other locations, which shows up as small trade costs τ ; (2) other locations have high demand, which shows up as

large total expenditure X ; (3) other locations have low levels of competition, which shows up as a high price level P). Intuitively, even if a location spends a large amount on an industry's products, there will be little room for firms elsewhere if the local market is already highly competitive, or equivalently, at a low price level. FMA thus captures the aggregate size of markets that a local firm can potentially reach.

It quickly follows that total demand/revenue for all firms in a location is

$$R_o(\varphi) = S_o \int_{\varphi} \left(\frac{c_o}{\varphi}\right)^{1-\sigma} FMA_o dG_o(\varphi) \quad (2)$$

3.2.2 Consumer Market Access (CMA)

The price index in each destination d is a CES aggregate of the prices of individual firms' varieties that sell in d . Competition among rival firms lowers the price index and enhances local consumers' welfare. We thus relate a location's price index to its consumer market access (CMA),

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$$\begin{aligned} P_d^{1-\sigma} &= \sum_o \left[M_o \int p_{od}(\varphi)^{1-\sigma} dG_o(\varphi) \right] \\ &= \sum_o \left[M_o \int \left(\frac{\sigma}{\sigma-1} \frac{c_o \tau_{od}}{\varphi} \right)^{1-\sigma} dG_o(\varphi) \right] \equiv CMA_d \end{aligned}$$

Eq.(1) gives $\left(\frac{c_o}{\varphi}\right)^{1-\sigma} = \frac{r_o(\varphi)}{FMA_o}$. Substituting this into the $P_d - CMA$ equation above, and making use of Eq.(2), we obtain

$$CMA_d = \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \sum_o \tau_{od}^{1-\sigma} \frac{R_o}{FMA_o} \quad (3)$$

A location has higher CMA, or more competition, if (1) it is better connected to other locations, which shows up as smaller trade cost τ ; (2) other locations have large competing firms, which shows up as larger total revenue R ; (3) firms in other locations can only reach a small market, which shows up as smaller FMA . Intuitively, if a location has many large firms, but at the same time sells to a very large market, the competitive pressure that local firms exert on firms elsewhere will be lower.

⁸ To the extent that firms in an industry use the output of all industries as intermediate input, and that the price of intermediate input is part of the composite cost of production, a location o 's higher CMA, or lower price index, of industry j will lower the cost of production c_{ko} for all industry k 's. We formalize this in Appendix A.1.2 and derive input market access (IMA) based on CMA.

Symmetrically, since $P_d^{1-\sigma} \equiv CMA_d$, we write FMA as

$$FMA_o = \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \sum_d \tau_{od}^{1-\sigma} \frac{X_d}{CMA_d} \quad (4)$$

Eq.(3) and (4) illustrate that, if total revenue R_{jo} is proportional to total expenditure X_{jo} across industry-location's,⁹ so is CMA to FMA. This is the case if there is only one traded sector, as in several previous papers on market access like [Donaldson & Hornbeck \(2016\)](#) and [Baum-Snow *et al.* \(2017\)](#). In our setting, CMA and FMA differ from each other because of the uneven distribution of production across locations.

Empirically, it is difficult to measure CMA as a recursive index. Again using $\left(\frac{c_o}{\varphi} \right)^{1-\sigma} = \frac{r_o(\varphi)}{FMA_o}$, we express CMA in unit cost of production,

$$CMA_d = \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \sum_o \tau_{od}^{1-\sigma} \left(\sum_{\omega \in \Omega_o} \left(\frac{\varphi_{o\omega}}{c_o} \right)^{\sigma-1} \right) \quad (5)$$

Clearly, a location has high CMA if it is well connected to locations that have many productive firms (large sum of high φ firms).

3.3 Local Productivity Distribution

In location o , a firm at the local productivity cutoff φ_o^* makes just enough profit $\pi(\varphi_o^*)$ to offset the fixed cost of production $c_o f_o$, Eq.(1) implies

$$\begin{aligned} \pi(\varphi_o^*) &= \frac{r(\varphi_o^*)}{\sigma} - c_o f_o = 0 \\ \Rightarrow (\varphi_o^*)^{\sigma-1} &= \frac{(c_o)^\sigma \sigma f_o}{FMA_o} \Rightarrow \varphi_o^* \propto (FMA_o)^{\frac{1}{1-\sigma}} \end{aligned} \quad (6)$$

Ceteris paribus, an increase in FMA lowers the cutoff φ_o^* : a larger market size allows local firms to spread their fixed costs of production over more product units, and hence unproductive firms can manage to enter or survive. By Eq.(4), FMA is decreasing in CMA, so an increase in CMA raises the cutoff φ_o^* : more competition makes it more difficult for unproductive firms to enter or survive. Similarly, by Eq.(1), local individual firms' revenue and total revenue of a location both increase in

⁹ An extreme case: each industry-location maintains trade balance, i.e. $R_{jo} = X_{jo}$.

the location's FMA and decrease in its CMA.¹⁰

Assume an underlying Pareto local productivity distribution with scale and shape parameters $(\varphi, \theta)_o$, so the probability density function $g(\varphi_{o\omega}) = \frac{\theta_o(\varphi_o)^{\theta_o}}{(\varphi_{o\omega})^{\theta_o+1}}$. Changes in CMA or FMA move $\varphi_o^* \geq \varphi$ around, but the lower-truncated Pareto distribution is still Pareto, with scale parameter φ_o^* and the same shape parameter θ_o . For $\theta_o > 1$,¹¹ the cutoff pins down the mean productivity of surviving firms,

$$\bar{\varphi}_o = \frac{\theta_o \varphi_o^*}{\theta_o - 1} = \frac{\theta_o}{\theta_o - 1} \left(\frac{(c_o)^\sigma \sigma f_o}{FMA_o} \right)^{\frac{1}{1-\sigma}} \quad (7)$$

All firms pay a fixed cost of entry $c_o e_o$ to draw from the underlying productivity distribution $G_o(\varphi)$, but only those who get a draw above the cutoff φ_o^* produce. Free-entry condition imposes that the expected ex-ante profit of firms that produce just offsets the fixed cost of entry,

$$\begin{aligned} \int_0^\infty \pi(\varphi) dG_o(\varphi) &= \int_{\varphi_o^*}^\infty \left(\frac{r(\varphi)}{\sigma} - c_o f_o \right) dG_o(\varphi) = c_o e_o \\ \Rightarrow \frac{R_o}{\sigma} &= h_o S_o c_o f_o + c_o e_o S_o \end{aligned} \quad (8)$$

where $h_o = \int_{\varphi_o^*}^\infty dG_o(\varphi)$ denotes the share of underlying firms that enter and produce, and thus $h_o S_o$ the observed mass of firms. For simplicity, we write $e_o S_o = E_o$. Under this free-entry condition, lowering barriers to entry in a location attracts more entrants there, intensifies local competition, and pushes down the local price level in equilibrium.

4 Trade Cost Measurement

Having derived explicit expressions of various market access, we proceed to the corresponding empirical measurement. A key missing piece in our setting is the trade cost between prefectures in China. Without inter-prefecture trade data, in particular data on spatial price gaps,¹² we are unable to directly estimate trade cost, and hence follow an indirect route in the economic geography

¹⁰ One can see this more clearly by dividing a location's FMA into that due to its home market and that due to its export market (selling to other locations),

$$FMA_o = FMA_{o,ex} + \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \frac{X_o}{CMA_o}$$

¹¹ For $\theta_o \in (0, 1]$, the mean approaches infinity.

¹² See [Atkin & Donaldson \(2015\)](#) for a recent advance in using spatial price gaps to identify intra-national trade costs. The authors also review a voluminous literature along this line.

literature to infer trade cost from road travel time between prefectures. ¹³

4.1 National Highway Construction

Since the early 1990s, and in particular during our sample period from 1998 to 2007, China went through massive expansion of highway networks. ¹⁴ In 1990, there were essentially no limited access highways between Chinese prefectures. Existing inter-city roads had at most two lanes with unrestricted access, and were often unpaved. Thus, [Baum-Snow *et al.* \(2017\)](#) assume merely 25 km/h for inter-prefecture traveling on local roads. Roads took care of less than 5% of freight ton-km's, and almost all goods were moved by railway or waterway.

In 1992 under the National Trunk Highway Development Program, the Chinese State Council approved the blueprint of the “5-7” system, which refers to 5 North-South vertical and 7 East-West horizontal axes [World Bank \(2007\)](#). The project aimed to connect all provincial capitals and cities with an urban registered population above half a million on a single highway network, and to connect targeted regional centers and the national border in border provinces as part of the Asian Highway Network. The Chinese Ministry of Communications (predecessor to the current Ministry of Transport) set 1992-1997 as the “kick-off” phase in which only a handful of highways were completed, and 1998-2007 as the “rapid development” phase in which large-scale construction took place. Originally earmarked for completion by 2020, this nationwide construction endeavor concluded ahead of schedule by the end of 2007, in large part due to the government’s stimulus spending in response to the 1997 Asian Financial Crisis [Asian Development Bank \(2007\)](#). In consequence, from 1998 to 2007, China’s total highway length grew from 8.7k km to 53.6k km. By 2010, highways and roads carried over 30% of freight ton-km’s. ¹⁵ Given the post-1998 acceleration of construction, the State Council approved an even more ambitious follow-up plan in Dec. 2004. The stated purpose of this “7-9-18” system was to bring highway connection to all cities with an urban registered population above 200k by 2020. ¹⁶

Prior to the advent of national trunk highways, national highways and provincial highways served as the main routes between prefectures, usually subject to a speed limit of 80 – 100 km/h

¹³ In Appendix A.1.3, we discuss why we focus on road transport rather than other modes of transport, like railway, air, and waterway.

¹⁴ This subsection that tells the history of China’s national highway system borrows heavily from Sec.2.1 of [Faber \(2014\)](#) and Sec.2 of [Baum-Snow *et al.* \(2017\)](#).

¹⁵ Source: China Statistical Yearbook, 2011, published by the National Bureau of Statistics of China.

¹⁶ “7-9-18” refers to 7 radial axes from the capital Beijing, 9 vertical axes, and 18 horizontal ones. In 2013, the Ministry of Transport added two additional vertical axes, aiming to having in total 118k km of highways by 2030.

and 70 km/h, respectively. However, many prefectures were not on existing national highways. Moreover, due to poor road quality and frequent congestion, the actual speed on these highways was often far below the limit. In contrast, newly built as 4-lane limited access tollways, the national trunk highways commonly feature a speed limit of 110 – 120 km/h, and run in parallel with existing major roads in many areas.

4.2 Road Travel Time and Trade Cost

We make use of 2 data sources to estimate by how much highway construction reduces inter-prefecture road travel time. First, the ACASIAN GIS data, which we describe in Appendix A.(1.1.2), provide historical maps of highway networks in China, allowing us to hand-collect in which year each prefecture received highway connection. If unclear based on maps, we supplement the data with news search on highway construction. As Figure 2 shows, while there were only sparse regional highways in 1998, the vast majority of prefectures in China had been connected by highways in an integrated national network by 2007.

Second, working with Google Maps APIs, we obtain contemporary (Nov. 2016, when this task was completed) travel distance and time matrices. Since very few, if any, prefectures are still off the national highway network, the normal travel time is almost completely based on highway travel, i.e. one spends the least time traveling between prefectures by staying on highways all the time. Recall that very few prefectures, typically the remote ones with little manufacturing activity, were still left behind during the highway boom by 2007, so the contemporary normal travel time provides a good proxy for the 2007 travel time. If we specify “avoid highways”, Google Maps will avoid highways altogether when choosing routes between prefectures, typically staying on national and provincial major roads that were already in place in 1998. This usually results in minimal changes in travel distance, but doubles travel time.

Since Google Maps can’t recover 1998-2007 travel time, we use the historical highway maps and contemporary travel time in 3 steps, incorporating two main adjustments.

1. For an origin location o and destination d in year y , if the highway map of year y shows that both o and d were connected to highways, then we use the normal travel time; otherwise, use the “avoid highways” time.
2. “Block” adjustment. The first step probably underestimates the actual travel time in the early years of our sample period. As shown in Figure 2, in the late 1990s, there were several regional

“blocks” in which highways connected regional centers and nearby cities, but sometimes no highways between different blocks. When o and d belong to different blocks, one can’t always stay on highways when going from o to d . Therefore, for each year, we identify a few highway blocks, and only use normal travel time if o and d are connected via the same block of highways. The number of blocks declined as the highway networks expanded over time, and by 2007, basically all prefectures lay on one nationwide highway block.

3. “Detour” or “fastest path” adjustment. Especially when o and d are far apart, the “avoid highways” travel time will likely exceed the actual travel time even if neither prefecture is directly connected to highway networks, since one may still go on highways between the two whenever available. We thus allow one to take “detours” between o and d as long as this reduces travel time.

- Let t_{od} denote travel time between o and d . Given a 3rd prefecture m , record $(t_{om} + t_{md})$.
- For all prefectures other than o and d , if $t_{od} > \min_m \{t_{om} + t_{md}\}$, replace t_{od} with $\min_m \{t_{om} + t_{md}\}$. Clearly, this is only possible if at least one of t_{om} and t_{md} is normal travel time.
- Iterate the above two steps until t_{od} doesn’t get smaller.

After these adjustments, Table 3 shows the reduction in travel time as a result of the nationwide highway expansion. In our sample period 1998-2007, there were 337 prefectures in China.¹⁷ We restrict our empirical analysis to 287 prefecture-level “cities” and leave out 50 prefecture-level “regions” that were mostly remote, underdeveloped areas in Western China with little manufacturing activity. Among all $\binom{287}{2} = 41041$ prefecture pairs, while the average travel distance stayed more or less the same, the average travel time decreased by over 40% from 1998 to 2007.

We then follow a widely used approach in economic geography to relate travel time to trade cost. [Baum-Snow *et al.* \(2017\)](#) specify the following formula to relate road travel time to trade cost,

$$\tau_{od} = 1 + 0.004\rho(\text{travel time}_{od})^\lambda \text{ where } \rho > 0 \text{ and } \lambda \in (0, 1) \quad (9)$$

and use $\rho \in [0.5, 2]$, travel time in hours, and $\lambda = 0.8$ to incorporate some concavity. These parameter values correspond to a modest ad-valorem tariff of 1.6 – 3.1% per day (24 hours) of travel time, consistent with estimates in [Limao & Venables \(2001\)](#) and [Hummels & Schaur \(2013\)](#).

¹⁷The number slightly changed over time, due to creation of new prefectures and merger of old ones.

However, this relationship likely varies across industries based on, say, the per-unit-value cost of transport. For instance, high weight-to-value industries such as timber and coking likely have a larger ρ . We thus empirically estimate this relationship between travel time and trade cost.

5 Structural Estimation and Model Fit

The structural model in Sec.(3) and trade cost in Sec.(4) pave the way for estimation of the model. This section estimates key parameters of the model based on Sec.(3). With these parameters in hand, we test the model’s fit, and show that such a simple model provides a decent description of the actual geographic distribution of productivity and production.

5.1 Estimation

To focus on the two main forces (import competition vs. export access) in local firm selection, we make an additional assumption that significantly simplifies the structural estimation: the homogeneous good (in sector $j = 0$) is produced in all locations with a unit cost and is costlessly traded. In such an incomplete specialization equilibrium, the unit cost of production is equal across all locations, $c_{j0} = c_j \forall o \in \{1, 2 \dots N\}$. While stringent, this assumption is in fact common in firm heterogeneity and trade literature, see [Melitz & Redding \(2014\)](#)) for an example. In Appendix A.1.2, we relax this assumption and point to an alternative method to measure market access empirically.

For the manufacturing sector (for which we have firm-level data), we also impose location-level trade balance on the income-expenditure relationship for each location. Under this assumption, although a location can spend more on an industry’s goods than it makes from selling this industry’s goods, a location’s total revenue from local firms in all industries is equal to its total expenditure on all industries’ goods, i.e. $X_{jd} = \gamma_j \sum_j R_{jd}$. γ_j represents the representative consumers’ proportion of total income from manufacturing (traded sector) spent on industry j ’s output, and we obtain γ_j from the 2002 national input-output matrix.

We now classify the model’s parameters into 3 categories: (1) taken from existing literature; (2) computed directly from data; (3) estimated by fitting simulated moments to actual moments in the data. To start with, we borrow from [Broda & Weinstein \(2006\)](#) and set the same CES elasticity for all 2-digit industries, i.e. $\sigma_j = 4 \forall j$.¹⁸

¹⁸ Without inter-prefecture trade data, we can’t directly estimate the CES elasticity as in Broda and Weinstein (2006). For robustness checks, we try different values of $\sigma \in [3, 5]$. For an industry, a larger σ implies more intense competition between firms.

We now directly estimate two sets of parameters for each industry-location $j-o$ from firm-level data.¹⁹ First, as we assume a Pareto distribution of firm productivity in each $j-o$, we follow Gabaix and Ibragimov (2011) to recover the shape parameter.²⁰ In each year, within each $j-o$, we rank firm productivity φ_{jow} in decreasing order, and estimate θ_{jo} in the following OLS regression,²¹

$$\ln \left(\text{rank}_{jow} - \frac{1}{2} \right) = \eta_{jo} - \hat{\theta}_{jo} \ln \varphi_{jow}$$

Note that the standard error here on θ_{jo} is not the OLS s.e. Recall that we use Levinsohn-Petrin output productivity, based on an estimated industry-specific production function, in the main empirical specification. We also replicate our main results using alternative productivity measures including Olley-Pakes, Akerberg-Caves-Frazer, and Gandhi-Navarro-Rivers in Appendix A.??.

Second, with the unbalanced panel data, for an industry-location $j-o$ that has at least appeared twice (i.e. has ≥ 1 firm for ≥ 2 years, we rely on the free-entry condition Eq.(8) to solve for $c_{jo}f_{jo}$ and $c_{jo}e_{jo}$.²² For example, observing total revenue R_{jo} and mass (number) of firms S_{jo} in years 1 and 2, we write (omitting $j-o$ subscripts and use $y \in \{1, 2\}$ to indicate years),

$$\begin{cases} \frac{R_1}{\sigma} = S_1cf + cE \\ \frac{R_2}{\sigma} = S_2cf + cE \end{cases} \Rightarrow \begin{cases} f = \frac{1}{c\sigma} \frac{R_2 - R_1}{S_2 - S_1} \\ E = \frac{R_1}{c\sigma} - S_1f \end{cases}$$

For industry-location's that appear in $T > 2$ years, we pick $\binom{T}{2}$ 2-year pairs, solve the system of equations above for each pair, and take the average for f and E .²³

Now we specify the parameters to recover from structural estimation, conducted at industry-year level.

- Parameters used to convert travel time to trade cost, ρ_j and λ_j as in Eq.(9). As discussed,

¹⁹ For this step, "location" refers to province, which typically contains 8 – 16 prefectures, so that there are sufficient firms in each industry-location and we obtain more robust estimates.

²⁰ Alternatively, maximum likelihood gives the following estimates

$$\hat{\varphi}_{jo}^* = \min\{\varphi_{jow}\} \text{ and } \hat{\theta}_{jo} = \frac{1}{\text{Mean}[\ln \varphi_{jow}] - \ln \hat{\varphi}_{jo}^*} \quad (10)$$

This approach is quite sensitive to outliers of firm productivity.

²¹ Around 6.2% of estimated θ 's are smaller than 1, often from industry-location's with few firms. In this case, we replace the θ 's with the national mean of the industry.

²² We ignore industry-location's that has appeared only once in the sample period, which account for a tiny fraction of output. For instance, industry-prefecture's that only appear in 2004 and not other years account for 0.7% of the total output in 2004.

²³ About 7.4% of estimated f 's and 9.0% of E 's are negative, often from industry-location's with few firms. In this case, we replace the f 's and E 's with the respective national mean of the industry.

this time-cost relationship likely differs by industry.

- Given the importance of international trade for China in our sample period, particularly since China joined the WTO in 2001, it is necessary to incorporate the market access effects due to rest of the world (RoW). Without firm-level data from RoW, we assume a point-like RoW that all Chinese prefectures trade with, and use a prefecture's travel time to the nearest port as its travel time to RoW.²⁴ This gives us two additional parameters: CMA-adjusted total expenditure $\frac{X}{\text{CMA}}$ and FMA-adjusted total revenue $\frac{R}{\text{FMA}}$ for RoW.

Having specified all parameters, we proceed to structural estimation based on Sec.(3). For each industry and year, we estimate $\Psi_j = \{\rho, \lambda, (\frac{X}{\text{FMA}})_{\text{RoW}}, (\frac{R}{\text{CMA}})_{\text{RoW}}\}_j$ as follows.

1. Compute the inter-prefecture trade cost matrix, \mathcal{T} .
2. Compute $\{\text{CMA}\}_j$ following Eq.(5). $\{\text{CMA}\}_j$ then gives $\{\text{FMA}\}_j$ by Eq.(4).²⁵
3. f_{jo} and FMA_{jo} then gives φ_{jo}^* by Eq.(6). Under the assumption of Pareto distribution of firm productivity in $j - o$, local mean productivity $\bar{\varphi}_{jo} = \frac{\theta_{jo}\varphi_{jo}^*}{\theta_{jo}-1}$ (this requires $\theta_{jo} > 1$).
4. The true $\Psi_j = \{\rho, \lambda, (\frac{X}{\text{FMA}})_{\text{RoW}}, (\frac{R}{\text{CMA}})_{\text{RoW}}\}_j$ will meet the moment condition

$$\mathbb{E}[y(\Psi_j)] = \mathbb{E}[\tilde{\varphi}(\Psi_j) - \bar{\varphi}] = 0$$

where $\tilde{\cdot}$ indicates moments from simulated data. We thus seek $\tilde{\Psi}_j$ that achieves

$$\tilde{\Psi}_j = \arg \min_{\Psi_j} \{y(\Psi_j)' \mathbf{W} y(\Psi_j)\} \quad (11)$$

where a location's weight in the weighting matrix \mathbf{W} is proportional to its mass/number of firms.

We follow Eaton *et al.* (2011) to calculate standard errors by bootstrapping, taking into account both sampling error and simulation error.

5.2 Model Fit

This subsection summarizes parameter estimates from the previous subsection and presents evidence that this simple model fits well the actual geographic distribution of firm production.

²⁴ 9 ports that handle the largest volume of international trade in 2001 (Baum-Snow *et al.*, 2017): Dalian, Qinhuangdao, Tianjin, Qingdao, Lianyungang, Shanghai, Ningbo, Guangzhou, and Shenzhen.

²⁵ $\{\text{CMA}\}_j$ denotes the set of CMA's (of every location) for industry j .

Figure 3(A) plots the estimated ρ , which relates travel time to trade cost, against weight-to-value ratios, across industries in 1998. Weight-to-value ratios, which measures the weight of an industry's output per unit value, serves as a proxy of the price of transportation per unit value.²⁶ For industries that pay a higher price for transportation, a decrease of one day in travel time likely means a larger decrease in trade cost. Indeed, Figure 3(A) shows a strong positive correlation between the estimated ρ and weight-to-value ratios. Since the weight-to-value ratios based on U.S. commodity flows may deviate from their counterpart in Chinese data, we also obtain the proportion of total expenses spent on road transport from the 2002 Chinese national input-output table, and conduct a similar exercise. As show in Figure 3(B) The strong positive correlation between ρ and the share of road transport expenses remains.²⁷

With the estimated $\tilde{\Psi}$ in hand, we compute CMA following Eq.(5), then FMA by Eq.(4), and finally industry-location total revenue R by Eq.(2). Since we do not target $\{R\}$ when searching for Ψ that satisfies the key moment condition (11), comparing the model-simulated $\{\tilde{R}\}$ with the actual $\{R\}$ in data will shed light on how well the model fits the geographic distribution of production. Figure 4 plots the simulated $\{\tilde{R}\}$ against the actual (both in natural logs), based on 1998 firm-level data (first year in our sample period). The simulated $\{\tilde{R}\}$ match with the actual quite well, with a slope almost equal to 1 and quite a small and insignificant constant term. The match becomes worse (1) at the very high end, due to a small number of extremely large outliers in firm productivity distribution; (2) at the low end, probably since the assumed Pareto distribution of firm productivity typically features a higher density than actual at the low end, but better approximates the actual distribution as one moves toward the high end.

Table 4 shows similar patterns about the actual vs. simulated geographic distribution of firm production, also based on 1998 data. In Panel A, within each of the 29 2-digit industries, we rank prefectures that have firms in this industry by total revenue, and examine the prefectures in different size groups (Top 10 vs. Bottom 40). Again, our model well matches the actual data in this respect: for an industry, the 10 prefectures with the most revenue in data are almost always (97.3% of the time) also among the Top 10 according to the model. This mean decreases to 83.5%, with a greater standard deviation, when it comes to the Bottom 40 prefectures. Panel B shows a similar

²⁶ Industry-level weight-to-value ratios, in 1k U.S. dollars per metric ton, come from 2007 U.S. Commodity Flow Surveys. See Duranton *et al.* (2014) for details. We can only match 22 of 29 2-digit industries in CIFD to sectors in CFS.

²⁷ Note that, if an industry spends a large fraction of total expenses on road transport, it can mean either a high price of transport per unit value (e.g. heavy output), or a large quantity of transport services used (e.g. producers are often far away from consumers).

story about the geographic concentration of firm production. Again across industries, the share of revenue accounted for by the Top 5 and 10 prefectures are almost identical between simulated and actual data. Nonetheless, the match deteriorates toward the low end for Bottom 20 and 40 prefectures, but the bottom prefectures typically accounted for less than 0.5% of the total revenue of an industry. Hence we feel confident that our simple model does a decent job approximating the geographic distribution of the bulk of firm production, and will generate meaningful counterfactuals when we estimate the general equilibrium effect of highway expansion in Sec.7.

6 Reduced-Form Evidence

This section reports reduced-form evidence about how a location’s market access affects local firm productivity and production. To the extent that the evidence supports the theoretical predictions in Sec.3, this section provides further confidence in the model’s fit.

Before presenting regressions, we note that a location’s productivity distribution and production are co-determined in equilibrium together with its market access, generating endogeneity bias if we simply regress local productivity and production outcomes on market access measures. Thus for regressions in this section, we exclude each industry-location $j - o$ ’s own contribution, $(\frac{X}{FMA})_{jo}$ and $(\frac{R}{CMA})_{jo}$, respectively from its CMA and FMA (recall Eq.(3) and (4)). These terms are usually so small that this adjustment hardly affects our main results. Still, because changes in one location’s market access will simultaneously induce changes in other locations’ market access, the point estimates on market access measures do not identify an average treatment effect, but rather empirically characterize the relationship between market access and outcomes of interest in equilibrium.

Table 5 presents summary statistics at industry-prefecture-year level. Firm productivity and production outcomes, such as mean productivity, number of firms, total revenue, etc., all increased dramatically from 1998 to 2007, so did CMA. The increase in FMA is relatively modest, due to the considerable increase in CMA and a smaller increase in expenditure (recall Eq.(4)).

6.1 Market Access and Industry-Location Mean Productivity

We first examine how market access affects productivity distribution at industry-location level. Recall that Eq.(6) predicts that local productivity cutoff increases in CMA but decreases in FMA. Since the minimum productivity in an industry-location is measured with much noise (extreme outliers are common), we investigate the empirical relationship between market access and local

mean productivity using the following regression,

$$\bar{\varphi}_{jot} = b_1 \text{CMA}_{jot} + b_2 \text{FMA}_{jot} + \epsilon_{jot} \quad (12)$$

where $\bar{\varphi}_{jot}$ is the mean productivity in industry-prefecture-year $j - o - t$, and all variables are in natural logs. We include industry*prefecture and industry*year fixed effects, and cluster standard errors at prefecture level. Table 6(A) present the results. In Column (1), we use the basic definition of CMA and FMA based on Eq.(5) and (4). Conditional on FMA, CMA exhibits a strong positive correlation with local average productivity, with an increase of 1 standard deviation (s.d.) in CMA corresponding to about 0.24 s.d increase in local mean productivity. In contrast, conditional on CMA, an increase of 1 s.d. in FMA is associated with 0.18 s.d. decrease in local mean productivity. Figures 4(A) and 4(B) show these empirical patterns visually. Column (2) replicates Column (1), but uses output-weighted mean productivity as the dependent variable. This puts higher weight on productive firms, due to the strong positive correlation between firm productivity and size. The empirical patterns in Column (1) remain in Column (2).

A key endogeneity concern is that local economic shocks might have affected both market access and firm productivity and production, for instance, if prefectures with promising prospects for industrial growth were given priority to receive highway connection. We first show that, in our sample period, an industry-prefecture’s baseline characteristics do not predict changes in its market access (see Appendix A.1). We then develop two alternative measures of market access: (1) “distant neighbor”, which excludes prefectures within 300km of travel distance from the prefecture in question, is less likely to be correlated with local economic conditions; (2) “baseline mass”, which uses contemporary travel time but sticks with baseline (1998) economic mass (firm productivity, output, etc.), alleviates the bias due to the endogenous response of local economic mass to changes in trade costs. In Table 6(A), Columns (3)-(6) replicate Columns (1)-(2), but use the two alternative measures of market access, and the strong correlations between local mean productivity and market access are insensitive to alternative measures. Note that, since economic mass and market access are determined jointly in equilibrium involving all locations in the network, these alternative measures are not theoretically founded, and merely serve as robustness checks.

Following Table 6(A), Table 6(B) explores heterogeneous effect of market access across industries that rely more or less on road transportation. We categorize the 29 2-digit industries into tertiles based on the share of road transport expenses in total input, and repeat Column (1) of

Table 6(A) on these 3 subsamples. From Column (1) to (3), the correlations between local mean productivity and market access become stronger and more significant as the share of road transport expenses rises.

6.2 Market Access and Individual Firm Production

Next, we test Eq.(1) that predicts a positive correlation between an industry-location’s FMA and a local individual firm’s revenue, conditional on the firm’s productivity. The regression specification resembles Eq.(12), but the dependent variable is now individual firm revenue, and we control for individual firm productivity on the RHS. Column (1) in Table 7(A) starts by confirming the well-established positive correlation between firm productivity and size. Remarkably, controlling for a firm’s own productivity, its industry-prefecture’s market access still strongly affects its revenue. Specifically, 1 s.d. increase in FMA corresponds to 0.32 s.d. increase in firm revenue. Columns (2) and (3) show that these patterns persist if we use alternative market access measures.

As discussed in Sec.3, a decline in trade costs results in competing effects on individual firm’s output: import competition compresses firm output, while export access works against import competition. Which effect dominates likely depends on a firm’s productivity: productive firms will benefit more from a larger export market than losing from more intense competition, and the other way round for unproductive firms. Following Table 7(A), Table 7(B) shows that, conditional on firm productivity, the positive correlation between FMA and firm revenue becomes stronger and more significant as firm productivity rises from Column (1) to (3).

6.3 Market Access and Firm Entry & Exit

We proceed to the entry & exit dynamics associated with market access, presenting results in Table 8. Our firm selection mechanism entails that higher CMA makes unproductive firms more likely to exit, while higher FMA makes it easier for them to stay. Columns (1)-(3) test this hypothesis. Given two years, we set the earlier one (2004 here) as baseline, the later one (2007 here) as endline, and define “firm exit” as an indicator of a firm being present at baseline but not at endline. We take the long difference between baseline and endline for market access measures, and categorize firms at baseline into tertiles based on a firm’s productivity ranking within its industry. It is clear that market access affects exit decisions mostly among the less productive firms. Column

(1) shows that a 1% increase in CMA is related to an increase of 2.1 percentage points, while a 1% increase in FMA to a decrease of 1.8 percentage points, in the exit probability of the less productive firms. This pattern diminishes as firm productivity rises in Columns (2) and (3).

Column (4) evidences the prediction that higher CMA deters, while higher FMA encourages, firm entry. We tag a firm as “entrant” if it is present at endline but not at baseline, and count the number of entrants at industry-prefecture level. As in Column (4), a 1% increase in CMA is related to an 0.62% fewer, while a 1% increase in FMA to 0.41% more, entrants. The evidence on firm entry and exit suggests that market access works through firm selection.

Since the CIFD excludes very small non-state firms, this paper misses the very low end of the national productivity distribution (given the strong correlation between firm productivity and size). Still, such firms account for a tiny fraction of aggregate output and export (recall Sec.??). Even without such firms, the import competition and export excess forces, captured by CMA and FMA respectively, are theoretically relevant and empirically present in the CIFD sample, as this section documents. Missing the very small non-state firms likely results in an under-estimation of the coefficients on market access measures, since firm selection due to import competition and export access effects happens at the lower end of each location’s productivity distributions. For instance, an increase in CMA will likely make unobserved low-productivity firms exit.

In summary, the reduced-form evidence on the relationship between market access and local productivity and production outcomes is consistent with our theoretical framework, reassuring that our simple model provides a good description of the actual trade dynamics and will likely generate meaningful counterfactuals. In comparison with many previous papers investigating the effect of trade cost shocks (see [Goldberg & Pavcnik \(2016\)](#) for a review), we decompose this effect into two, namely import competition and export access, capture them with respective market access measures, and find evidence of their counteracting effects.

7 Counterfactuals: Evolving Highway Networks

7.1 Fixed-Point Iteration

The reduced-form evidence in Sec.6, while informative, is insufficient for estimating the effect of trade cost changes in general equilibrium because of the inter-location spillovers and the inter-dependence between market access and productivity distribution in the network of locations, as explained at the beginning of Sec.3. The spillovers and inter-dependence also make it challenging

to write moments of interest, for example the mean productivity in an industry after some trade cost shocks, as explicit functions of parameters of the model. Therefore, we conduct fixed-point iteration to characterize counterfactual equilibria: given (observed) initial firm-level and trade cost data, what will the new equilibrium look like if one changes trade costs to a different set? ²⁸

1. Compute the initial and endpoint iceberg trade cost matrices, \mathcal{T}_I and \mathcal{T}_E .
2. Denote empirical measures based on initial raw data with subscript 0. Assume everything except trade costs stays the same (in particular, hold FMA's constant), compute $\{\text{CMA}\}_1$ using endline trade cost \mathcal{T}_E by Eq.(3). $\{\text{CMA}\}_1$ then gives $\{\text{FMA}\}_1$ by Eq.(4).
3. By Eq.(6), we find a new set of local productivity cutoffs $\{\varphi^*\}_1$, for every industry-location $j - o$,

$$\frac{\varphi_{jo,1}^*}{\varphi_{jo,0}^*} = \left(\frac{\text{FMA}_{jo,1}}{\text{FMA}_{jo,0}} \right)^{\frac{1}{1-\sigma_j}}$$

and hence the mass of producing firms

$$\frac{h_{jo,1}S_{jo}}{h_{jo,0}S_{jo}} = \frac{\int_{\varphi_{jo,1}^*}^{\infty} dG_{jo}}{\int_{\varphi_{jo,0}^*}^{\infty} dG_{jo}} = \left(\frac{\varphi_{jo,1}^*}{\varphi_{jo,0}^*} \right)^{-\theta_{jo}}$$

4. By Eq.(8), total firm revenue

$$\frac{\frac{R_{jo,1}}{\sigma_j} - c_{jo}E_{jo}}{\frac{R_{jo,0}}{\sigma_j} - c_{jo}E_{jo}} = \frac{h_{jo,1}S_{jo}f_{jo}}{h_{jo,0}S_{jo}f_{jo}} \Rightarrow R_{jo,1} = \left(\frac{\text{FMA}_{jo,1}}{\text{FMA}_{jo,0}} \right)^{\frac{\theta_{jo}}{\sigma_j-1}} R_{jo,0} + \left[1 - \left(\frac{\text{FMA}_{jo,1}}{\text{FMA}_{jo,0}} \right)^{\frac{\theta_{jo}}{\sigma_j-1}} \right] \sigma_j c_{jo} E_{jo}$$

5. Given trade balance at location level, $\{R\}_1$ gives total expenditure: $X_{jo,1} = \sum_j R_{jo,1}$. $\{R\}_1$ and $\{X\}_1$, together with $\{\text{CMA}\}_1$ and $\{\text{FMA}\}_1$ computed in Step 2, give $\{\text{CMA}\}_2$ and $\{\text{FMA}\}_2$ by Eq.(3).
6. Iterate Steps 2 – 5 until both $\{\text{CMA}\}$ and $\{\text{FMA}\}$ converge. ²⁹

Denote empirical measures at fixed point with subscript F . Given $\{\varphi^*\}_F$ and $\{\theta\}$, we draw a number of firms from every $j - o$ in proportion to $S_{jo,F}$ and obtain the national distribution of firm productivity and production. ³⁰

Note that this method rules out the extensive margin at industry-location level. Baseline

²⁸ A similar approach has been formalized by Allen & Arkolakis (2014), and applied in Donaldson & Hornbeck (2016) (see Sec.III.B “Procedure for Counterfactual Simulations” in their online appendix).

²⁹ Lacking firm-level data from RoW, we assume that $\frac{X}{\text{FMA}}$ and $\frac{R}{\text{CMA}}$ stay constant for RoW during the iteration.

³⁰ One may also derive explicitly empirical moments to match with raw data, yet it easily becomes messy to aggregate local productivity distributions to the national level.

“zeros”, i.e. industry-location’s without a single firm at baseline, may see entrants as highway networks expand. Yet we do not observe the mass of firms or total revenue of these baseline zeros, so the above method is inapplicable. Still, baseline zeros do not seem to matter much for our counterfactual characterization. At baseline in 1998, there were 6,672 non-zero’s and 1,561 zeros, 273 of which became non-zero’s but only accounted for 0.82% of the total output in 2007. In other words, the sizable growth in firm production between 1998 and 2007 comes largely from industry-location’s that already had producing firms in 1998, validating the fixed-point iteration approach above.

7.2 Counterfactual: 1998 Firms, 2007 Highways

A key question of policy significance is: how much did the large-scale highway expansion contribute to the observed dramatic productivity and output growth observed between 1998 and 2007 (recall Table 1(A))? In addition to aggregate growth, what about inclusive growth across regions, given that the highways connected relatively developed and underdeveloped prefectures? To answer these questions, we apply 2007 travel time to 1998 firm data, and examine the resulting equilibrium now that only the market access forces associated with highway expansion are at work. Panel A of Table 9 compares this counterfactual equilibrium to the actual 1998 data. Overall, the highway construction between 1998 and 2007 raised aggregate productivity and, less powerfully, reduced productivity dispersion. Production became slightly less concentrated in the largest prefectures, and aggregate firm mass and revenue both increased substantially. This suggests the importance of both the import competition and export access effects of highway connection. On the one hand, unproductive firms in the least productive prefectures (where average firm productivity was very low to begin with) were forced to exit under intense import competition, resulting in higher aggregate productivity and smaller productivity dispersion. On the other hand, more productive prefectures saw a large number of entrants due to market expansion. While the entrants were less productive than their local incumbents, they were still more productive than the exiting firms in very unproductive prefectures. This massive entry then had a relatively small effect on the aggregate productivity level, but a much larger effect on the aggregate number of firms and revenue. The growth of the most productive incumbents also contributed considerably to aggregate revenue growth.

We then compare this counterfactual equilibrium to the actual 2007 data, presenting the results in Panel B of Table 9. Comparison between the counterfactual and the actual changes shows that

the firm selection mechanism fueled by highway construction alone accounts for about 24% of the observed productivity growth, and almost 40% of the reduction in productivity dispersion. Highway-induced changes in market access are less powerful in explaining the observed more-than-doubled sum of firms and 4-fold increase in aggregate output, accounting for around 16% of the actual changes.

The aggregate patterns mask enormous heterogeneity across industries and locations. In Table 10, we examine how the counterfactual changes vary by industry and location characteristics at baseline (in this case, 1998 data). Productivity dispersion decreases more for industries with a higher share of output in (often inefficient) state-owned enterprises, suggesting that the import competition effect is stronger where there are initially many inefficient, close-to-exit firms. Highly productive prefectures tend to see a large number of entrants and a sizable increase in total revenue, suggesting that the export access effect dominates at the higher end of the productivity distribution. In contrast, unproductive prefectures tend to see more of their firms exit, and experience a decrease in total revenue.

We keep in mind that highway expansion was among a myriad of factors that contributed to the observed evolution of productivity and production distributions. During the 1998-2007 decade, surviving individual firms experienced substantial productivity growth (Brandt *et al.*, 2012) by learning from the best performers, both domestic and abroad, and investing in R&D by themselves. The Chinese economy became increasingly market-oriented as the government reformed SOEs and pushed for privatization (Chen *et al.*, 2016). China’s admission to the WTO also allowed domestic firms to interact with global markets in more complex ways than our model assumes. Given more relevant forces than enumerated here, it is encouraging that our simple model explains a significant part of the actual evolution of the Chinese manufacturing sector.

8 Conclusion

This paper develops a “market access” approach to studying the geographic distribution of firm productivity and production in an economy. In the Melitz framework, we distinguish between two distinct effects, import competition and export access, of trade cost changes, and derive CMA and FMA measures respectively to capture each effect. We empirically examine how market access forces shape the distribution of firm productivity and production across locations in China’s manufacturing sector, taking advantage of the dramatic expansion of highway networks from 1998 to 2007 that

brought about substantial reduction in inter-regional trade costs. Consistent with the theoretical framework, we find strong reduced-form evidence that, conditional on FMA, CMA raises local average productivity, shrinks local firms' output, and make unproductive firms more likely to exit, while FMA works in the opposite direction. We use our model to recover counterfactuals, and find that a significant proportion of the observed productivity growth and reduction in productivity dispersion is attributable to the massive highway construction.

This paper sheds lights on an under-researched role of transportation infrastructure in the course of economic development: lifting inter-regional trade barriers and fostering economic integration in a national market. Our results suggest that a low level of integration may explain the greater productivity dispersion in developing countries than in developed countries, as documented in [Hsieh & Klenow \(2009\)](#), and point to higher marginal returns to transportation infrastructure investments in less economically integrated countries or regions. We emphasize that economic integration generates competing effects on local firms, and firm heterogeneity is essential to evaluating the net benefit. Our “market access” approach highlights the importance of examining economic integration in general equilibrium, taking into account how local economic mass can endogenously respond to lower trade costs, and how such responses propagate through the network of geographic locations in an economy.

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Table 1. CIFD Summary Statistics, 1998-2007

Table 1(A). Firm Balance Sheet Items

This table present national aggregates of the firm-level Chinese Industrial Firms Database (CIFD), 1998-2007.

Year	Firm	Labor						
		Employment	compensation	Capital stock	Intermediate input	Value added	Industrial output	Export
1998	129,502	45.85	0.39	3.57	4.33	1.32	5.66	1.01
1999	129,142	44.27	0.41	3.90	4.75	1.49	6.23	1.09
2000	132,072	43.21	0.45	4.07	5.40	1.74	7.15	1.39
2001	142,395	42.84	0.51	4.29	6.22	1.96	8.18	1.55
2002	151,674	43.60	0.54	4.41	7.22	2.39	9.61	1.88
2003	169,147	46.53	0.64	4.70	8.95	3.14	12.09	2.46
2004	229,491	51.66	0.82	5.21	10.97	4.69	15.67	--
2005	234,359	55.93	0.98	5.76	12.95	5.71	18.66	4.53
2006	257,896	59.32	1.20	6.49	15.46	7.48	22.94	5.69
2007	287,931	63.39	1.53	7.43	18.82	9.61	28.44	6.85

Notes: (1) Real values in trillion CNY (deflated to 1998 level), employment in million.

Table 1. CIFD Summary Statistics, 1998-2007

Table 1(B). Firm Entry & Exit

This table counts the number of entrants and exitors every year in the CIFD. A firm is labeled "exitor" if it appears in the current year but not the following year, and is labeled "entrant" when it appears in the sample for the first time and reports a starting year no more than two years earlier.

Year	Total	Continuing	Exiting	Incumbents	Entrants
1998	128,583	109,083	19,500		
1999	128,365	109,450	18,915	122,350	6,015
2000	130,446	107,514	22,932	123,413	7,033
2001	140,941	122,892	18,049	128,562	12,379
2002	150,102	132,314	17,788	138,660	11,442
2003	169,139	133,424	35,715	153,253	15,886
2004	229,004	196,632	32,372	183,425	45,579
2005	234,002	211,045	22,957	214,680	19,322
2006	257,826	231,291	26,535	232,435	25,391
2007	287,786			258,710	29,076

Notes: (1) N (10-year balanced panel) = 34881. Firms that exit and later re-enter the sample (less 1% of all firms) are considered to be operating throughout.

Table 1. CIFD Summary Statistics, 1998-2007

Table 1(C). Productivity Dispersion

This table shows summary statistics of firm-level Levinsohn-Petrin productivity (in natural logs). For each of the 29 2-digit industries, we estimate a production function. Within each industry, we rank firms by productivity, take some statistic of the productivity distribution, and then average across industries.

	(ln) Levinsohn-Petrin output productivity				
	Unweighte d mean	Weighted mean	S.D.	IQR	p90-p10
1998	1.1808	1.3278	0.2903	0.3420	0.6683
1999	1.1897	1.3356	0.2860	0.3389	0.6676
2000	1.2159	1.3610	0.2819	0.3305	0.6605
2001	1.2335	1.3845	0.2641	0.3215	0.6334
2002	1.2619	1.4040	0.2641	0.3322	0.6379
2003	1.2915	1.4339	0.2605	0.3149	0.6366
2004	1.3672	1.5231	0.2959	0.3391	0.6721
2005	1.3838	1.5285	0.2643	0.3180	0.6155
2006	1.4238	1.5571	0.2773	0.3152	0.6286
2007	1.4588	1.5942	0.2796	0.3315	0.6674

Note: (1) "Weighted mean" refers to mean productivity weighted by firm output.

Table 2. Productivity Expansion: Variance Explained

This set of tables explore what explain between-firm productivity dispersion, and show the cumulative percent of variance explained (CPVE).

"Prefecture": individual prefecture dummies; "ownership": type of ownership dummies (state-owned, private ...); "age" and "size": dummies for respective quartiles.

Table 2(A). No Industry-Specific Effects

For all industries, regress firm productivity on each set of dummies, and take the adjusted R-squared.

Year	Prefecture	Ownership	Age	Size
1998	1.92%	0.08%	0.02%	0.05%
1999	1.89%	0.07%	0.04%	0.06%
2000	2.02%	0.06%	0.04%	0.06%
2001	2.12%	0.09%	0.11%	0.05%
2002	2.25%	0.11%	0.09%	0.05%
2003	2.37%	0.13%	0.09%	0.06%
2004	2.63%	0.05%	0.09%	0.08%
2005	2.52%	0.07%	0.07%	0.08%
2006	2.56%	0.06%	0.07%	0.15%
2007	2.77%	0.06%	0.05%	0.22%

Table 2(B). Industry-Specific Effects

For each industry, regress firm productivity on each set of dummies, and take the adjusted R-squared. Then take the mean adjusted R-squared across industries.

Year	Prefecture	Ownership	Age	Size
1998	11.5%	1.5%	2.8%	16.2%
1999	11.7%	1.7%	2.5%	17.1%
2000	12.9%	1.9%	2.4%	17.3%
2001	12.3%	1.8%	1.9%	17.0%
2002	11.6%	1.9%	1.6%	17.7%
2003	13.3%	1.4%	1.3%	17.8%
2004	7.5%	1.6%	0.9%	14.6%
2005	10.5%	1.1%	0.6%	18.3%
2006	13.0%	1.0%	0.5%	18.8%
2007	14.4%	0.8%	0.5%	18.6%

Table 3. Road Travel Distance and Time

This table provides summary statistics of road travel time and distance between Chinese prefecture pairs, in the first and last year of our sample period.

287 prefecture-level cities, 41041 prefecture pairs every year.

<i>Year 1998</i>					
	Mean	Median	SD	p10	p90
Travel distance (km)	1676.62	1561.70	938.57	553.96	2952.80
Travel time (h)	29.66	27.69	17.02	9.52	52.06
Avg. speed (km/h)	57.70	57.40	9.68	45.63	68.76

<i>Year 2007</i>					
	Mean	Median	SD	p10	p90
Travel distance (km)	1559.27	1439.80	879.53	526.00	2750.90
Travel time (h)	17.63	15.99	10.66	6.03	30.53
Avg. speed (km/h)	89.26	92.28	9.80	75.30	98.26

Table 4. Industry-Prefecture Total Revenue, Data vs. Model

This set of tables compare the industry-prefecture total revenue between actual data and model-simulated data, for the year 1998.

Table 4(A): Size Groups

Within each of the 29 2-digit industries, we rank prefectures by total revenue, and record the set of prefectures in a certain size group (Top 10, Bottom 40) in simulated data. We then compute the share of these prefectures that fall in the same size group in actual data, and show summary statistics of this share across industries.

	mean	median	s.d.	IQR
% in size group				
Top 10	97.3	96.5	6.5	8.1
Bottom 40	83.5	86.3	12.9	13.5

Table 4(B): Geographic Concentration of Production

Within each of the 29 2-digit industries, we rank prefectures by total revenue, and record how much prefectures in a certain size group (largest 5, smallest 20, etc.) account for the industry's aggregate revenue. We show summary statistics of this revenue share across industries.

	Data		Model	
	mean	s.d.	mean	s.d.
Prefecture share (%)				
Top 5	28.5	8.3	28.2	7.6
Top 10	41.9	10.3	41.1	9.2
Bottom 20	0.1	0.1	0.3	0.1
Bottom 40	0.4	0.3	0.6	0.5
Log-log rank-size	-0.424 (0.012)		-0.403 (0.012)	

Table 5. Industry-Prefecture Summary Statistics

This table provides summary statistics at industry-prefecture level. Market access measures are computed based on parameter estimates from the structural model, and exclude home market.

<i>Year 1998, N = 6672</i>					
	Mean	Median	SD	p10	p90
Mean productivity	7.77	1.73	20.80	1.41	19.88
Firm count	19	7	40	3	44
Total employment	6,744	2,123	14,281	181	16,615
Total revenue	0.83	0.16	2.56	0.01	1.91
CMA basic	92.62	0.31	169.58	0.15	362.82
FMA basic	204.99	225.29	170.90	0.08	439.71
<i>Year 2007, N = 6706</i>					
	Mean	Median	SD	p10	p90
Mean productivity	15.73	2.01	40.52	1.50	36.51
Firm count	43	12	106	4	97
Total employment	9,455	2,296	29,296	174	21,714
Total revenue	4.24	0.69	19.87	0.03	9.02
CMA basic	203.92	0.68	379.01	0.33	822.40
FMA basic	235.89	255.75	197.28	0.09	520.24

Notes: (1) Mean productivity is the mean Levinsohn-Petrin output productivity across firms in an industry-prefecture-year.
(2) Total revenue is in billion CNY.

Table 6(A). Market Access and Industry-Prefecture Average Productivity

This table presents panel regressions of industry-prefecture mean productivity on market access measures. "Weighted" refers to mean productivity weighted by firm output, across all firms in an industry-prefecture-year. Market access measures are computed in 3 different ways: (1) "basic" follows the basic definitions in the theoretical framework, using all locations in the economy and contemporary economic mass (firm productivity, revenue, etc.); (2) "distant neighbors" excludes prefectures within 300km of travel distance from the prefecture in question; (3) "baseline mass" restricts the economic mass to baseline (Year 1998).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: id-pf-yr mean productivity	Basic		Distant neighbor		Baseline mass	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
Consumer market access	0.064*** (0.015)	0.115*** (0.036)	0.049*** (0.014)	0.082*** (0.025)	0.040*** (0.011)	0.067*** (0.023)
Firm market access	-0.023*** (0.007)	-0.027*** (0.009)	-0.033*** (0.007)	-0.036*** (0.008)	-0.025*** (0.005)	-0.031*** (0.006)
R-squared	0.315	0.342	0.332	0.330	0.283	0.292
N	67416	67416	66402	66402	66784	66784

Notes: (1) All variable in natural logs.

(2) Fixed effects: industry*prefecture, industry*year. Standard errors clustered at prefecture level.

**Table 6(B). Market Access and Industry-Prefecture Average Productivity,
Heterogeneous Effects**

This table presents the same regressions as in the preceding Table 6(A), but on 3 subsamples based on an industry's share of road transport expenses in its total input. This variable comes from the 2002 Chinese national input-output table.

	(1)	(2)	(3)
Dependent variable: id-pf-yr mean productivity % of road transport expenses in total inputs			
	1st tertile	2nd tertile	3rd tertile
Consumer market access - basic	0.023*** (0.011)	0.057*** (0.021)	0.083*** (0.033)
Firm market access - basic	-0.007 (0.012)	-0.026** (0.012)	-0.034*** (0.013)
R-squared	0.159	0.305	0.326
N	16406	20923	28745

Notes:

(1) All variable in natural logs.

(2) Fixed effects: industry*prefecture, industry*year. Standard errors clustered at prefecture level.

Table 7(A). Market Access and Individual Firm Revenue

This table presents panel regressions of individual firm revenue on firm productivity and market access measures. See Table 6(A) for how the 3 types of market access measures are defined.

	(1)	(2)	(3)
Dependent variable: individual firm revenue			
	Basic	Distant neighbor	Baseline mass
Firm productivity	0.827*** (0.145)	0.805*** (0.184)	0.841*** (0.177)
Consumer market access	-0.078*** (0.021)	-0.035 (0.023)	-0.024 (0.018)
Firm market access	0.251*** (0.081)	0.207*** (0.073)	0.193** (0.071)
R-squared	0.166	0.134	0.119
N	1813549	1808502	1781445

Notes: (1) All variable in natural logs.

(2) Fixed effects: industry*prefecture, industry*year.
Standard errors clustered at prefecture level.

Table 7(B). MA and Individual Firm Revenue, Heterogen. Effects

This table presents the same regressions as in the preceding Table 7(A), but on 3 subsamples based on a firm's productivity.

	(1)	(2)	(3)
Dependent variable: individual firm revenue			
Firm productivity tertile			
within industry-year	1st tertile	2nd tertile	3rd tertile
Firm productivity	0.721*** (0.166)	0.794*** (0.209)	0.903*** (0.250)
Consumer market access	-0.118*** (0.029)	-0.055 (0.036)	-0.051 (0.043)
Firm market access	0.121 (0.094)	0.240*** (0.077)	0.389*** (0.133)
R-squared	0.125	0.194	0.203
N	608325	624406	631065

Notes: (1) All variable in natural logs.

(2) Fixed effects: industry*prefecture, industry*year.

Standard errors clustered at prefecture level.

Table 8. Market Access, Firm Productivity, and Entry & Exit

This table shows how market access affects firm entry and exit. In Columns (1)-(3), we define "firm exit" as an indicator of an individual firm being present at baseline year (2004 here) but not at endline (2007 here), and take the long difference between baseline and endline for market access measures. We categorize firms at baseline into tertiles based on a firm's productivity ranking within its industry. In Column (4), we tag a firm as "entrant" if it is present at endline but not at baseline, and count the number of entrants at industry-prefecture level.

	(1)	(2)	(3)	(4)
	Firm exit by endline			(ln) Number of entrants
Firm productivity tertile within industry-year, at baseline.	1st tertile	2nd tertile	3rd tertile	
(LD) (ln) Consumer market access	0.021** (0.009)	0.008** (0.004)	0.006 (0.008)	-0.618** (0.314)
(LD) (ln) Firm market access	-0.018** (0.004)	-0.006* (0.003)	0.003 (0.004)	0.406* (0.245)
R-squared	0.151	0.127	0.109	0.215
N	75980	76241	76295	6610

Notes:

- (1) Baseline year 2004, endline year 2007. Cross-section regression at endline.
- (2) LD for long difference (between baseline and endline), LL for long lag (variable at baseline).
- (3) FE: industry*prefecture for (1)--(3); industry & prefecture for (4). Standard errors clustered at prefecture level.

Table 9. Highway Network Expansion: Counterfactual

This table presents results from the counterfactual equilibrium that we arrive at by applying 2007 trade cost to 1998 firm data. This counterfactual describes what would happen had if only the highway-induced market access forces were at work between 1998 and 2007. Panel A compares this counterfactual to 1998 data. Panel B compares this counterfactual to 2007 data, showing how much of the observed evolution of firm productivity and production the highway-induced market access forces can account for.

	Panel A			Panel B		
	1998 Data	1998 firms, 2007 highways	Change	2007 Data	2007-1998 Change	Counterfactu al vs. actual
At industry level, then average across industries						
Productivity distribution						
Weighted mean	1.382	1.441	0.058	1.629	0.246	23.7%
s.d.	0.314	0.302	-0.012	0.288	-0.026	45.1%
IQR	0.368	0.362	-0.006	0.353	-0.016	39.0%
p90-p10	0.731	0.720	-0.012	0.701	-0.030	39.2%
Production (revenue) distribution						
Top 5 prfc's	0.285	0.282	-0.002	0.276	-0.008	28.9%
Bottom 20 prfc's	0.004	0.004	0.000	0.004	0.001	38.3%
National aggregate (real, deflated to 1998 level)						
Mass of firms	128,583	143,295	11.4%	287,786	123.8%	9.2%
Total revenue (trillion CNY)	5.625	9.268	64.8%	28.442	405.6%	16.0%

Notes: (1) Levinsohn-Petrin productivity in natural logs.

(2) In the "Change" and "2007-1998 Change" columns, numbers without % indicate difference in levels, numbers with % indicate changes in percent.

Table 10. Counterfactual Change: Heteogeneity across Industries and Prefectures

This table documents how the effect of the highway expansion, as recovered from the counterfactual analysis in Table 9, varies by industry and location characteristics at baseline (Year 1998). Dependent variables are the difference between an outcome Y (mean productivity, total revenue, etc.) in the "1998 firms, 2007 trade costs" counterfactual scenario of Table 9 and Y itself in the actual 1998 data. Independent variables are actual moments in the 1998 data. Regressions (1)-(2) are at industry level, while (3)-(4) are at industry-prefecture level.

	(1)	(2)	(3)	(4)
Dependent variable: % change: 1998 data - 2007 counterfactual	(ln) Weighted mean productivity	s.d. of industry-wide productivity distribution	(ln) Total firm revenue	Net number of entrants (entrants minus exitors)
Independent variable: 1998 data				
% revenue from SOE	0.426* (0.225)	-0.208* (0.114)		
(ln) Mean productivity			0.304** (0.129)	4.062** (1.955)
R-squared	0.134	0.119	0.227	0.098
N	29	29	7540	7540

Notes:

(1) For Regressions (3)-(4), industry & prefecture fixed effects included, standard errors clustered at prefecture level.

Figure 1: Geography-Related Characteristics across Industries

This set of figures show geography-related characteristics across 29 2-digit industries, for the year 2006.

Figure 1(A): Cumulative % of Variance in Firm Productivity Explained by Prefecture

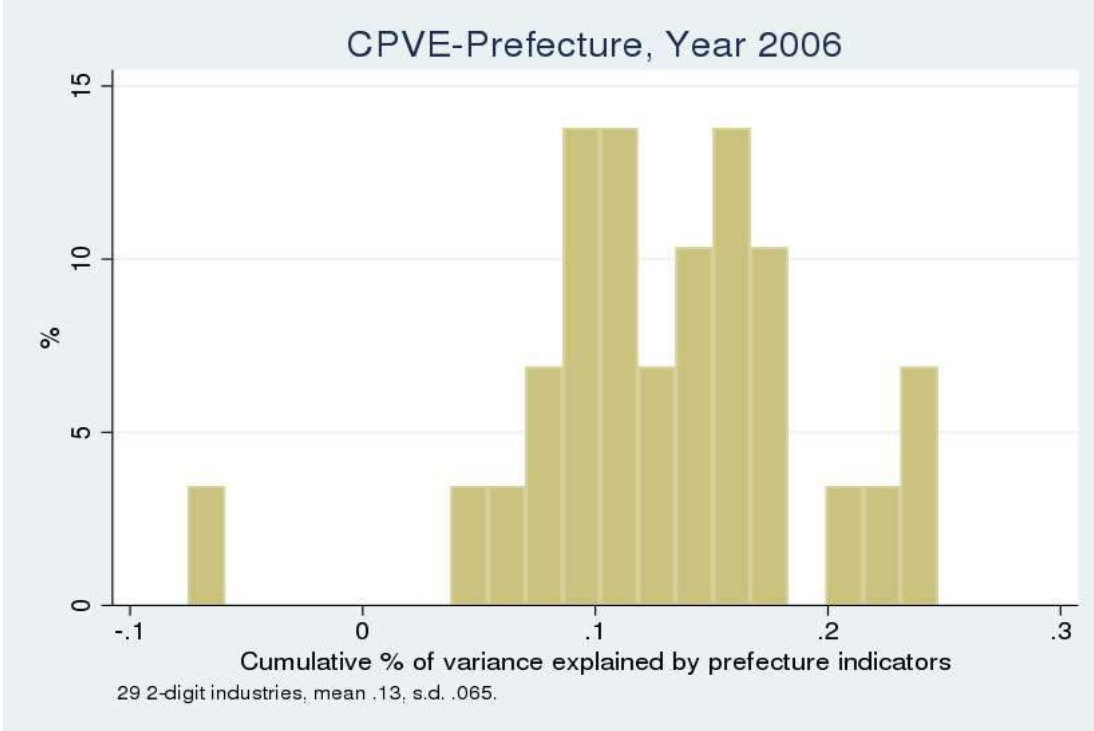


Figure 1(B): Ellison-Glaeser Agglomeration Index across Industries

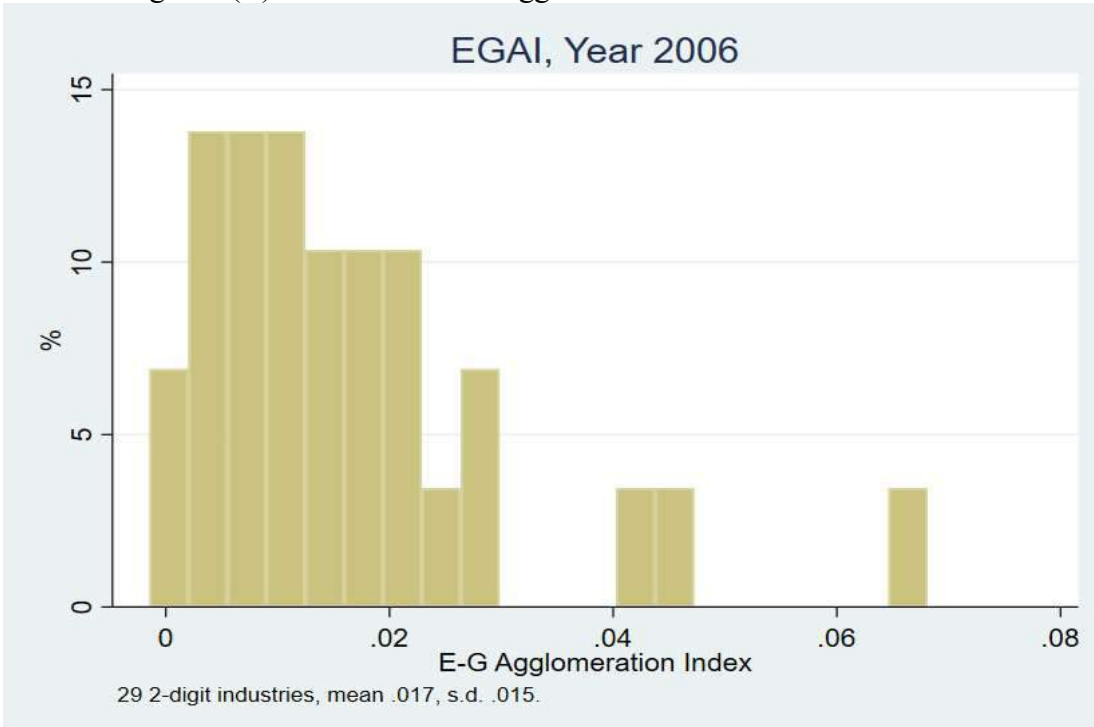


Figure 1: Figure 1

Figure 2. Highway Networks in China

Maps of highway networks in China, based on ACASIAN GIS data.

Figure 2(A): Highway Networks in 1998

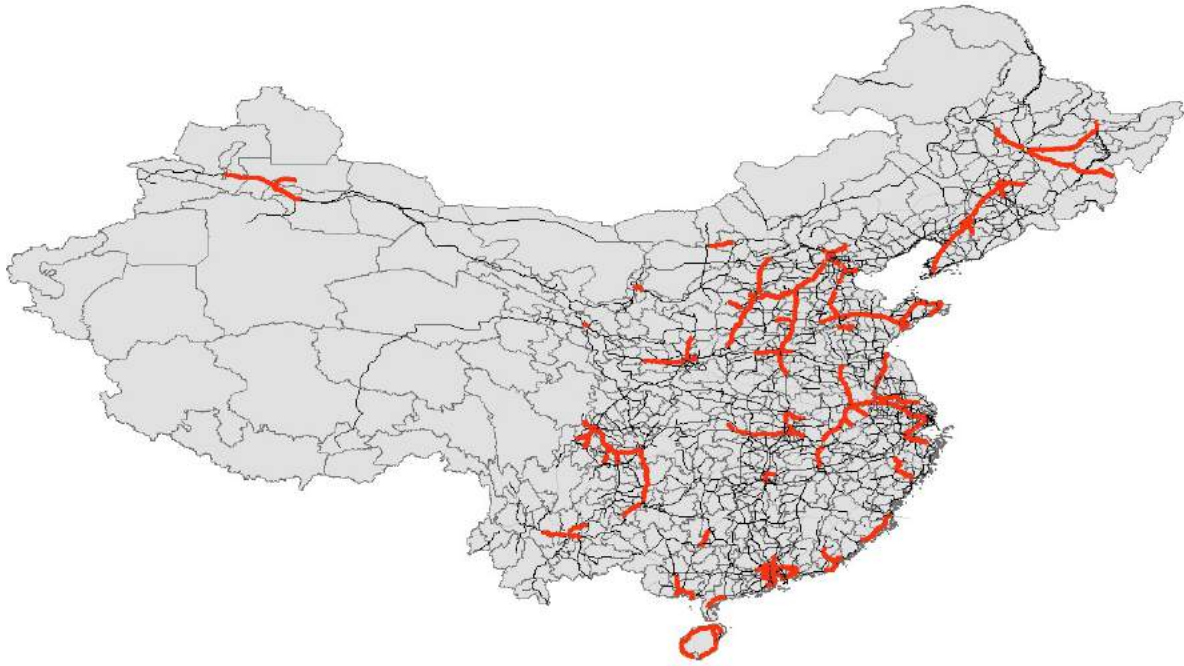


Figure 2(B): Highway Networks in 2007

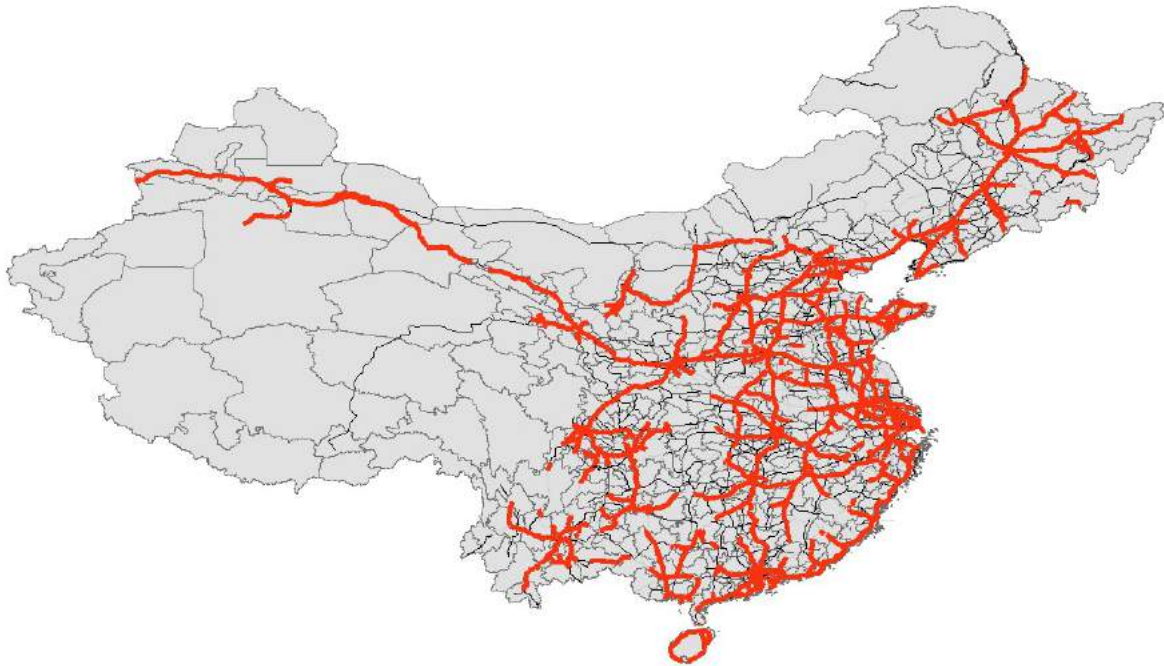


Figure 3. Rho Estimates and Industry Characteristics

This set of figures show the correlation between estimates of rho, which shows how fast trade cost increases in travel time for an industry, correlates with the industry's characteristics.

Figure 3(A): Rho and Weight-to-value Ratio

Industry-level weight-to-value ratios, in 1k U.S. dollars per metric ton, come from 2007 U.S. Commodity Flow Surveys. We are able to match 21 2-digit industries in CIFD data to CFS industries.

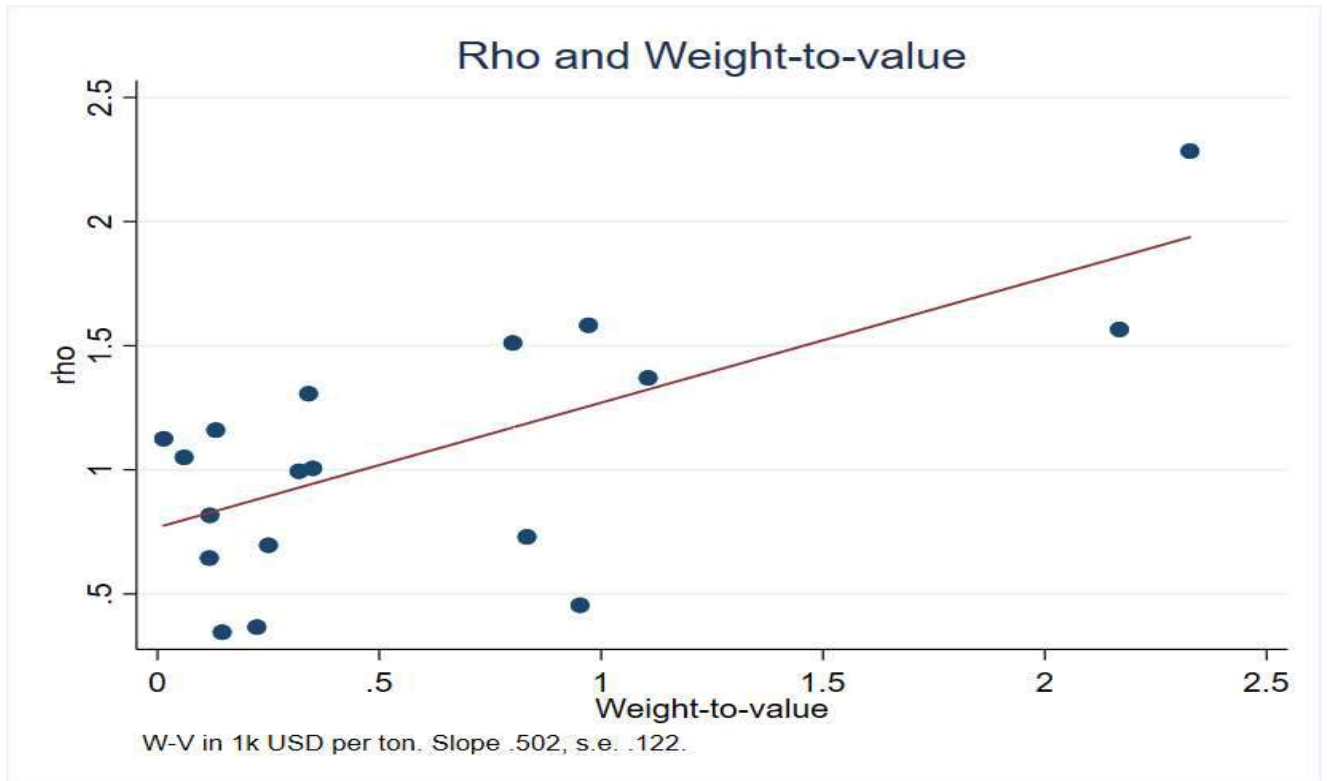
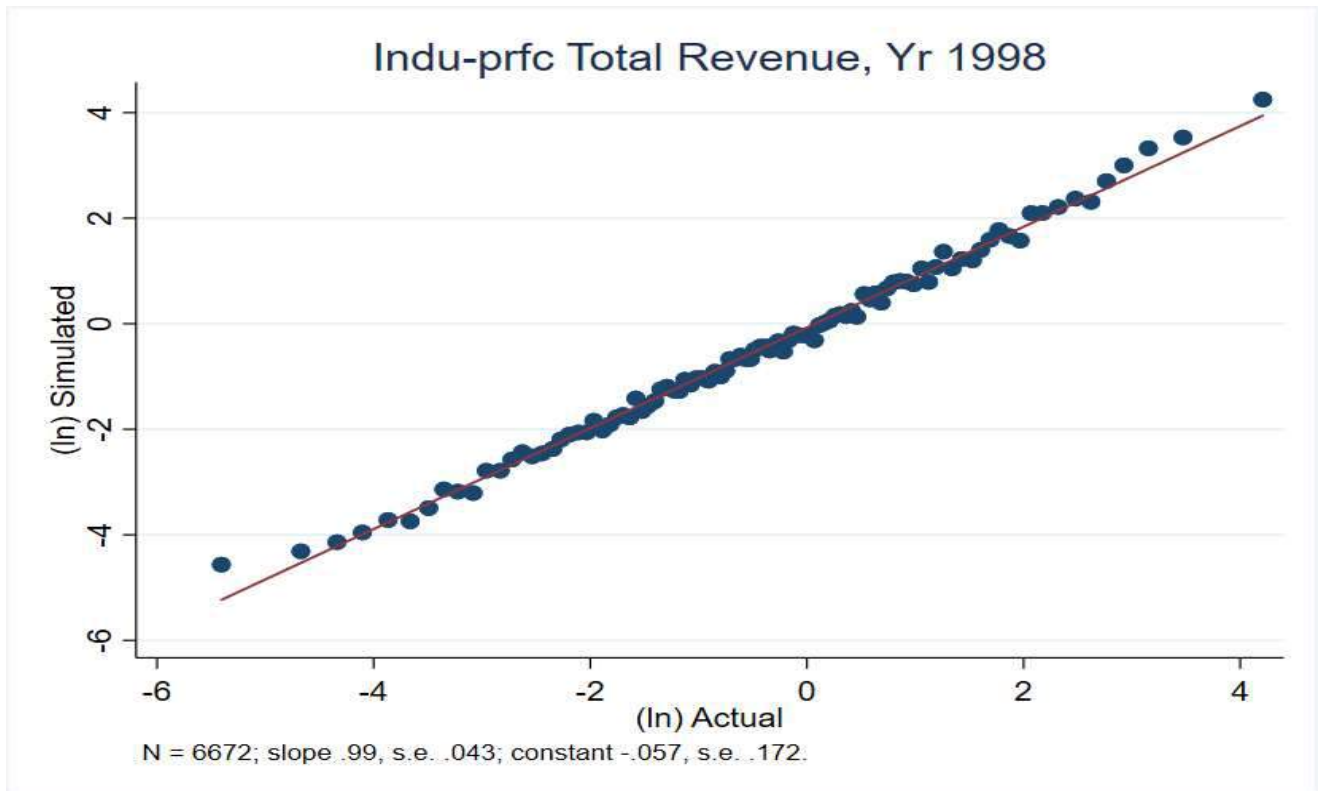


Figure 4: Industry-Prefecture Total Revenue, 1998 Data vs. Model

This bin-scatter plot shows the industry-prefecture total revenue (billion CNY, in natural logs) between actual data and model-simulated data, for the year 1998.



Notes: (1) OLS regression of (ln) simulated revenue on actual revenue, standard errors clustered at industry level.

A Appendices

1.1 Data Sources

1.1.1 CIFD

A substantial amount of data work is necessary before empirical analysis. Key issues include standardizing industry codes and address IDs, constructing an unbalanced firm-year panel, deflating nominal variables, etc. (Brandt *et al.*, 2012) provides a comprehensive description of such data work in their [online appendix](#). This paper follows their steps and has largely replicated their results.

We take additional steps to further clean the data. First, we adjust prefecture IDs to the 2004 standard,³¹ as a large number of prefectures experienced ID changes around 2000. Second, we clean and reformat a series of string variables, including firm name, corporate representative, zip code, telephone number, etc. to identify individual firms. Third, when matching firms over time, at each step, we match firms based on a primary identifier such as firm name or corporate representative, together with a secondary identifier such as starting year or zip code, in order to improve the accuracy of matching.

1.1.2 ACASIAN Data

We obtain highway GIS data from the Chinese Spatio-Temporal Expressway Database maintained by the [ACASIAN Data Center](#) at Griffith University in Brisbane, Australia. To construct this database, ACASIAN staff digitized dozens of high-resolution road atlases published by Chinese national and regional authorities of road transportation. The entire database records the evolution of China’s highway networks from 1992 to 2011. For the decade 1998-2007 (due to CIFD availability, as described above), we have nationwide highway maps for 1998, 2000, 2002, 2003, 2005, and 2007.

1.2 Input Market Access (IMA)

This appendix supplements the theoretical framework in Sec.3 with an input channel: as trade costs decline, so will the prices that local firms pay for intermediate inputs from elsewhere. This formalizes the input-output linkages between industries, as firms in industry-location $j - o$ source

³¹ Administrative division code, as of Sep. 30 2004, available on [NBS website](#).

inputs from all other industries k to obtain composite intermediate input (similar to [Caliendo & Parro \(2015\)](#)). To highlight the link between input price and transportation cost, we add to the original Melitz set-up how firms source intermediate inputs from other locations. Assume a Cobb-Douglas production function at industry level, for a firm,

$$Y = AK^{\beta_K}L^{\beta_L}M^{\beta_M} \quad (13)$$

where Y, K, L, M denote output, capital, labor, and materials (intermediate input). Denote the price of capital, labor, materials by P_K, P_L, P_M , respectively. To produce Y unit of output, a firm's cost minimization problem is

$$\min_{K,L,M} P_K * K + P_L * L + P_M * M \text{ s.t. } AK^{\beta_K}L^{\beta_L}M^{\beta_M} \geq Y$$

which implies that, under constant returns to scale ($\beta_K + \beta_L + \beta_M = 1$), the marginal cost of production

$$MC = \frac{Z_Y}{A} P_K^{\beta_K} P_L^{\beta_L} P_M^{\beta_M} \quad (14)$$

where Z_Y is a constant with only β 's, not factor prices.

Further assume the composite intermediate input M_j as a Cobb-Douglas aggregate of output from all industries M_k^j , again under constant returns to scale,

$$M_j = \prod_k (M_k^j)^{\alpha_k^j} \text{ with } \sum_k \alpha_k^j = 1$$

where α_k^j is the share of industry k 's output as industry j 's input in the total intermediate input of industry j , and empirically comes from the national input-output table. Similarly, cost minimization implies that, for firms in location o , the price of this composite intermediate input as a C-D aggregate of P_{o,M_k^j} , the prices of output from all industries,

$$P_{M_j o} = Z_{M_j} \prod_k (P_{o,M_k^j})^{\alpha_k^j}$$

where Z_{M_j} is again a constant (with only α_k^j 's, not P_{o,M_k^j} 's). Recall that CMA_{ko} is the price index

of industry k 's output at location o , $CMA_{ko} = (P_{ko})^{1-\sigma_k}$, we thus define input market access,

$$IMA_{jo} = \prod_k (CMA_{ko})^{\frac{\alpha_k^j}{\sigma_k - 1}} \quad (15)$$

and write the unit/marginal cost of production,

$$\frac{c_{jo}}{\phi_{jo\omega}} = \frac{Z_{Y_{jo}}(Z_{M_{jo}})^{\beta_{j,M}}}{A_{jo\omega}} P_{jo,K}^{\beta_{j,K}} P_{jo,L}^{\beta_{j,L}} (IMA_{jo})^{-\beta_{j,M}} \propto (IMA_{jo})^{-\beta_{j,M}} \quad (16)$$

Write this into Eq.(1), and take logs on both sides,

$$\begin{aligned} \ln r_{jo\omega} = & (\sigma_j - 1) * \ln A_{jo\omega} + \ln FMA_{jo} \\ & + (1 - \sigma_j) * (\ln Z_{C_{jo}} + \beta_{j,K} \ln P_{jo,K} + \beta_{j,L} \ln P_{jo,L} - \beta_{j,M} \ln IMA_{jo}) \end{aligned} \quad (17)$$

Under the standard assumption in Melitz framework that factor prices are uniform across firms in an industry-location, we simplify the above equation to

$$\ln r_{jo\omega} = (\sigma_j - 1) * \ln A_{jo\omega} + \delta_{jo}$$

where δ_{jo} is an industry-location specific constant. In our unbalanced firm-year panel data, we observe firm-level revenue $r_{jo\omega}$, and estimate firm productivity $A_{jo\omega}$ (say, Levinsohn-Petrin TFPR) based on firm production function Eq.(13). We then run this regression for each industry j , with location*year fixed effects, to recover σ_j . Note that we should use TFPQ rather than TFPR here.

1.3 Discussion: Different Transport Modes

One may question how good road travel time is a proxy of trade cost. Cutting road travel time by building highways is one of many approaches to lower trade cost between prefectures: speeding up railway transportation, building more airports . . . , improving port facilities for navigable waters, can perhaps serve the same purpose. In fact, from 1997 to 2007, the Chinese Ministry of Railways implemented 6 speed-up campaigns that raised the average speed of trains from about 50km/h to 120km/h, together with a sizable increase in train capacity (Fang, 2013). Unlike highways, however, railways do not directly connect most prefectures in China, at least by the end of 2007 before the start of the historic high-speed railway boom (and high-speed railways are passenger-dedicated

lines). For robustness, we also confirm that our reduced-form results hold across subsamples of industries with varying proportions of total expenses spent on road transport. Air traffic, by the number of passengers, also increased by around 400% from 2003 to 2010, although the total number of passengers remained minimal in comparison with road traffic. More importantly, air traffic is predominantly about passenger traffic and unlikely very relevant for large volumes of manufactured goods. Waterways connect a fairly small set of prefectures in China, and was generally considered under-utilized in our sample period, in which waterway-associated infrastructure remained quite poor and experienced little upgrading.

Table A.1. Baseline Industry-Prefecture Characteristics and Changes in Market Access

This table shows how an industry-prefecture's baseline (1998) characteristics predict changes in its market access from baseline (1998) to endline (2007). "Basic" market access measures follow the basic definitions in the theoretical framework, using all locations in the economy and contemporary economic mass (firm productivity, revenue, etc.). "All firms exit" is an indicator that an industry-prefecture has at least one firm at baseline but no firms at endline. "New entry" is an indicator that an industry-prefecture has no firms at baseline but at least one firm at endline.

	(1)	(2)	(3)	(4)
	<u>Baseline-endline change in</u>			
	Consumer market access - basic	Firm market access - basic	All firms exit	New entry
Baseline characteristics				
Number of firms	0.063 (0.048)	-0.027* (0.014)	-0.007 (0.013)	-0.013 (0.016)
Number of employees	-0.047 (0.091)	0.012 (0.020)	0.014 (0.009)	-0.009 (0.010)
Total revenue	0.051 (0.078)	0.022 (0.028)	-0.004* (0.002)	0.008 (0.006)
R-squared	0.122	0.104	0.074	0.081
N	8293	8293	8293	8293

Notes:

(1) For all regressions: industry & prefecture fixed effects included, standard errors clustered at prefecture level.