The Last Mile Matters: How Delivery Infrastructure Shapes Online Trade and Consumption Inequality

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Abstract

To what extent do investments in delivery infrastructure drive the rise of online trade? Do they narrow or widen spatial inequality in consumption? Using *unique* city-level e-Commerce data from China spanning 2015 to 2019, we document a positive relationship between a city's online consumption share and the density of last-mile delivery stations. Guided by this empirical pattern, we develop a multi-city general equilibrium model in which consumers optimally choose between online and offline shopping channels. Crucially, online trade costs decline as the importing city's delivery infrastructure becomes denser. Calibrating our model to the observed 2015 equilibrium, we find that the observed delivery infrastructure accounts for over 80% of online trade volume and nearly 90% of its associated welfare gains. It also reduces spatial inequality by raising real income more in smaller cities. We show that reallocating delivery infrastructure uniformly across space would further reduce inequality but at the cost of lower aggregate welfare gains.

Keywords: E-commerce; Last-Mile Delivery; Logistics Density; Consumption Inequality; Gravity of Online Trade

JEL code:

1 Introduction

The rapid growth of online trade over the last two decades has dramatically reshaped how consumers purchase goods. This transformation is driven not only by digital platforms (websites and apps) that reduce search and matching frictions, but also by the physical infrastructure enabling delivery. While economic research has predominantly emphasized digital technologies, offline delivery infrastructure has received comparatively less attention. Yet, offline delivery infrastructure plays a critical role in facilitating online transactions by ensuring timely and efficient fulfillment. Understanding the geographic distribution of this infrastructure is therefore crucial for analyzing both the aggregate growth and the spatial patterns of online trade.

This interplay between digital platforms and offline delivery infrastructure naturally leads to two related questions. First, *to what extent do investments in delivery infrastructure drive the growth of online trade?* Second, *how does the geographic distribution of delivery infrastructure affect spatial inequality in consumption—does it narrow or widen existing gaps?*

To address these questions, we proceed in four steps. First, we construct a *novel* dataset covering 295 Chinese cities from 2015 to 2019. For each city, we measure two key variables: the *delivery station density* and the *online consumption share*. The former is defined as the number of last-mile delivery stations per unit area, while the latter represents the percentage of total consumption conducted online. We obtain detailed geographic data on delivery station locations from Amap's point-of-interest (POI) database. City-level online consumption shares are derived from proprietary transaction data from Alibaba's Taobao and Tmall platforms, China's largest online marketplaces. Using these data, we document a robust positive correlation between a city's delivery station density and its online consumption share. This empirical relationship sets the stage for our subsequent theoretical and quantitative analysis.

Second, we develop a parsimonious multi-city general equilibrium model to analyze how delivery infrastructure shapes online trade. Each city produces a distinct set of differentiated varieties, which consumers purchase either offline or online. Trade costs between cities differ across offline and online channels and are shaped by both geographic distance and delivery infrastructure. Offline trade costs rise with geographic distance, consistent with standard trade theory. Online trade costs also increase with distance but decline as the delivery station density in the importing city increases. As a result, denser delivery stations lower online trade costs and

encourage greater reliance on online purchases. By explicitly linking city-level delivery station density to trade costs, our model provides a clear mechanism through which delivery infrastructure drives both the aggregate growth and the spatial distribution of online trade.

Third, we calibrate the parameters governing trade costs by matching model-generated moments to their empirical counterparts. In particular, we calibrate the distance elasticities—i.e., the elasticity of trade costs with respect to distance—for offline and online channels using gravity equations based on observed trade flows. The elasticity of online trade costs with respect to delivery station density (delivery elasticity, henceforth) is disciplined by the observed correlation between delivery station density and online consumption share.

Finally, to quantify the contribution of last-mile delivery infrastructure to the rise of online trade, we compare the observed 2015 equilibrium to a counterfactual in which delivery station density has no effects on online trade costs. We implement this by setting the delivery elasticity to zero, removing the mechanism through which delivery infrastructure reduces online trade costs. To benchmark these effects, we also consider a second counterfactual in which online trade is shut down entirely by setting online trade costs to infinity. Together, these exercises isolate the welfare and trade implications of delivery infrastructure versus digital platforms.

The results show that delivery infrastructure plays a central role in enabling online trade. Nationally, more than 80 percent of online trade in 2015 can be attributed to this channel. Cities with denser delivery stations exhibit higher online consumption shares in the observed data, but this advantage reverses in the counterfactual equilibrium when setting the delivery elasticity to zero.

The reversal arises because, in the counterfactual scenario where delivery infrastructure has no effects on online trade costs, those costs depend solely on geographic distance. Although both offline and online trade costs increase with distance, the online channel is less sensitive to distance. This makes the online channel relatively more attractive for sourcing goods from other cities. However, cities that initially had denser delivery networks—typically the larger ones—tend to consume more goods produced locally. Since fewer goods are imported from other cities, and online trade is relatively more attractive for nonlocal purchases, these cities exhibit lower online consumption shares once the infrastructure advantage is removed.

In contrast, when delivery station density lowers online trade costs as in the observed equilibrium, denser infrastructure increases the probability that consumers shop online for both locally

produced and imported goods. This mechanism explains why cities with denser delivery stations exhibit higher online shares under the observed equilibrium, but lose their advantage when the effects of delivery infrastructure are removed.

Welfare gains follow a similar pattern: delivery infrastructure accounts for nearly 90 percent of the total welfare gains from online trade. It reduces spatial consumption inequality, as smaller cities gain more in absolute terms, although the relative contribution of delivery infrastructure is larger in bigger cities.

We then ask whether a more equal distribution of delivery infrastructure could further reduce spatial inequality. We solve a counterfactual in which the total number of delivery stations remains fixed, but delivery density is made uniform across cities. This scenario removes the advantage currently held by large cities. We find that such a uniform allocation reduces spatial inequality further. However, these equity gains come at the cost of smaller aggregate welfare gains.

This paper contributes to the strand of literature that examines the effects of trade technology on domestic trade. A large number of studies in this area focus on traditional transportation infrastructure, including railroads, highways, and ports, and their role in facilitating market integration and regional development (e.g., Donaldson (2018); Fajgelbaum and Redding (2022); Duranton et al. (2014)). In contrast, relatively few studies have investigated the implications of e-commerce for domestic trade, with the notable exception of Fan et al. (2018), who emphasize consumers' access to online and offline retail channels. Distinct from their focus, we study a key but understudied feature of e-commerce: the role of delivery infrastructure in shaping online trade patterns. Our contribution is twofold. First, we document a robust positive correlation between online consumption share and the density of last-mile delivery stations across Chinese cities. Second, we quantify the contribution of delivery infrastructure to online trade, welfare gains, and the spatial consumption inequality.

The remainder of the paper proceeds as follows. Section 2 documents the positive correlation between online consumption share and delivery station density in China. Section 3 introduces the multi-city general equilibrium model with online and offline trade channels. Section 4 describes the model parameterization. Section 5 presents a series of counterfactual experiments that quantify the contribution of delivery infrastructure to online trade, welfare, and spatial inequality. Section 6 concludes.

2 Last-mile Delivery and Online Trade in China

In this section, we examine the unique role of last-mile delivery in online trade, highlighting key patterns related to delivery station density in China. We also present evidence on how the online consumption share is correlated with delivery station density across Chinese cities. Appendix A provides further details on the data sources used in our analysis.

2.1 The Role of Last-mile Delivery in Online Trade

Online trade has been significantly boosted by the development of e-commerce platforms over the last two decades, such as Amazon in the U.S. and Alibaba in China. These platforms serve as digital marketplaces that bring together sellers and buyers, facilitating online transactions by significantly reducing search and matching frictions. However, while digital platforms enable the initiation of online transactions, the completion of these transactions requires the physical movement of goods from sellers to buyers. This brings us to a crucial point: the rise of online trade depends not only on digital platforms but also on the offline delivery infrastructure that supports them.

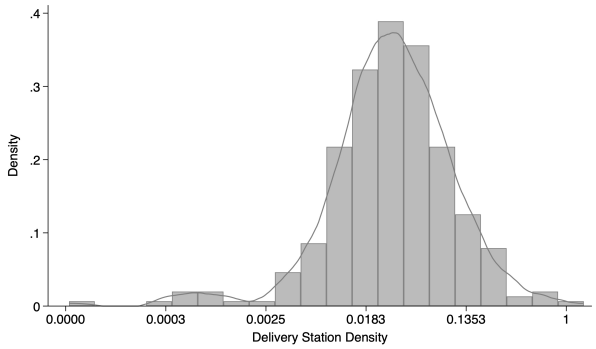
The offline fulfillment of an online transaction typically follows a sequence of steps. Once a customer places an order, the seller hands the package to a courier firm. The package is then sent to a nearby sorting hub, where it is scanned and sorted alongside other packages heading to similar destinations. Next, it travels to a sorting hub near the buyer, moving closer to its final destination. Finally, the package reaches a last-mile delivery station near the consumer, from which it is either delivered directly to their doorstep or made available for pickup. The transportation of packages between sorting hubs, known as line-haul transportation, is a feature shared by both online and traditional offline trade. However, last-mile delivery stations are unique to online trade.

The "last mile" of delivery, often the most expensive and time-consuming part of the logistics process, is heavily influenced by the density of delivery stations, which refers to the concentration of these stations within a specific area. A higher density means more strategically located hubs from which packages can be dispatched, reducing the distance and time it takes to complete the delivery process. In cities with more densely distributed stations, packages can reach consumers faster and more efficiently, significantly lowering the cost of fulfillment. This increased

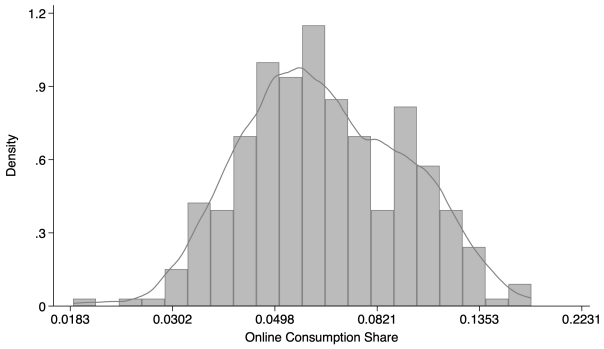
density reduces trade costs by shortening delivery times, minimizing logistical inefficiencies, and addressing the high costs associated with the final leg of delivery, which is critical for facilitating the continued growth of online consumption.

2.2 Last-mile Delivery Stations in China

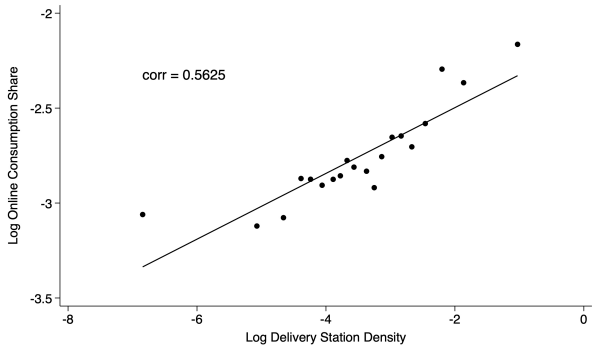
In Section 2.1, we highlighted the importance of last-mile delivery stations in the growth of online trade. Here, we focus on the density of these stations, a crucial factor in determining the efficiency of delivery infrastructure and the cost of online trade. Between 2015 and 2019, the national density of delivery stations in China grew from 1.7 to 5.4 per 100 square kilometers. This increase in logistics capacity coincided with a rise in the share of consumption directed toward Alibaba



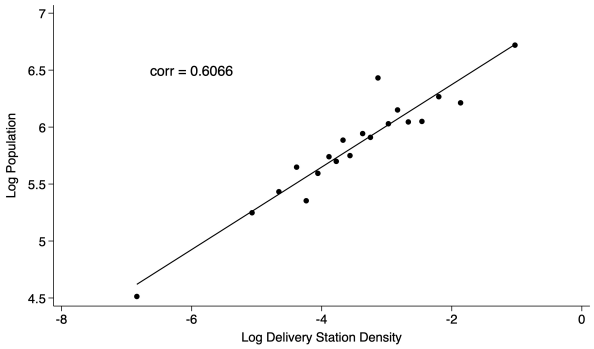
(a) Distribution of Delivery Station Density



(b) Distribution of Online Consumption Share



(c) Online Consumption Share and Delivery Station Density



(d) City Size and Delivery Station Density

Notes: This figure displays stylized facts on delivery station density in 2015. Panel (a) shows the distribution of delivery station density, measured as the number of delivery stations divided by the administrative area. It is illustrated as a normal distribution with a peak around 0.03. Panel (b) shows the distribution of online consumption share, which is defined as the ratio of online consumption from Alibaba to total consumption. It is similarly illustrated as a normal distribution with a peak around 0.06. Panel (c) plots the relationship between online consumption share and delivery station density, whose correlation is 0.5625. Panel (d) plots the relationship between city size, measured as population, and delivery station density, indicating a positive correlation of 0.6066. The sample includes 295 Chinese cities in 2015, i.e. 291 prefecture-level cities and 4 municipalities. Sansha and Danzhou in Hainan Province are excluded here due to missing variables.

Figure 1: Stylized Facts on Delivery Station Density

platforms—Taobao and Tmall—rising from 6.8% in 2015 to 10.4% in 2019.

However, national averages obscure significant variation across cities. Panels (a) and (b) of Figure 1 illustrate this heterogeneity. Panel (a) shows the distribution of delivery station density in 2015, with the 90th and 10th percentiles ranging from 0.82 to 12.18 stations per 100 square kilometers. Panel (b) shows the variation in the share of online consumption across cities, ranging from 1.86% to 17.44%. These disparities highlight the importance of examining delivery station density at the city level, which can provide a clearer understanding of the role infrastructure plays in online trade.

Panel (c) shows the correlation between delivery station density and online consumption share, where cities with a higher online consumption share tend to have denser delivery stations. Panel (d) of Figure 1 presents a scatter plot of delivery station density against city size (measured by population). The positive correlation suggests that larger cities tend to have more densely distributed delivery stations.

2.3 Delivery Station Density and Online Consumption Share

A central hypothesis of this study is that denser delivery stations within a city reduce the costs associated with online trade. By improving logistical efficiency, higher delivery station density shortens delivery times, reduces transportation costs, and enhances the reliability of online shopping. These reductions in trade costs make online shopping a more attractive option for consumers, leading to an increase in the share of total consumption conducted online.

To test this hypothesis, we estimate the relationship between delivery station density and the logarithm of city-level online consumption share using data from 295 Chinese cities. Table 1 presents regression results linking city-level online consumption share to delivery station density. In all specifications, The coefficient on the log of delivery station density is positive and statistically significant. Column (1) provides a simple bivariate regression using 2015 data only. The coefficient is 0.173, implying that a 10% increase in station density is associated with a 1.73% increase in the online consumption share. The R^2 of 0.316 suggests that delivery infrastructure alone explains a sizable portion of the variation in online trade across cities.

Column (2) adds log city population as a control. Column (3) further includes market potential, measured as the population-weighted average inverse distance to all other cities. The coef-

Table 1: Baseline results

Dependent variable:	Logarithm of Online Consumption Share			
	(1)	(2)	(3)	(4)
Logarithm of Delivery Station Density	0.173***	0.196***	0.204***	0.086***
	(0.016)	(0.019)	(0.021)	(0.024)
Logarithm of Population		-0.063*	-0.058*	-0.972***
		(0.032)	(0.032)	(0.106)
Logarithm of Market Potential			-0.090	2.428**
			(0.105)	(0.955)
Constant	-2.151***	-1.706***	-1.612***	0.950
	(0.058)	(0.232)	(0.257)	(1.102)
City FE	NO	NO	NO	YES
Year FE	NO	NO	NO	YES
R^2	0.316	0.326	0.327	0.955
Observations	295	295	295	885

Notes: Table reports the response of city-level online consumption share to delivery station density. The sample includes 295 Chinese cities, i.e. 291 prefecture-level cities and 4 municipalities. Sansha and Danzhou in Hainan Province are excluded here due to missing variables. Column (1)-(3) use only the 2015 sample while column (4) uses the full sample. The dependent variable is the city-level online consumption share, which is defined as the ratio of online consumption from Alibaba to total consumption. And the key independent variable is the city-level delivery station density, measured as the number of delivery stations divided by the administrative area. Column (1) captures the elasticity of online consumption share with respect to delivery station density. Columns (2)-(3) control for population and market potential, respectively. Column 4 adds the city and year fixed effects. Significance: *0.10,** 0.05,*** 0.01.

ficient on log delivery station density rises slightly from 0.196 in Column (2) to 0.204 in Column (3), indicating that the positive association with online consumption is not simply due to city size or proximity to markets. Appendix B extends this analysis by introducing additional controls on both the supply and demand side. In all cases, the coefficient on delivery station density remains positive and statistically significant.

Column (4) expands the sample to include 2015, 2017, and 2019 and incorporates city and year fixed effects. The coefficient on the log of delivery station density drops to 0.086 but remains highly significant. This specification absorbs all time-invariant city characteristics and common national shocks. The result confirms that even after accounting for unobserved heterogeneity, denser delivery stations predict higher online consumption. Overall, the results point to a robust, positive relationship between delivery station density and online consumption share.

In the next section, we develop a multi-city general equilibrium model to analyze the role of delivery station density in shaping online trade. The model incorporates delivery station density as a key city characteristic that directly affects online trade costs, providing a structural interpretation of the empirical correlation identified in Section 2.3. Furthermore, this correlation is used

to discipline the model's key parameters, particularly those governing how online trade costs change with respect to delivery station density. By linking the empirical results to the theoretical framework, the model offers a richer understanding of the mechanisms driving online trade and the role of delivery infrastructure in enabling its growth.

3 Model

This section develops a parsimonious multi-city general equilibrium model to study how delivery infrastructure affects online trade. There are N cities, indexed by i and j ($i, j \in \{1, 2, ..., N\}$). Each city i is endowed with L_i units of labor, and produces a unit measure of distinct varieties, indexed by $\omega \in [0, 1]$. Consumers in each city j can purchase any variety ω from city i using either offline or online channels, with trade costs differing between the two.

Offline trade costs depend on geographic distance between cities, following the standard gravity framework in the trade literature (e.g., Anderson and Van Wincoop, 2003). Online trade costs, in contrast, depend on both geographic distance and the density of delivery stations in the importing city j. The model assumes that higher delivery station density in the importing city reduces online trade costs. This feature highlights the role of delivery infrastructure in shaping trade costs and, ultimately, facilitating online trade flows.

3.1 Preferences

Consumers in city j derive utility from a constant elasticity of substitution (CES) aggregator of varieties produced across all cities. Their utility function is given by:

$$U_j = \left[\sum_{i=1}^{N} \int_0^1 \left(\frac{q_{ij}(\omega)}{\alpha_{ij}(\omega)} \right)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $q_{ij}(\omega)$ denotes the quantity consumed of variety ω from city i by consumers in city j, and $\alpha_{ij}(\omega)$ represents the idiosyncratic preference shock for that variety. The term $\frac{q_{ij}(\omega)}{\alpha_{ij}(\omega)}$ can be interpreted as the effective quantity of quality-adjusted consumption. The parameter $\sigma > 1$ is the elasticity of substitution.

3.2 Production

Each city i produces a unit measure of distinct varieties, indexed by $\omega \in [0,1]$, with varieties differing not only within each city but also across cities. Varieties produced in city i are unique to that city and differ from those produced in any other city j. Labor is the only input. Productivity in city i is uniform across all varieties and is denoted by T_i. Production takes place under conditions of perfect competition, leading to a common producer price for each variety ω

$$p_i(\omega) = \frac{w_i}{T_i}, \tag{2}$$

where w_i is the wage rate in city i.

3.3 Online vs. Physical Stores

For a given variety ω produced in city i, consumers in the city j can choose between two purchasing channels: online (O) or physical stores (P). The consumer price is determined by the producer price and the channel-specific iceberg trade cost, denoted as τ_{ij}^C, where $C = O$ or P. Following Fan et al (2018), we assume that Channel-specific idiosyncratic preference shocks, denoted by $\alpha_{ij}^C(\omega)$, are drawn independently from a Fréchet distribution with the cumulative distribution function:

$$F(x) = e^{-x^{-\theta}}. \tag{3}$$

Consumers choose the channel that minimizes the effective cost of delivering one quality-adjusted unit:

$$c_{ij} = \min \left\{ \frac{w_i \tau_{ij}^O}{T_i \alpha_{ij}^O(\omega)}, \frac{w_i \tau_{ij}^P}{T_i \alpha_{ij}^P(\omega)} \right\}. \tag{4}$$

The share of expenditure directed towards online purchases by consumers in city j for varieties from city i, denoted by ρ_{ij}, is then expressed as:

$$\rho_{ij} = \frac{\left(\tau_{ij}^O\right)^{-\theta}}{\left(\tau_{ij}^O\right)^{-\theta} + \left(\tau_{ij}^P\right)^{-\theta}}. \tag{5}$$

3.4 Trade Costs and Delivery Station Density

We model trade costs differently for offline and online purchases. Offline trade costs are given by:

$$\tau_{ij}^{P} = \begin{cases} 1, & \text{if } i = j; \\ e^{\delta_1}(d_{ij})^{\delta}, & \text{if } i \neq j, \end{cases} \tag{6}$$

where d_{ij} is the geographic distance between cities i and j. The parameter δ is referred to as the offline trade cost elasticity, indicating how trade costs change with distance in the offline market. For intra-city offline trade, we normalize the trade cost to 1, as is standard in trade literature. For inter-city offline trade, e^{δ_1} adds a constant component to trade costs that is independent of distance.

The trade cost for online purchases is given by:

$$\tau_{ij}^{O} = \begin{cases} e^{\gamma_0}(s_j)^{-\eta}, & \text{if } i = j; \\ e^{\gamma_1}(d_{ij})^{\gamma}(s_j)^{-\eta}, & \text{if } i \neq j, \end{cases} \tag{7}$$

where s_j represents the density of delivery stations in city j. The parameter γ is termed the online trade cost elasticity, capturing how online trade costs change with distance, while η is the delivery elasticity, measuring how online trade costs change with the density of delivery stations. The constants e^{γ_0} and e^{γ_1} are the constant components in intra- and between-city online trade cost, respectively.

The key difference between offline and online trade costs lies in their dependence on delivery station density. While offline trade costs are driven solely by geographic distance, online trade costs incorporate the cost reduction from a denser delivery network, highlighting the crucial role of delivery infrastructure in facilitating online trade.

3.5 Equilibrium

The total expenditure of consumers in city j equals the labor income

$$X_j = w_j L_j. \tag{8}$$

The share of expenditure by consumers in city j for varieties from city i is given by

$$\pi_{ij} = \frac{(w_i \tau_{ij}/T_i)^{1-\sigma}}{\sum_{k=1}^{N}(w_k \tau_{kj}/T_k)^{1-\sigma}}, \tag{9}$$

where

$$\tau_{ij} = \kappa \left[\left(\tau_{ij}^{O}\right)^{-\theta} + \left(\tau_{ij}^{P}\right)^{-\theta} \right]^{-1/\theta}, \tag{10}$$

in which $\kappa = \Gamma(\frac{\theta+1-\sigma}{\theta})$ and $\Gamma(t) = \int_0^{+\infty} x^{t-1} e^{-x} dx$.

The aggregate price index in city j is given by

$$P_j = \left[\sum_{i=1}^{N} \left(\frac{w_i \tau_{ij}}{T_i} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{11}$$

The trade balance of each city i implies that

$$\sum_{j=1}^{N} \pi_{ij} X_j = \sum_{i=1}^{N} \pi_{ji} X_i. \tag{12}$$

Definition: Given parameters $\{\sigma, \theta, \delta_1, \delta, \gamma_0, \gamma_1, \gamma, \eta\}$, the exogenous city characteristics $\{d_{ij}, L_i, T_i, s_i\}$, and the offline and online trade costs specified in equation (6) and (7), respectively, the equilibrium consists of $\{w_i, P_i\}_{i=1}^{N}$ that solves equation (8), (9), (10), (11) and (12).

4 Model Parameterization

This section describes how we calibrate model parameters. We calibrate the model to the year 2015 and 295 Chinese cities. To quantify the contribution of delivery infrastructure to the aggregate level and spatial pattern of online trade, we need data on city population L_i, city-level productivity T_i, city-level delivery station density s_i, bilateral city distance d_{ij}, and parameters $\Theta \equiv (\sigma, \theta, \delta_1, \delta, \gamma_0, \gamma_1, \gamma, \eta)$.

4.1 Parameters Calibrated Externally

We set the elasticity of substitution, $\sigma = 5$, and the dispersion of idiosyncratic preference shocks, $\theta = 6$, following the values used in Fan et al. (2018). We take city population L_i from the 2015

edition of the Chinese City Statistical Yearbook. City-level delivery station density s_i is defined as the number of last-mile delivery stations per unit area. We obtain the number of delivery stations in each city from Amap's POI database, and the administrative area of each city from the China City Statistical Yearbook.

4.2 Parameters Calibrated in Equilibrium

We calibrate city-level productivity T_i jointly with the key parameters governing trade costs: $(\delta_1, \delta, \gamma_0, \gamma_1, \gamma, \eta)$ using a nested optimization procedure. In the inner loop, we solve for T_i such that the model matches the observed nominal income per capita in each city, given an arbitrary set of parameters. Data on nominal income is from the China City Statistical Yearbook.

In the outer loop, we estimate the trade cost parameters using a method of moments approach. We choose values that minimize the squared distance between model-implied and empirical moments. Specifically, we target six moments. Five of these are following Fan et al. (2018), and the sixth is new: the correlation between online consumption share and delivery station density. Although the parameters are jointly determined, each moment provides key information for identifying a specific parameter. We describe each moment and identification as follows.

We identify the offline distance elasticity, δ, by matching the estimated coefficient of the log distance from a gravity equation for offline trade. Specifically, we regress the log of offline trade flows between provinces on the log of geographic distance, including fixed effects for both the origin and destination provinces. The trade flow data come from the 2002 China Inter-Provincial Input-Output Table, which records bilateral trade between provinces. We interpret these flows as offline transactions, since online trade played a negligible role in the economy at that time.

To identify the online distance elasticity, γ, we estimate a parallel gravity regression using bilateral online trade flows between provinces, constructed from Alibaba data. The structure mirrors the offline regression but substitutes online for offline trade flows.

We identify the between-city offline trade cost constant, δ_1, by matching the average province offline absorption ratio. It is defined as the share of offline consumption sourced locally within a province. We calculate this share using the 2002 China Inter-Provincial Input-Output Table. Similarly, we identify the between-city online trade cost constant, γ_1, by matching the average province offline absorption ratio, which is defined as the share of online consumption sourced

Table 2: Model Parametrization

Parameters Calibrated Externally				
Parameter	Definition	Value	Source	
σ	Elasticity of substitution	5	Fan et al. (2018)	
θ	Shape para. of preference shock distribution	6	Tintelnot (2017)	
Parameters Calibrated in Equilibrium				
Parameter	Definition	Value	Target Moment	Data
δ_1	Between-city offline trade cost constant	0.729	Province offline absorption ratio in 2002	0.808
δ	Offline distance elasticity	0.144	Distance elasticity in offline gravity in 2002	-0.999
γ_0	Intra-city online trade cost	1.178	Average online share in 2015	0.082
γ_1	Between-city online trade cost constant	1.529	Province online absorption ratio in 2015	0.166
γ	Online distance elasticity	0.104	Distance elasticity in online gravity in 2015	-0.394
η	Delivery elasticity	0.057	Delivery elasticity of online consumption share in 2015	0.173
T_i	City-level productivity	-	Nominal income per capita in 2015	-

Notes: We calibrate our model to the economy in 2015 with 295 Chinese cities.

locally within a province. We compute this share using the data from Alibaba. We pin down the online intra-city trade cost constant, γ_0, by matching the average online consumption share.

Finally, we identify the delivery elasticity, η, by targeting the empirical relationship between online consumption share and delivery station density. Specifically, we regress the log of a city's online consumption share on the log of its delivery station density. The estimated coefficient on delivery density, reported in Column (1) of Table 1, serves as the moment used to discipline η.

Table 2 reports the calibrated parameters alongside their corresponding target moments. The offline distance elasticity, $\delta = 0.144$, implies that doubling geographic distance raises offline trade costs by approximately 10%. In comparison, the online distance elasticity, $\gamma = 0.104$, is notably smaller, indicating that online trade costs are less sensitive to distance—rising by only 7% when distance doubles. The delivery elasticity, $\eta = 0.057$, captures how delivery infrastructure shapes online trade costs. A doubling of delivery station density reduces these costs by roughly 4%.

4.3 Delivery Station Density and Online Trade Costs

Figure 2 shows how trade costs vary with distance and delivery infrastructure. Both axes are displayed on logarithmic scales. The solid line plots online trade costs as a function of distance, holding delivery station density at the national average. Trade costs rise with distance, and the slope of the line corresponds to the distance elasticity of online trade costs.

The dashed line plots offline trade costs. Its slope is steeper, reflecting a larger distance elastic-

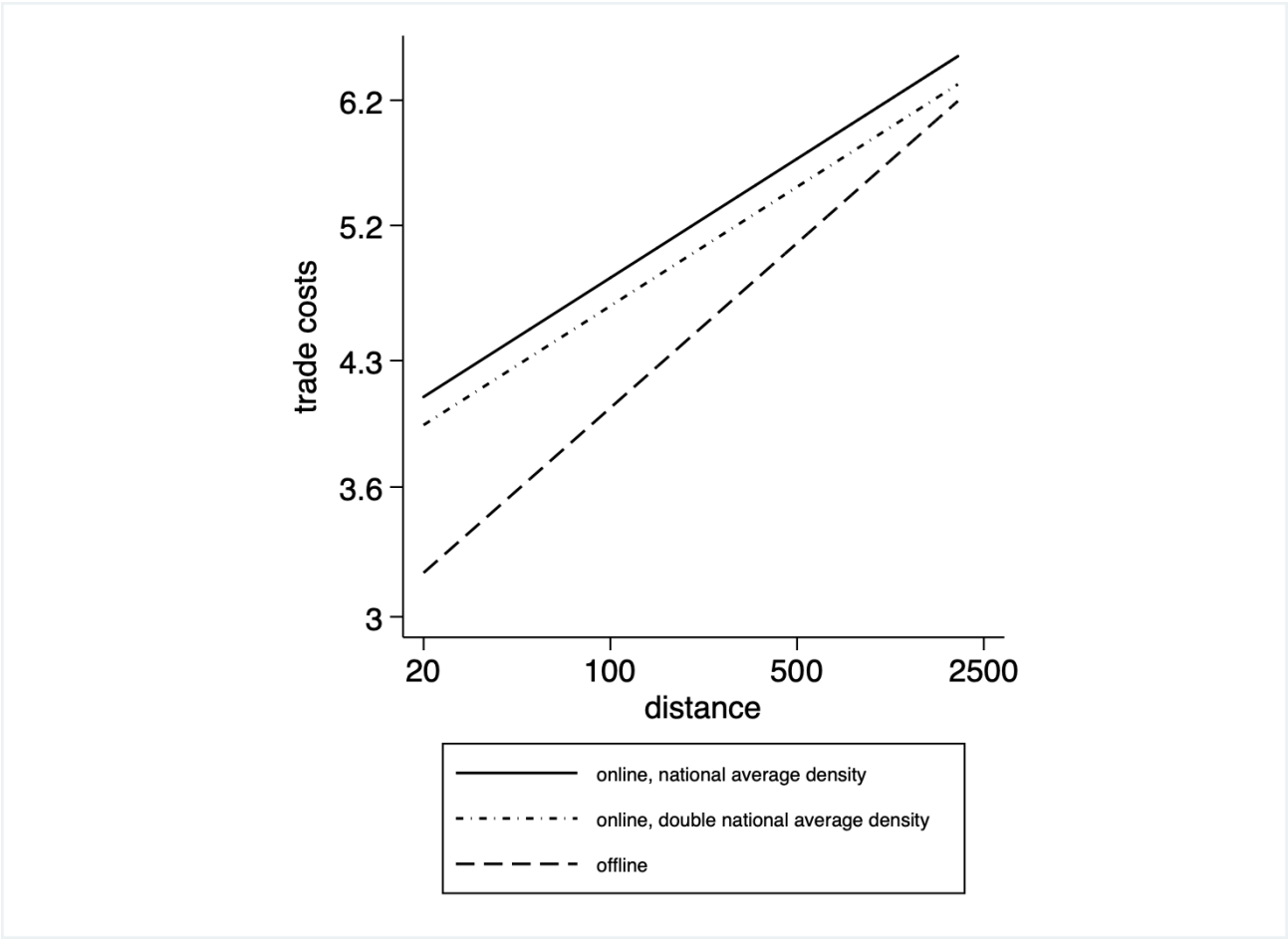


Figure 2: Online Trade Costs and Delivery Station Density

ity relative to the online channel. This difference implies that the relative cost advantage of online trade increases with distance. Consumers are therefore more likely to rely on the online channel when sourcing goods from cities farther away.

The dashed-dotted line shows online trade costs when delivery station density is doubled. The slope remains constant compared to that of the dashed line, since the distance elasticity of online trade costs does not depend on delivery station density. What changes is the level: online trade costs shift downward uniformly across all distances. At any given distance, doubling delivery station density reduces online trade costs by approximately 4%. This uniform reduction raises the likelihood that consumers choose the online channel when sourcing goods—not just from distant cities but from all locations—underscoring the broad role of delivery infrastructure in facilitating online consumption.

5 Counterfactuals

In this section, we use the model to quantify the role of last-mile delivery infrastructure in shaping online trade, welfare, and spatial inequality. We begin by isolating the contribution of delivery infrastructure to the rise of online trade. We then assess the corresponding welfare effects, separating the gains attributable to delivery infrastructure from those driven by digital platforms. Moreover, we move to examine how delivery infrastructure affects the spatial distribution of consumption. Finally, we explore a counterfactual in which delivery infrastructure is allocated uniformly across cities.

5.1 The Contribution of Delivery Infrastructure to Online Trade

We begin by quantifying the role of last-mile delivery infrastructure in supporting online trade. Specifically, we compare the observed 2015 equilibrium to a counterfactual scenario in which delivery station density does not affect online trade costs. In the model, this is implemented by setting the logistics elasticity $\eta = 0$, thereby removing the channel through which delivery infrastructure reduces the cost of fulfilling online orders. This experiment isolates the contribution of delivery infrastructure to shaping both the aggregate level and distribution of online trade.

At the national level, we find that delivery infrastructure plays a substantial role in enabling online trade. In the observed 2015 equilibrium, the online consumption share at the national level is 7.53%. In contrast, in the counterfactual equilibrium with $\eta = 0$, this share drops to just 0.93%. This implies that about 88% of the observed online trade in 2015 can be attributed to the presence of delivery infrastructure, underscoring its importance in lowering trade frictions and facilitating the expansion of online trade.

We next examine how the effects of delivery infrastructure vary across cities with different levels of delivery station density. In the observed 2015 equilibrium, cities with denser delivery stations exhibit consistently higher online consumption shares. As reported in Column (3) of Panel A in Table 3, cities in the top quartile of the delivery station density distribution record an average online share of 9.99%, compared to just 5.05% percent in the bottom quartile.

When we set $\eta = 0$ to remove the effects of delivery infrastructure on online trade costs, cities initially with denser delivery stations experience larger reductions in online consumption shares. As shown in Columns (4) and (5) of Panel A, cities in the top quartile experience the largest

Table 3: The Contribution of Delivery Infrastructure to Online Trade by City Characteristics

	Delivery Station Density (*per square kilometers*)	City Size (*millions*)	Online Consumption Share *(percentage points)*		
	2015 (1)	2015 (2)	2015 (3)	$\eta = 0$ (4)	Difference (5) = (3) - (4)
National Average	0.06	4.41	7.53	0.93	6.60
Panel A: by Delivery Station Density					
Low	0.01	2.35	5.05	1.16	3.89
Medium-Low	0.02	3.45	6.07	1.08	4.99
Medium-High	0.05	5.36	6.60	0.92	5.68
High	0.17	6.46	9.99	0.77	9.22
Panel B: by City Size					
Small	0.03	1.42	5.96	1.45	4.51
Medium-Small	0.03	2.83	6.18	1.17	5.01
Medium-Large	0.06	4.51	7.00	1.01	5.99
Large	0.12	8.84	8.49	0.73	7.76
Panel C: by Region					
East	0.13	6.15	9.56	0.81	8.75
Central	0.05	4.43	6.68	1.05	5.63
West	0.03	3.30	5.78	0.97	4.81
Northeast	0.02	3.08	5.37	1.03	4.34

absolute reductions in online consumption, with their average share falling by 9.22% to just 0.77%. In contrast, cities in the bottom quartile see a more modest decline of 3.89%, ending at 1.16%. Intermediate quartiles follow a similar pattern, with the average online consumption share falling from 6.07% to 1.08% in the medium-low quartile, and from 6.60% to 0.92% in the medium-high quartile. As a result, the rank ordering of cities reverses in the counterfactual equilibrium: those that initially had the highest online consumption shares now exhibit the lowest. This reversal highlights the central role of delivery infrastructure in shaping the spatial allocation of online trade.

The reversal arises because, in the counterfactual scenario where delivery infrastructure has no effect on online trade costs, those costs depend solely on geographic distance. Although both offline and online trade costs increase with distance, the online channel is less sensitive to distance. This makes the online channel relatively more attractive for sourcing goods from other cities. However, cities that initially had denser delivery networks—typically the larger ones—tend to consume more goods produced locally. Since fewer goods are imported from other cities, and

online trade is relatively more attractive for nonlocal purchases, these cities exhibit lower online consumption shares once the infrastructure advantage is removed.

In contrast, when delivery station density lowers online trade costs as in the observed equilibrium, denser infrastructure increases the probability that consumers shop online for both locally produced and imported goods. This mechanism explains why cities with denser delivery stations exhibit higher online shares under the observed equilibrium, but lose their advantage when the effects of delivery infrastructure are removed.

We further explore the distributional effects of delivery infrastructure by grouping cities by population size and geographic region. Because city size is strongly positively correlated with delivery station density, we observe that larger cities tend to have higher online consumption shares in the observed 2015 equilibrium. As reported in Panel B of Table 3, the average online consumption share in the top population quartile is 8.49%, compared to 5.96% in the bottom quartile. In the counterfactual where $\eta = 0$, this ranking also reverses: larger cities exhibit lower online consumption shares. The average for the top quartile falls sharply to 0.73%, while the bottom quartile records a higher 1.45%.

A similar pattern emerges across regions as reported in Panel C of Table 3. Eastern cities, generally more populous and better served by delivery infrastructure, record an average online consumption share of 9.56% in the observed 2015 equlibrium, compared to 5.78% in the West and 5.37% in the Northeast. Yet, under the counterfactual scenario, eastern cities experience the most pronounced declines, with their average share dropping to just 0.81%, now falling below the western and northeastern regions.

In summary, we find that about 88% of observed online trade in 2015 is attributable to delivery infrastructure. Cities with denser delivery stations exhibit higher online consumption shares in the observed equilibrium, but this advantage reverses once the effects of delivery infrastructure are removed.

5.2 Welfare Implications of Delivery Infrastructure in Online Trade

We now examine the welfare implications of last-mile delivery infrastructure. To quantify its role, we compare real income in the observed 2015 equilibrium to a counterfactual in which delivery station density has no effect on online trade costs. This isolates the gains attributable to delivery

Table 4: Welfare Gains from Delivery Infrastructure by City Characteristics

Percentage Change	Overall (1)	Delivery Infrastructure (2)	Digital Platforms (3)
National Average	1.56	1.40	0.16
Panel A: by Delivery Station Density			
Low	1.42	1.22	0.20
Medium-Low	1.57	1.38	0.19
Medium-High	1.51	1.35	0.16
High	1.64	1.51	0.13
Panel B: by City Size			
Small	2.12	1.86	0.26
Medium-Small	1.78	1.58	0.20
Medium-Large	1.65	1.48	0.17
Large	1.34	1.22	0.12
Panel C: by Region			
East	1.55	1.41	0.14
Central	1.73	1.55	0.18
West	1.40	1.23	0.17
Northeast	1.47	1.29	0.18

infrastructure. To place these gains in perspective, we also compare the observed equilibrium to a second counterfactual in which online trade is eliminated entirely by setting online trade costs to infinity. The difference between these two scenarios captures the total welfare gain from online trade. The remaining gap, between the delivery infrastructure and total gains, is attributed to digital platforms. Column (1) of Table 4 reports the total welfare gains from online trade, while Columns (2) and (3) assign those gains to delivery infrastructure and digital platforms, respectively.

At the national level, delivery infrastructure accounts for most of the welfare gains from online trade. Relative to a counterfactual in which delivery station density has no effect on trade costs, real income rises by 1.56%. Starting instead from a world without online trade, the gain is only slightly larger at 1.56%. The comparison implies that roughly 90% of the total benefit from online trade is due to the delivery infrastructure. This finding aligns with our earlier result that about 88% of online trade is attributed to delivery infrastructure.

We next consider how these gains vary across cities with different levels of delivery station density. Starting from the $\eta = 0$ counterfactual, cities with denser delivery stations experience

larger increases in real income when we move to the observed 2015 equilibrium. As reported in Column (2) of Panel A in Table 4, cities in the top quartile of the delivery station distribution experience a welfare gain of 1.51%, compared to 1.22% for those in the bottom quartile. When we instead compare the no-online-trade scenario to the $\eta = 0$ counterfactual, the pattern reverses. As reported in Column (3) of Panel A in Table 4, cities that initially had dense delivery stations now experience smaller welfare gains. This reversal mirrors our earlier findings that cities initially with denser delivery stations exhibit lower online consumption shares once the infrastructure advantage is removed.

We further explore the welfare effects of delivery infrastructure by city size. As shown in Column (2) of Panel B in Table 4, smaller cities experience larger welfare gains. Real income rises by 1.86% in the bottom quartile of the population distribution, compared to 1.22% in the top quartile. This result may seem surprising, given that larger cities tend to have denser delivery stations. However, larger cities also source more of their consumption from locally produced goods, limiting the gains from improved access. However, this masks an important distinction in the relative importance of delivery infrastructure.

To highlight this, we compute the relative welfare contribution of delivery infrastructure: the ratio of welfare gains from delivery infrastructure to total gains from online trade. We find that the relative importance of delivery infrastructure increases with both city size and delivery station density. As shown in Table 4, delivery infrastructure accounts for 92% of total welfare gains in the top quartile of city size, compared to 86% in the bottom quartile. Similarly, it accounts for 91% of total gains in cities with the densest delivery networks, but only 88% in the sparsest group.

Finally, we examine geographic variation in the welfare gains from delivery infrastructure. This variation reflects both differences in delivery station density and population size across cities. Central cities experience the largest gains, with real income rising by 1.55% when moving from the $\eta = 0$ counterfactual to the observed equilibrium. Eastern cities gain less, at 1.41%, despite having denser delivery stations. The muted effect in the East reflects the fact that larger cities consume more locally produced goods. Western cities see the smallest gains, at just 1.23%, due to their relatively sparse delivery stations.

Table 5: The Effects of Delivery Infrastructure on Spatial Consumption Inequality

Percentage Change	Overall (1)	Delivery Infrastructure (2)	Digital Platforms (3)
Panel A: Delivery Density in 2015			
Theil Index	-1.53	-1.22	-0.31
Real Income (National Average)	1.56	1.40	0.16
Panel B: Uniform Delivery Density			
Theil Index	-2.45	-2.14	-0.31
Real Income (National Average)	1.27	1.11	0.16

5.3 The Effects of Delivery Infrastructure on Spatial Inequality

We turn next to the role of delivery infrastructure in shaping spatial consumption inequality. To quantify inequality, we use the Theil index of per capita real income across cities, a standard entropy-based measure of dispersion. Moving from the $\eta = 0$ counterfactual to the observed 2015 equilibrium, we find that the delivery infrastructure in 2015 reduces spatial consumption inequality. As reported in Column (2) in Panel A of Table 5, the Theil index falls by 1.22%. To place this reduction in perspective, we also compare the observed equilibrium to the no-online-trade counterfactual. The decline in the Theil index from the no-online-trade counterfactual to the observed 2015 equilibrium, is 1.53% as reported in Column (1) in Panel A of Table 5. Taken together, these findings imply that roughly 80% of the total equalizing force of online trade can be attributed to the delivery infrastructure.

To better understand the decline in spatial inequality, we examine how the relationship between city size and real income varies across the three equilibria. In each case, we regress the logarithm of real income on the logarithm of population. As shown in Table 6, the slope is positive and statistically significant in all scenarios, indicating that larger cities tend to have higher real incomes. But the slope varies in magnitude. It is steepest in the no-online-trade counterfactual, flatter when delivery in 2015, and intermediate—but close to the no-online-trade case—with $\eta = 0$. This pattern mirrors the changes in the Theil index. Together, these findings suggest that delivery infrastructure in 2015 disproportionately benefits smaller cities, flattening the income-population gradient and contributing to lower spatial consumption inequality.

This raises a natural policy question: what if delivery infrastructure were allocated more evenly across cities, rather than concentrated in large markets as observed in 2015? To address

Table 6: Welfare Gain from E-commerce and Delivery

Dependent variable:	Logarithm of Real Wage			
	2015	No Online Trade	$\eta = 0$	Uniform Delivery Density
	(1)	(2)	(3)	(4)
Logarithm of Population	0.1292***	0.1329***	0.1322***	0.1270***
	(0.0264)	(0.0266)	(0.0265)	(0.0265)
Constant	-2.7679***	-2.8071***	-2.8006***	-2.7569***
	(0.1547)	(0.1560)	(0.1560)	(0.1555)
R^2	0.170	0.177	0.175	0.165
Observations	295	295	295	295

Notes: Standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

this, we consider a counterfactual in which all cities are assigned the same delivery station density, while keeping the total number of stations fixed at the national level. This exercise allows us to assess the distributional and aggregate consequences of a uniform delivery infrastructure policy.

Panel B of Table 5 evaluates the equity-efficiency trade-off of uniform delivery infrastructure. Equalizing delivery density across cities leads to a further reduction in spatial inequality, as measured by the Theil index. However, this comes at the cost of aggregate welfare. National real income rises by 1.11% relative to the $\eta = 0$ counterfactual, compared to a larger 1.40% gain under the observed 2015 infrastructure. In short, while uniform delivery achieves a more equal spatial distribution of consumption, it delivers smaller overall gains in real income.

Table 7 provides a more detailed look at the effects on online trade. Nationally, the average online consumption share declines from 7.53% under the observed delivery infrastructure to 6.97% with uniform infrastructure. Cities with initially sparser delivery stations experience larger increases in online consumption share. For example, cities in the bottom quartile of station density see their online share rise from 5.05% to 8.60%, a gain of 3.55%. In contrast, cities originally in the top quartile experience sharpest declines. Their average online share falls by over 4%. Similar redistribution patterns are evident across city size and region: smaller cities and those in western and northeastern China gain from a more uniform allocation, while larger and more connected cities lose ground.

In summary, delivery infrastructure plays a key role in narrowing spatial inequality by disproportionately benefiting smaller cities. A uniform allocation further reduces inequality but

Table 7: The Contribution of Uniform Delivery Infrastructure to Online Trade by City Characteristics

	Delivery Station Density (*per square kilometers*)	City Size (*millions*)	Online Consumption Share *(percentage points)*		
	2015 (1)	2015 (2)	2015 (3)	Uniform (4)	Difference (5) = (3) - (4)
National Average	0.06	4.41	7.53	6.97	0.56
Panel A: by Delivery Station Density					
Low	0.01	2.35	5.05	8.60	-3.55
Medium-Low	0.02	3.45	6.07	8.05	-1.98
Medium-High	0.05	5.36	6.60	6.89	-0.29
High	0.17	6.46	9.99	5.84	4.15
Panel B: by City Size					
Small	0.03	1.42	5.96	10.65	-4.69
Medium-Small	0.03	2.83	6.18	8.72	-2.54
Medium-Large	0.06	4.51	7.00	7.53	-0.53
Large	0.12	8.84	8.49	5.50	2.99
Panel C: by Region					
East	0.13	6.15	9.56	6.08	3.48
Central	0.05	4.43	6.68	7.85	-1.17
West	0.03	3.30	5.78	7.25	-1.47
Northeast	0.02	3.08	5.37	7.64	-2.27

sacrifices aggregate real income.

6 Conclusion

This paper quantifies the role of last-mile delivery infrastructure in shaping the rise and spatial distribution of online trade in China. Using a unique dataset combining detailed delivery station locations from Amap and online transaction shares from Alibaba for nearly 300 cities, we document a strong positive relationship between delivery station density and the share of consumption conducted online. Guided by this empirical fact, we develop and calibrate a multi-city general equilibrium model in which online trade costs decline with local delivery infrastructure, and consumers choose between online and offline channels subject to location-specific frictions.

We use the model to conduct a series of counterfactual experiments. First, we find that over

80% of observed online trade in 2015 is attributable to delivery infrastructure, and nearly 90% of the welfare gains from online trade are driven by it rather than by digital platforms alone. These gains are unevenly distributed: smaller and less connected cities benefit more, reducing spatial inequality in consumption. A counterfactual with uniform delivery station density—keeping the total number of stations fixed at the national level—achieves even greater equalization across space, but at the cost of lower aggregate welfare. The trade-off is sharp: flattening the delivery infrastructure reduces inequality but sacrifices efficiency. These results highlight the central role of delivery infrastructure in shaping not just the volume of online trade, but also its distributional consequences.

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Appendix

A Data Source and Variable Construction

A.1 Online Consumption Share

City-year-level online consumption share is defined as the percentage of total consumption conducted online, i.e.

$$Onl_Cs_Share_{jt} = \frac{Onl_Cs_{jt}}{Total_Cs_{jt}} \tag{13}$$

, where Onl_Cs_{jt} in the numerator denotes the online consumption in city j in year t and $Total_Cs_{jt}$ in the denominator is the total consumption in city j in year t. This metric provides a direct measure of e-commerce penetration, capturing the extent to which digital platforms have reallocated economic activities from traditional retail channels.

A.1.1 Online Consumption

Online trade flow data is derived directly from Alibaba, China's largest online retail platform, which accounted for 57.4% of the country's B2C online retail market in 2015. This ensures that Alibaba data is not only representative but also comprehensive, providing a robust lens through which we can examine the Chinese online shopping landscape.

It provides detailed records of online transactions, including supplier city as well as consumer city, transaction year and transaction value. Information on supplier city and consumer city enables us to analyze the flow of online trade between cities, thus exploring the influence of distance on online trade flows. Information on the transaction year allows us to track trends over time, thereby assessing the dynamic evolution of online trade. Additionally, information on detailed transaction value offers a potent indicator of the magnitude of online transactions.

This paper leverages data for online trade flow in 2015, 2017 and 2019, a timeframe that has been pivotal in the maturation of China's e-commerce sector. This era, marked by the burgeoning

proliferation of e-commerce and the concomitant rise of online payment technologies, can be aptly described as the golden age of digital commerce in China.

Equipped with the city-pair-level online trade flow data mentioned above, this paper is able to calculate the city-level online consumption by aggregating the total online transaction value for each consumer city. Till now, we have obtained the numerator in equation 13.

A.1.2 Total Consumption

City-level total consumption is calculated from City Statistical Yearbook. It is computed through a weighted aggregation of urban and rural per capita consumption, adjusted for respective population shares to account for urban-rural heterogeneity. By providing an accurate portrayal of the total consumption expenditure, we have obtained the denominator in equation 13.

A.1.3 Summary statistics

Table 8 captures the dual trajectory of China's e-commerce expansion (2015-2019). First, mean online consumption share increases from 0.068 to 0.104, signaling deepening e-commerce penetration. Second, spatial heterogeneity also intensifies, as evidenced by the widening standard deviation from 0.028 to 0.034. These patterns reflect both the rapid growth and the uneven diffusion of e-commerce across cities.

Table 8: Summary Statistics of Online Consumption Share

year	N	Min	Max	Mean	SD	p1	p10	p25	p75	p90	p99
2015	295	0.019	0.174	0.068	0.028	0.027	0.040	0.048	0.085	0.109	0.161
2017	295	0.028	0.207	0.083	0.030	0.038	0.054	0.061	0.104	0.130	0.172
2019	295	0.033	0.236	0.104	0.034	0.047	0.068	0.079	0.124	0.152	0.192
Total	885	0.019	0.236	0.085	0.034	0.032	0.047	0.060	0.105	0.134	0.185

Notes: Table displays the summary statistics of online consumption share across different years, calculated as the ratio of online consumption from Alibaba to total consumption. The sample includes 295 cities for each year, totaling 885 observations. To be specific, 295 cities can be decomposed into 291 prefecture-level cities and 4 municipalities. Sansha and Danzhou in Hainan Province are excluded here due to missing variables. Here also reports the number of observations (N), minimum (Min), maximum (Max), mean (Mean), standard deviation (SD), and selected percentiles (p1, p10, p25, p75, p90, p99) for each year.

A.2 Delivery Station Density

City-year-level delivery station density is defined as the number of last-mile delivery stations per unit area, i.e.

$$Del_Stat_Density_{jt} = \frac{Del_Stat_Number_{jt}}{Area_{jt}} \tag{14}$$

, where $Del_Stat_Number_{jt}$ in the numerator denotes the number of delivery stations in city j in year t and $Area_{jt}$ in the denominator is the administrative area of city j in year t. It ensures the construction of a high-fidelity measure of delivery station network, therefore facilitating a detailed analysis of delivery infrastructure development and its impact on e-commerce.

A.2.1 Delivery Station Number

Delivery station data is sourced from Amap, China's foremost provider of digital location service. It is renowned for its high-precision Geographic Information System (GIS). Notably, the Point of Interest (POI) data from Amap, a critical component of GIS, systematically records granular spatial coordinates of economic nodes integral to daily economic activities, such as stores, parks, etc. Each POI entry includes metadata such as entity name, location, telephone number and category, enabling robust spatial-economic analyses.

This paper obtains detailed information on delivery station points using POI data from Amap through the following steps:

Data Selection: First, this paper utilizes POI data categorized under "life service", which encompasses various subcategories, including "logistics express" [1]. And the analysis focuses on the year 2015, 2017, and 2019—a period coinciding with the rapid scaling of China's e-commerce sector—to capture structural shifts in last-mile delivery infrastructure.

Delivery Station Identification: Second, within the "life service" category, delivery stations are identified by filtering POI entries containing names of several major express companies [2].

Data Refinement: Third, the initial extraction above reveals that 87.7% of candidate POIs

[1] Besides "logistics express", "life service" category also contains some other subcategories, such as "ticket office", "post office", "telecommunication", "beauty salon" and so on.

[2] The major express companies here are as follows, ZTO Express, YTO Express, STO Express, Yunda Express, SF Express, JD Express, Deppon Express, Best Express, Postal EMS, U-Express, Tiantian Express, Quanfeng Express, and ZJS Express. As documented in the China Logistics Statistical Yearbook, these are the top express delivery companies in China in terms of total express delivery business volume.

fall under the "logistics express" (54.3%) and "post office" (33.4%) subcategories, with residual observations distributed across auxiliary subcategories. In order to enhance precision, this paper further refines our identification method. To be precise, a two-stage algorithm is implemented for those geographic points not in "logistics express" and "post office".

Inclusion Criteria: Include those containing delivery-related keywords (e.g., "delivery hub", "distribution center", "parcel pickup", etc) from an extensive lexicon of over 70 operational terms.

Exclusion Criteria: Exclude false positives using over 20 suspect terms (e.g., "hair salon", "ticket office", etc) that frequently co-occur with non-logistics POIs in the "life service" category.

Delivery Station Aggregation: Forth, employing the detailed location information provided by POI data, this paper aggregates all the delivery station points for each city in each year, thus obtaining the city-year level delivery station point number.

A.2.2 City Administrative Area

City administrative area is obtained from City Statistical Yearbook. This variable is measured in square kilometers, in order to normalize delivery station counts into density metrics.

A.2.3 Summary statistics

Table 9 reveals two defining characteristics of China's delivery infrastructure evolution (2015-2019). First, there is a pronounced secular expansion in delivery infrastructure: mean delivery station density surges from a mere 0.061 in 2015 to a formidable 0.134 by 2019. Second, its standard deviation more than doubles, from 0.114 to 0.286, which reflects rising spatial heterogeneity.

A.3 Other Variables

A.3.1 Input-Output Table

Offline trade flow data is sourced from the 2002 Provincial Input-Output Table. This table provides a granular depiction of inter-industry offline input-output trade flow between provinces in 2002. By capturing the inter-industry economic linkages at the inter-province level, it offers a comprehensive foundation for examining the structure and magnitude of offline trade flows across regions. This data is updated every five years.

Table 9: Summary Statistics of Delivery Station Density

year	N	Min	Max	Mean	SD	p1	p10	p25	p75	p90	p99
2015	295	0.000	1.438	0.061	0.114	0.000	0.008	0.016	0.063	0.122	0.561
2017	295	0.000	3.080	0.101	0.252	0.000	0.009	0.017	0.084	0.184	1.615
2019	295	0.000	3.658	0.134	0.286	0.000	0.013	0.027	0.129	0.283	1.364
Total	885	0.000	3.658	0.099	0.231	0.000	0.009	0.020	0.090	0.202	1.109

Notes: Table displays the summary statistics of delivery station density across different years, measured as the number of delivery stations divided by the administrative area. The sample includes 295 cities for each year, totaling 885 observations. To be specific, 295 cities can be decomposed into 291 prefecture-level cities and 4 municipalities. Sansha and Danzhou in Hainan Province are excluded here due to missing variables. Here also reports the number of observations (N), minimum (Min), maximum (Max), mean (Mean), standard deviation (SD), and selected percentiles (p1, p10, p25, p75, p90, p99) for each year.

By aggregating the input-output value across different industries for each province pair, this paper calculates the inter-provincial offline trade flow. Therefore, we are able to generate a consolidated metric that reflects the offline value of economic exchange between provinces.

A.3.2 City Statistical Yearbook

Some other city-year-level data are procured from City Statistical Yearbook, including GDP per capita and population. As a nationally standardized statistical compendium compiled and published by China's National Bureau of Statistics, this authoritative Yearbook provides comprehensive city-level socioeconomic indicators.

GDP per capita serves as the principal indicator of regional economic development, capturing spatial disparities in productivity and income levels across cities.

Population measures city size. Moreover, we can calculate a gravity-model-based market potential index using population. To be specific, market potential is articulated as

$$MP_j = \sum_{i \neq j} \frac{population_i}{distance_{ij}}$$

, following Harris (1954). It serves as a metric of the city economic potential, contingent upon the demographic size of proximate locales discounted by the geographical separation.

B Robustness

Table 10: Robustness, Supply Side

Dependent variable:	Logarithm of Online Consumption Share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Logarithm of Delivery Station Density	0.173***	0.196***	0.204***	0.173***	0.209***	0.106***	0.120***	0.096***
	(0.016)	(0.019)	(0.021)	(0.022)	(0.025)	(0.031)	(0.021)	(0.031)
Logarithm of Population		-0.063*	-0.058*	-0.106***	-0.116***	-0.018	-0.113***	-0.060*
		(0.032)	(0.032)	(0.034)	(0.032)	(0.032)	(0.030)	(0.032)
Logarithm of Market Potential			-0.090	0.150	0.116	0.228**	-0.502***	-0.168
			(0.105)	(0.116)	(0.112)	(0.104)	(0.137)	(0.137)
Provincial Capital Dummy				0.318***	0.304***	0.185***	0.415***	0.297***
				(0.056)	(0.053)	(0.045)	(0.052)	(0.047)
Logarithm of Distance to Highway					-0.003			0.002
					(0.006)			(0.005)
Logarithm of Distance to Rail					0.023***			0.010**
					(0.005)			(0.005)
Logarithm of Broadband Penetration Rate						0.351***		0.281***
						(0.063)		(0.068)
Logarithm of Online Market Potential							0.418***	0.261***
							(0.051)	(0.054)
Constant	-2.151***	-1.706***	-1.612***	-1.720***	-1.626***	-1.896***	-10.190***	-7.100***
	(0.058)	(0.232)	(0.257)	(0.257)	(0.253)	(0.250)	(1.046)	(1.082)
R^2	0.316	0.326	0.327	0.373	0.423	0.486	0.495	0.566
Observations	295	295	295	295	280	287	295	278

Notes: Table reports the robustness check from supply side, following Fan et al. (2018). The sample includes 295 Chinese cities in 2015, i.e. 291 prefecture-level cities and 4 municipalities. Sansha and Danzhou in Hainan Province are excluded here due to missing variables. The dependent variable is the city-level online consumption share, which is defined as the ratio of online consumption from Alibaba to total consumption. And the key independent variable is the city-level delivery station density, measured as the number of delivery stations divided by the administrative area. Column (1)-(3) are the same as Table 1. And the additional controls are listed as follows. In column (4), we add a dummy variable indicating whether or not the city is a provincial capital. Column (5) includes two direct measures of transportation infrastructure, i.e. distance to highway and railway. Column (6) controls for broadband internet rate and column (7) adds online market potential. Column (8) control for all the covariates mentioned above. Significance: *0.10,** 0.05,*** 0.01.

Table 11: Robustness, Demand Side

Dependent variable:	Logarithm of Online Consumption Share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Logarithm of Delivery Station Density	0.096***	0.090***	0.078***	0.088***	0.085***	0.086***	0.072**	0.064
	(0.031)	(0.031)	(0.028)	(0.030)	(0.029)	(0.029)	(0.028)	(0.067)
Logarithm of Population	-0.060*	-0.060*	-0.054*	-0.041	-0.057*	-0.050*	-0.055*	-0.055*
	(0.032)	(0.032)	(0.029)	(0.031)	(0.030)	(0.030)	(0.031)	(0.031)
Logarithm of Market Potential	-0.168	-0.088	-0.125	-0.117	-0.085	-0.048	-0.019	-0.021
	(0.137)	(0.145)	(0.133)	(0.135)	(0.139)	(0.147)	(0.152)	(0.152)
Provincial Capital Dummy	0.297***	0.253***	0.209***	0.258***	0.283***	0.272***	0.166***	0.165***
	(0.047)	(0.053)	(0.053)	(0.048)	(0.046)	(0.047)	(0.054)	(0.055)
Logarithm of Distance to Highway	0.002	0.003	0.002	0.003	0.002	0.002	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Logarithm of Distance to Rail	0.010**	0.008*	0.015***	0.013***	0.012**	0.013**	0.014***	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Logarithm of Broadband Penetration Rate	0.281***	0.268***	0.217***	0.255***	0.256***	0.263***	0.209***	0.209***
	(0.068)	(0.070)	(0.067)	(0.070)	(0.070)	(0.072)	(0.071)	(0.071)
Logarithm of Online Market Potential	0.261***	0.231***	0.266***	0.267***	0.253***	0.234***	0.223***	0.224***
	(0.054)	(0.056)	(0.052)	(0.055)	(0.053)	(0.056)	(0.057)	(0.057)
Logarithm of Per Capita Income		0.207**					0.205**	0.208**
		(0.101)					(0.098)	(0.098)
Logarithm of Average Years of Schooling			0.841***				0.852***	0.851***
			(0.242)				(0.314)	(0.313)
Logarithm of Urban Rate				0.085*			-0.024	-0.025
				(0.049)			(0.069)	(0.070)
Share of Working Age					0.009**	0.009*	0.002	0.002
					(0.005)	(0.005)	(0.006)	(0.006)
Sex Ratio						0.485	0.249	0.258
						(0.405)	(0.433)	(0.444)
Logarithm of Delivery Station Density Squared								-0.001
								(0.009)
Constant	-7.100***	-8.821***	-9.337***	-7.763***	-7.818***	-7.940***	-11.135***	-11.199***
	(1.082)	(1.304)	(1.210)	(1.198)	(1.097)	(1.109)	(1.416)	(1.510)
R^2	0.566	0.571	0.585	0.571	0.574	0.576	0.592	0.592
Observations	278	278	278	278	278	278	278	278

Notes: Table reports the robustness check from demand side, following Fan et al. (2018). The sample includes 295 Chinese cities in 2015, i.e. 291 prefecture-level cities and 4 municipalities. Sansha and Danzhou in Hainan Province are excluded here due to missing variables. The dependent variable is the city-level online consumption share, which is defined as the ratio of online consumption from Alibaba to total consumption. And the key independent variable is the city-level delivery station density, measured as the number of delivery stations divided by the administrative area. Column (1) replicates column (8) in Table 10. And the additional controls are listed as follows. Column (2) controls for per capita income and column (3) add average years of schooling. In column (4), we include the urban rate and in column (5), the share of working age is added. Column (6) also controls for the sex ratio. In the end, column (7) add all the covariates mentioned above and column (8) tests the nonlinearity of our main explaining variable. Significance: *0.10,** 0.05,*** 0.01.