The Alibaba Effect: Spatial Consumption Inequality and the Welfare Gains from E-commerce*

Jingting Fan, Lixin Tang, Weiming Zhu, Ben Zou†

Abstract

Domestic trade costs reduce aggregate welfare and result in worse access to consumption goods in small and remote cities. As a new trade technology, e-commerce can increase inter-city trade and alleviate spatial consumption inequality because it (1) eliminates the fixed cost of market entry, and (2) reduces the effects of distance on trade costs. Using unique data from China’s leading e-commerce platform, we provide evidence consistent with these two features: online trade is less hindered by distance relative to offline trade, and residents from smaller and more remote cities spend a larger fraction of their income online. We then build a multi-region general equilibrium model to quantify the impacts of e-commerce on domestic trade and welfare. We find that although it partially crowds out inter-city trade originally taking place offline, the emergence of e-commerce increases the aggregate domestic trade. The welfare gains from e-commerce are 1.6% on average, and are about 30% larger for cities in the smallest population and market potential quintiles.

Key Words: domestic trade, spatial consumption inequality, gains from e-commerce, online trade

JEL Code: R13 F15 R12

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1 Introduction

Firms face significant trade costs in reaching consumers in other cities within a country: setting up storefronts in destination cities requires upfront investment; shipping goods from the locations of production to destination cities is also costly. These frictions not only have important implications for the aggregate income of a country,\(^1\) but also shape the inequality in living standards across regions within a country. Indeed, recent studies have found that residents in smaller and more remote cities have access to fewer varieties of goods and at higher prices (see, for example, Handbury and Weinstein, 2014; Feenstra et al., 2016).

This paper studies how e-commerce affects inter-city trade and welfare. In recent years, e-commerce has become an integral part of the modern economy. According to eMarketer.com, a research company for digital marketing, the global retail sales of e-commerce increased from $0.8 trillion to $1.3 trillion between 2008 and 2013. In China, which is our country of focus, the growth of e-commerce has been even more spectacular. Between 2008 and 2015, the nominal value of total online retail sales in China increased by more than 30 times. By 2015, online sales accounted for about 12.6% of total retail sales (Yue, 2017). Numerous news articles have noted that online shopping has transformed the economic landscape in China,\(^2\) yet we still do not have a systematic understanding of how e-commerce impacts domestic trade and welfare.

This paper fills this void. We view e-commerce as a new trade technology with two important differences compared with the traditional offline trade. First, e-commerce largely eliminates the need to set up brick-and-mortar stores and an offline distributional network, allowing firms to reach consumers in cities that otherwise would not be served. Second, online shopping platforms allow consumers to obtain information on goods from distant locations. Consequently, trade volumes via e-commerce are less affected by geographic distance than those through the traditional offline channel. Together, by eliminating fixed costs of entry and reducing the effects of distance on trade, e-commerce is expected to be especially beneficial to residents in small and remote cities. This implies that e-commerce can not only increase aggregate welfare by facilitating the overall inter-city trade, but also reduce spatial consumption inequality.

We start by documenting empirical facts consistent with these two features of e-commerce using unique data from Alibaba Inc., the dominant online platform in China. First, we estimate the gravity equation for online and offline trade flows separately. We find that the distance elasticity for online trade is only about one third of that for offline trade, which is consistent with online trade being less hindered by distance than offline trade. Second, a direct implication of the two features of e-commerce is that consumers in smaller and more remote markets spend a larger share of their expenditure on online goods. Using population as a measure for market size and market potential (Harris, 1954) as a measure for remoteness, we document strong negative relationships

\(^1\)See, for example, Ramondo et al. (2016) for a quantification of how domestic trade frictions affect the aggregate welfare of a country. See Fan (2015) for a quantitative study on China.

between the online sales as a share of total retail sales (hereafter ‘online expenditure share’) and both population and market potential. According to our preferred specification, the online expenditure share for a city in the smallest population quintile is about 2 percentage points higher than that for a city in the largest population quintile; the online expenditure share for a city in the lowest market potential quintile is 7.4 percentage points higher than that for a city in the largest quintile.

Building on these empirical findings, we develop a multi-region general equilibrium model of online and offline trade for quantitative analysis. In the model, to sell its products to each destination city through the offline channel, a firm incurs a fixed cost of setting up a store and a per-unit offline shipping fee. Alternatively, a firm can use the online channel to sell to any city without the need to pay any fixed cost, although the per-unit shipping fee is potentially higher. The decision of whether to enter a city through the online or offline channel therefore depends on the tradeoff between the variable shipping fee and the fixed entry cost, as in Helpman et al. (2004).

In reality, many firms sell to each destination city through both online and offline channels. To allow for this possibility, we assume that a firm produces a continuum of varieties, each of which having an idiosyncratic channel-specific preference draw. With these assumptions, when a firm enters a destination city through the offline channel, it will continue to sell to the city through the online channel because some varieties might have higher preference draws for the online channel. Nevertheless, offline sales will partially crowd out this firm’s online sales to the same city. Because selling via the offline channel is profitable only when the net profit increase exceeds the fixed cost, only the more productive firms will set up offline stores. Conversely, after a reduction in the trade cost for online sales, some firms might switch from operating a brick-and-mortar store to selling exclusively through the online channel. We close the model by assuming free entry of firms.

The model features several channels through which e-commerce affects the welfare of a city. First, the emergence of e-commerce can affect the nominal wage by changing the demand for each of the three uses of labor—as fixed cost in setting up physical stores, as variable input in goods production, or as firm entry cost. Second, e-commerce can also affect the ideal price index through three primary channels—price, variety, and new entrant effects. The price effect captures the decrease in prices due to e-commerce of varieties originally available in a city; the variety effect captures the increasing access to varieties originally not sold in a city through the offline channel; the new entrants effect captures the decrease in price index from the entry of new firms. The welfare effect of e-commerce on a city is then the change in the real wage, defined as the ratio between the nominal wage and the price index.

We use our reduced-form findings and additional economic indicators to discipline the parameters of the model for quantitative exercises. The parameterized model performs well in terms of non-targeted moments, including those relating to patterns of trade flows and differences in costs of living and firm entry activities. The calibration suggests variable shipping costs are substantially lower for offline than online, so firms can indeed save on shipping cost by establishing an offline network. Consistent with the gravity estimates, the distance elasticity of the online ship-
ping cost is much smaller than that for the offline shipping cost. With the calibrated market entry and domestic trade costs, the model generates substantial inequality in living standards across cities. Our model thus provides a lens through which we can measure spatial consumption inequality without relying on barcode-level scanner data.

We perform counterfactual experiments to understand how the emergence of e-commerce affects inter-city trade and welfare. We first solve for a counterfactual equilibrium in which e-commerce is prohibitively costly. Moving from this counterfactual equilibrium to the calibrated equilibrium, the share of online inter-city trade in total expenditure increases from zero to around 8% for the average city. However, since growing e-commerce crowds out offline trade, import as a share of total expenditure for the medium-size city increases by only around 1.2 percentage points. The welfare gains from e-commerce, measured as changes in real wages, are 1.6% for the average city.

An alternative modeling approach might be to view the emergence of e-commerce as a reduction in variable trade costs, without distinguishing the newly-available online channel from the traditional offline channel. Under this alternative approach and according to Arkolakis, Costinot and Rodríguez-Clare (2012), the changes in inter-city trade levels due to e-commerce are sufficient statistics for the welfare effects of e-commerce. For an increase of 1.2 percentage points in import ratio, the alternative modeling approach would yield welfare effects that are much lower than predicted by our model. This highlights the need to model online sales formally to understand the impacts of e-commerce.

Turning to the distributional effects, we find that e-commerce substantially reduces spatial consumption inequality. The average welfare gains from e-commerce are 2.01% for cities in the smallest population quintile and 1.11% for those in the largest quintile; they are 2.06% for the lowest market potential quintile and 1.23% for the highest quintile. Using partial elasticities of real income with respect to population and market potential as measures of spatial inequality, we find that the arrival of e-commerce reduces the inequality associated with population by 2.1%, and the inequality associated with market potential by 6.7%.

We decompose the changes in real wages and find that the changes in both the nominal wage and the price level are larger for smaller and more remote cities. Examining the channels underlying the change in nominal wages, we find that the increase in labor demand from new entrants due to e-commerce are especially important for the higher wage growth in smaller cities. Finally, we decompose the change in the price index. We find the variety effect to be the most significant source of the decrease in price index for most cities, especially for the smallest ones. On the other hand, the price effect is more important for the largest cities. This result is consistent with consumer survey evidence: when asked about the reasons to choose shopping online over offline, ‘lower price’ is most cited by consumers from big cities, while ‘more varieties’ is most cited by consumers from small cities (Dobbs et al., 2013).

This paper contributes to the literature that studies the effects of trade technology on domestic trade. Different from most existing studies in this literature, which focus on improvements
in transportation infrastructure (see, for example, Donaldson, 2018, Coșar and Fajgelbaum, 2016),
we study e-commerce, focusing on its two unique features in comparison with offline trade. Our
contribution to this literature is twofold. Empirically, we provide evidence in support of the two
features of e-commerce using unique data. Quantitatively, we develop the first general equilib-
rium model of e-commerce that explicitly takes into account firm’s choice of selling through online
and offline channels. We show that incorporating this choice is important for our understanding
of the welfare effects of e-commerce.3

Our paper is also related to the research on spatial consumption inequality in urban economics.
Recent studies show that there are substantial spatial differences in access to varieties. These in-
clude studies on tradable goods, especially groceries (Handbury, 2013; Handbury and Weinstein,
2014; Hottman, 2014), and non-tradable goods and services such as restaurants and local amenities
(Couture, 2015; Diamond, 2015). The literature has focused on only traditional retailing so far. We
make two contributions to this literature. First, by showing that e-commerce could have signifi-
cant implications for welfare, we highlight the importance of accounting for the access to online
goods in measuring the spatial inequality in consumption. Given that e-commerce is becoming
increasingly common throughout the world, the biases from not taking online sales into account
are likely to increase further in the future. Our second contribution is in terms of measurement.
The literature has largely focused on the U.S. and neglected developing countries, where such
spatial inequality might be more severe.4 By combining online sales data with a structural model,
this paper demonstrates considerable spatial inequality in access to consumption across Chinese
cities.

Existing studies on e-commerce have identified specific mechanisms through which it benefits
consumers.5 Most of these studies do not have a spatial dimension. Exceptions include Forman
et al. (2009) and Couture et al. (2018), which study the effects of e-commerce on consumers with
different access to goods, focusing either on a specific category, or a small number of regions.6
Different from these two papers, our paper uses data covering almost all prefecture cities in China
and all categories sold online, and therefore sheds light on the broader impacts of e-commerce
on consumer welfare across cities of different sizes. More importantly, we add to the literature of
e-commerce by proposing a tractable quantitative model that allows realistic geographic features
and is thus amenable to the data.

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3While some existing studies also examine e-commerce through a trade perspective (Lendle et al., 2016; Chen et al.,
2015), they typically do not model online and offline sales jointly, and do not examine the effect on spatial inequality.
4Notable exceptions include Faber (2014), Atkin et al. (2018), and Feenstra et al. (2016). The first two papers, which
use data from Mexico, do not focus on spatial inequality. A recent paper by Feenstra et al. (2016) shows that big cities
in China have more varieties offered at lower prices than small cities, but they only use four categories of products
(toothpaste, laundry detergent, body wash, and shampoo) across 60 cities.
5For example, online markets might offer products at lower prices (Brynjolfsson and Smith, 2000; Clay et al., 2002;
Brown and Goolsbee, 2002), improve the match quality between consumers and products (Goldmanis et al., 2010; Glenn
and Ellison, 2014), and increase the number of product varieties available to consumers (Brynjolfsson et al., 2003).
6Forman et al. (2009) use data from top-selling books from Amazon.com and find that, when a local store opens,
people substitute away from online purchases. Couture et al. (2018) uses experimental evidence at the village and
household level from eight counties to study how the arrival of e-commerce affects household consumption and firm
production.
The rest of the paper is organized as follows: Section 2 describes the retailing industry and e-commerce in China and provides motivating facts of e-commerce as a new trade technology. Section 3 introduces the empirical approach and establishes evidence for the two distinct features of e-commerce. Section 4 develops a quantitative model. Section 5 calibrates the model and quantifies the implications of e-commerce on trade and welfare. Section 6 concludes.

2 Retail Industry and E-commerce in China

Over the past decade, the growth of e-commerce in China has been spectacular. The nominal value of total online retail sales in China increased by more than 30 times, from 0.126 trillion yuan in 2008 to 3.90 trillion yuan in 2015 (Yue, 2017). The online share of total retail sales increased from 1.1 percent in 2008 to 12.6 percent in 2015.

The rise of e-commerce in China has an important geographic dimension. Although bigger and better-connected cities on the east coast have the highest per capita online retail consumption, smaller and more remote cities spend a larger fraction of their income online. According to a survey conducted by the McKinsey Global Institute (Dobbs et al., 2013), conditional on shopping online between 2011 and 2012, residents in tier-1 and tier-2 cities, which are China’s largest cities, spend around 17 percent of their disposable income online, while residents in smaller and less connected tier-3 and tier-4 cities spend 21 and 27 percent, respectively.

China’s relatively less developed traditional retail industry helps explain both the rapid rise of e-commerce and its spatial distribution. The traditional offline retail industry in China is dominated by small-scale local retailers that provide limited numbers of varieties—the top 100 retail chains in China collectively accounted for only 9% of retail sales in 2013, in contrast to 36% in the US. Furthermore, existing large retailers are concentrated in large and rich cities. For example, when foreign retail chains such as Walmart and Carrefour entered China, their first stores were predominantly located in the biggest metropolitan areas. This is in sharp contrast to the the big-box retail industries in developed countries, which penetrate many small and medium cities as well as rural areas.

Two sources of costs involved with traditional offline retailing contribute to its spatial distribution. First, there is a fixed cost to be paid in order to sell to a new market: it can be the cost involved in setting up a brick-and-mortar store or the cost involved in contracting with local retailers and distributors. These upfront costs can only be justified by a sufficiently-large local demand. Therefore, everything else equal, a traditional retailer is less likely to find it profitable to enter a small market. Second, the shipping costs make it more expensive to serve a remote market.

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8In 2013, China’s top 100 retailers’ sales was 2.04 trillion CNY (about 300 billion USD), accounting for about 8.7% of the country’s total retail sales of consumer goods. (Source: Deloitte. ‘China Powers of Retailing 2013.’ http://goo.gl/aQbF7j.) In the same year, the total sales from the top 100 retailers in the United States was 1.8 trillion USD while the aggregate national sales was about 5 trillion. (Source: the National Retail Federation, https://nrf.com/2014/top100-table; Monthly Retail Trade Report of the U.S. Census Bureau, https://www.census.gov/retail/index.html. Accessed June 20, 2018.)
Table 1: Gravity Regressions with Province-Level Trade Flows

<table>
<thead>
<tr>
<th></th>
<th>(1) Log offline trade flow</th>
<th>(2) Log online trade flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>log distance</td>
<td>-1.366***</td>
<td>-0.470***</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>origin FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>destination FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>observations</td>
<td>900</td>
<td>900</td>
</tr>
</tbody>
</table>

Note: Data on inter-provincial offline trade flows are from the 2002 China Regional Input-Output table. Inter-provincial online trade flows are proxied by province-level transaction flows on the Taobao platforms in 2013. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As a new trade technology, e-commerce is a more economical way for many producers to reach customers in small and remote markets. First, e-commerce essentially eliminates the fixed costs associated with serving a new market. After signing up with an e-commerce platform for a small fee, there is no additional charge for a producer to enter any market. Therefore, a producer may find it profitable to sell a small number of items to consumers in markets that it would not have found profitable to enter via traditional retailing. Shopping online is therefore particularly attractive to residents in small and remote cities because it can substantially increase their access to varieties. Second, e-commerce can significantly reduce information costs associated with trade. With online shopping platforms, consumers can easily obtain information on numerous goods from a distant location. As a result, e-commerce might be less hindered by distance.

Table 1 reports results from gravity regressions of inter-provincial trade flows on origin and destination fixed effects, and the distance between provinces, for online and offline trade separately. Both regressions show significant negative impacts of distance on trade flows, but the distance elasticity for online trade is only about a third of that for offline trade. When we quantify our formal model in Section 5, we allow the elasticity of shipping cost with regard to distance to differ by online and offline, and the elasticities estimated in Table 1 will help us pin down these two parameters.

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9Distance is between the centroids of prefecture pairs and is weighted by population. Data on offline trade flows are from the 2002 China Regional Input-Output Table, which reports the total production at the province level and bilateral trade volume between provinces. We treat these trade flows as offline flows because e-Commerce was an insignificant part of the economy in 2002. Data on online trade flows come from Taobao. We obtain data on inter-provincial e-commerce sales from Taobao for 17 of its biggest categories that collectively account for 57% of its total sales in 2013.

10Admittedly, the data underlying the two regressions are ten years apart and one may worry that the offline trade elasticity might have changed over time. Using a meta-analysis of 2508 estimates, Head and Mayer (2013) shows that the distance elasticity of trade flow is remarkably stable across sample countries and time periods. Furthermore, our finding that distance matters more for offline trade than for online trade online elasticity is also consistent with Lendle et al. (2016) and Hortaçsu et al. (2009).
3 Market Size and Online Expenditure Share

Because of the two features of e-commerce discussed above, consumers under-served by traditional retailers—those from small and remote cities—should benefit more from e-commerce. If this is the case, everything else equal, we should expect that consumers from these cities rely more on online shopping than their counterparts in bigger and better-connected cities. We test this prediction in this section. Both our empirical and subsequent quantitative analysis will be at the prefecture city level. In China, each prefecture city includes both rural and urban areas. There are around 340 non-overlapping prefecture cities. Together, they cover the entire country.

3.1 Econometric Model and Measurement

We run various versions of the following regression:

$$\ln \text{OnlineExpenditureShare}_i = \beta_0 + \beta_1 \ln \text{MarketSize}_i + \beta_2 \ln \text{MarketPotential}_i + X_i \cdot \beta_3 + \epsilon_i. \quad (1)$$

The outcome variable captures how much consumers in city $i$ spend on e-commerce. Our baseline measure is the log of online sales to a city as a share of the city’s total retail sales in 2013. We measure market size by population from the 2010 census and calculate market potential (Harris, 1954) for city $i$ as $MP_i = \sum_{j \neq i} \frac{L_j}{\tau_{ij}}$, where $L_j$ is the population size (in millions) in city $j$ and $\tau_{ij}$ is the bilateral distance (between two centroids, in kilometers). Market potential is larger if a city is closer to large cities. As e-commerce eliminates the fixed cost of market entry and reduces the impacts of distance, we expect both $\beta_1$ and $\beta_2$ to be negative. To isolate our interpretation of the mechanisms from alternative explanations, we control for a set of city-level characteristics in $X_i$, which we explain in detail below.

3.2 Data and Sample

The data used in this paper come from several sources. Data for online sales are from Taobao, which is the online retail sales arm of Alibaba. It includes both a B2C platform (Tmall.com) and a C2C platform (Taobao.com). Together, these two platforms sell millions of unique products, and account for 82 percent of China’s total online retail sales in 2014. We obtain confidential data for the total sales and purchases by category for all prefecture cities in China in 2013 from both platforms.\(^\text{12}\)

We supplement online sales data with data on city-level characteristics. The primary sources for these characteristics are the 2010 census tabulations and the 2013 Regional Statistical Yearbook. The yearbook reports the total retail sales by city. From these two data sources, we further

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\(^{11}\)We adopt the log-log specification because it is unit free and allows easy interpretation of coefficients. The results are robust to specifications in levels (or in log-levels).

\(^{12}\)The categories are defined by Taobao. We start with 139 product categories and consolidate them into 81 product categories. The original list of categories can be found here: https://goo.gl/kFvNqQ. The consolidated list of categories is reported in Table C.2 in the online appendix.
construct variables related to factors affecting the demand and supply of online shopping, which include city-level demographic characteristics such as education, age and gender composition, per capita income and consumption, urban rate, and shares of households with broadband connection and smart phones. We also construct the distance to highways and railways for each city from the transportation network database developed by Baum-Snow et al. (2017).

Our benchmark regression is at the prefecture city level. Our sample includes 320 prefecture cities for which benchmark control variables are available. To shed light on the channels behind the correlations between online expenditure share, and market size and remoteness, we also conduct analyses at the city-category level, using city-by-category expenditure shares based on household surveys by China’s National Bureau of Statistics (NBS). The details of this analysis are described in Section 3.5.

Table 2 provides the summary statistics of the key variables. In 2013, Taobao accounted for 7.9 percent of total retail sales in an average city. The average city has a population of about 4 million, and the market potential for the average city is 1.7. Adults in an average city have an average of 8.8 years of education and have a per capita annual income of 15 thousand yuan (about 2,272 USD). For an average city, the urban rate (measured as the share of employment in non-agricultural sectors) is 48%, the share of working age population is 74%, and the share of households with access to broadband Internet is 59%.

3.3 Benchmark Results

Table 3 shows the baseline results. Column 1 reports the simple correlations. Both log population and log market potential are negatively correlated with log online expenditure share. The coefficient is -0.073 for the former and -0.229 for the latter. These negative coefficients indicate that consumers in smaller and more remote cities spend a larger share of their expenditure on online shopping.

We hypothesize that this result arises because consumers from smaller and more remote cities have more limited options and face higher prices through traditional retailers. Without detailed information on the products offered in offline stores and their prices, we cannot directly test this mechanism. Instead, we try to include additional controls to rule out alternative explanations.

First, the negative correlations from Column 1 can potentially be explained by supply-side factors: smaller and more remote cities may face greater supply of e-commerce. This may be true if these cities have higher Internet penetration, or if they somehow are closer to online sellers and are better connected to where online purchases are easily delivered, despite being more distant from large population centers. We explicitly control for these alternative supply factors. The remaining columns of Table 3 report the results.

To obtain city-level average distance to railroads/highways, we compute the minimum distance to railroads/highways for each county within the city, and then use the population-weighted average county-level distance as the city-level distance.

The household surveys include the Urban Household Survey and the Rural Fixed-Point Household Survey. These surveys sample households in cities and rural areas and ask about respondents’ daily expenditures.
### Table 2: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>mean</th>
<th>st. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Online share and market size</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>online sales as a share of total retail sales</td>
<td>320</td>
<td>0.079</td>
<td>0.034</td>
</tr>
<tr>
<td>population (million)</td>
<td>320</td>
<td>4.043</td>
<td>3.212</td>
</tr>
<tr>
<td>market potential ($MP_i = \sum_{j \neq i} \frac{L_{ij}}{\tau_{ij}}$)</td>
<td>320</td>
<td>1.676</td>
<td>0.55</td>
</tr>
<tr>
<td><strong>Demand and supply factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>average income (thousand yuan)</td>
<td>320</td>
<td>15.199</td>
<td>6.364</td>
</tr>
<tr>
<td>average years of schooling</td>
<td>320</td>
<td>8.827</td>
<td>0.977</td>
</tr>
<tr>
<td>urban share</td>
<td>320</td>
<td>0.484</td>
<td>0.206</td>
</tr>
<tr>
<td>share of working age residents</td>
<td>320</td>
<td>0.742</td>
<td>0.044</td>
</tr>
<tr>
<td>sex ratio</td>
<td>320</td>
<td>1.158</td>
<td>0.093</td>
</tr>
<tr>
<td>log distance to highway</td>
<td>320</td>
<td>6.453</td>
<td>3.797</td>
</tr>
<tr>
<td>log distance to railroad</td>
<td>320</td>
<td>6.385</td>
<td>3.904</td>
</tr>
<tr>
<td>share of household with access to Internet</td>
<td>318</td>
<td>0.594</td>
<td>0.629</td>
</tr>
<tr>
<td>log online market potential</td>
<td>320</td>
<td>0.645</td>
<td>0.55</td>
</tr>
<tr>
<td>provincial capital = 1</td>
<td>320</td>
<td>0.094</td>
<td>0.292</td>
</tr>
<tr>
<td><strong>Alternative measures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>online sales as a share of consumption</td>
<td>309</td>
<td>0.088</td>
<td>0.041</td>
</tr>
<tr>
<td>online sales as a share of non-hospitality retail sales</td>
<td>317</td>
<td>0.084</td>
<td>0.047</td>
</tr>
<tr>
<td>total income (billion yuan)</td>
<td>317</td>
<td>64.336</td>
<td>71.381</td>
</tr>
<tr>
<td>total consumption (billion yuan)</td>
<td>309</td>
<td>48.988</td>
<td>73.349</td>
</tr>
<tr>
<td>log market access</td>
<td>320</td>
<td>35.841</td>
<td>4.154</td>
</tr>
<tr>
<td>log market potential (to GDP)</td>
<td>320</td>
<td>31.864</td>
<td>0.426</td>
</tr>
</tbody>
</table>

**Notes:** Each observation is a prefecture city.

Column 2 includes a dummy variable indicating whether the city is a provincial capital. In China’s hierarchical system of cities, provincial capitals have access to more resources and better infrastructure than other cities. The regression indicates that residents in provincial capital cities spend more on online shopping, but the inclusion of this dummy variable does not change the coefficients of interest by much.

We then turn to direct measures of infrastructure related to e-commerce. Column 3 includes log distances to highway and railway. Access to highway and railway facilitates both online and offline shopping so their signs are ambiguous. When included in the regression together, being close to a highway is associated with higher online expenditure share, while being close to a railway has the opposite effect. Column 4 controls for broadband Internet penetration rate. As expected, better access to broadband Internet is associated with higher online expenditure share. In both Columns 3 and 4, the two coefficients of interest are essentially unaffected.

If smaller and more remote cities are home to a larger number of online sellers, then the coefficients might simply pick up the effects of easier access to online sellers in these cities. To rule out this concern, we include a measure of online market potential: $MP_{i,\text{Online}} = \ln(\sum_{j \neq i} (\text{OnlineSales}_j \div \tau_{ij}))$,.
Table 3: Online Expenditure Share and Market Size

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dep var:</td>
<td>log online expenditure as a share of total retail sales</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln population</td>
<td>0.073**</td>
<td>0.113***</td>
<td>-0.124***</td>
<td>-0.108***</td>
<td>-0.141***</td>
<td>-0.148***</td>
<td>-0.131***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.034)</td>
<td>(0.035)</td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.033)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>ln market potential</td>
<td>-0.229***</td>
<td>-0.189***</td>
<td>-0.203***</td>
<td>-0.219***</td>
<td>-0.695***</td>
<td>-0.636***</td>
<td>-0.993***</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.059)</td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.092)</td>
<td>(0.097)</td>
<td>(0.225)</td>
</tr>
<tr>
<td>= 1 if provincial capital</td>
<td>0.248***</td>
<td>0.250***</td>
<td>0.205**</td>
<td>0.295***</td>
<td>0.297***</td>
<td>0.140*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>(0.081)</td>
<td>(0.080)</td>
<td>(0.072)</td>
<td>(0.079)</td>
<td>(0.075)</td>
<td></td>
</tr>
<tr>
<td>ln distance to highway</td>
<td>-0.019***</td>
<td>-0.010</td>
<td>-0.006</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln distance to rail</td>
<td>0.027***</td>
<td>0.021***</td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln broadband penetration rate</td>
<td>0.061**</td>
<td>0.014</td>
<td>0.092**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.028)</td>
<td>(0.046)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln online market potential</td>
<td>0.462***</td>
<td>0.407***</td>
<td>0.619***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.072)</td>
<td>(0.165)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.056)</td>
<td>(1.067)</td>
<td>(1.091)</td>
<td>(1.103)</td>
<td>(1.863)</td>
<td>(1.951)</td>
<td>(4.796)</td>
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<td>province FE</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.110</td>
<td>0.137</td>
<td>0.194</td>
<td>0.149</td>
<td>0.251</td>
<td>0.282</td>
<td>0.627</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses. * p < 0.1 , ** p < 0.05 , *** p < 0.01.

in which OnlineSalesj is the total sales by online sellers from city j. According to Column 5, lnMPiOnline has an expected positive sign. However, the coefficient associated with lnMPi remains negative, so this alternative story is unlikely to be driving our results.15

Column 6 adds all the covariates included in Columns 2 through 5 while Column 7 further adds a set of province dummies. Throughout all the columns, both log population and log market potential have negative and statistically significant signs, so differences in supply shifters cannot explain our main findings.

Another alternative explanation for the negative correlations is that the demand for online shopping might be higher in smaller and more remote cities for reasons other than offline product availability. There are several possibilities. First, residents in smaller cities might be younger, more educated, and more capable of navigating the online marketplace. Second, the correlations may be due to non-homothetic preferences. Residents in smaller and more remote cities are typically poorer than their larger city counterparts. Differences in income can lead to differences in consumption structure. For example, richer households may spend a larger share of their income on services and luxury goods, which are typically not sold on Taobao. This channel might also drive the negative correlations we find.

15The magnitude of the coefficient triples compared to Column 1. This is likely driven by the positive correlation between online and offline market access (correlation between the two is 0.64).
Table 4: Adding Demand Shifters

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dep var:</td>
<td>log online sales share of total retail sales</td>
<td>log online sales share of total retail sales</td>
<td>log online sales share of total retail sales</td>
<td>log online sales share of total retail sales</td>
<td>log online sales share of total retail sales</td>
<td>log online sales share of total retail sales</td>
<td>log online sales share of total retail sales</td>
</tr>
<tr>
<td>In population</td>
<td>-0.133***</td>
<td>-0.130***</td>
<td>-0.123***</td>
<td>-0.138***</td>
<td>-0.110***</td>
<td>-0.574</td>
<td>-0.109***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.038)</td>
<td>(0.036)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.580)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>In market potential</td>
<td>-0.975***</td>
<td>-0.992***</td>
<td>-0.953***</td>
<td>-0.914***</td>
<td>-0.863***</td>
<td>-0.867***</td>
<td>-1.997</td>
</tr>
<tr>
<td></td>
<td>(0.239)</td>
<td>(0.225)</td>
<td>(0.227)</td>
<td>(0.243)</td>
<td>(0.252)</td>
<td>(0.251)</td>
<td>(7.727)</td>
</tr>
<tr>
<td>In per capita income</td>
<td>0.044</td>
<td>0.044</td>
<td>0.044</td>
<td>0.044</td>
<td>0.044</td>
<td>0.044</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.142)</td>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.141)</td>
</tr>
<tr>
<td>In average years of schooling</td>
<td>-0.042</td>
<td>-0.042</td>
<td>-0.042</td>
<td>-0.042</td>
<td>-0.042</td>
<td>-0.042</td>
<td>-0.042</td>
</tr>
<tr>
<td></td>
<td>(0.314)</td>
<td>(0.426)</td>
<td>(0.426)</td>
<td>(0.426)</td>
<td>(0.426)</td>
<td>(0.426)</td>
<td>(0.426)</td>
</tr>
<tr>
<td>In urban rate</td>
<td>0.143**</td>
<td>0.242***</td>
<td>0.238***</td>
<td>0.244***</td>
<td>0.244***</td>
<td>0.244***</td>
<td>0.244***</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.090)</td>
<td>(0.090)</td>
<td>(0.090)</td>
<td>(0.090)</td>
<td>(0.090)</td>
<td>(0.090)</td>
</tr>
<tr>
<td>share of working age</td>
<td>1.377</td>
<td>2.035**</td>
<td>2.032**</td>
<td>2.027**</td>
<td>2.027**</td>
<td>2.027**</td>
<td>2.027**</td>
</tr>
<tr>
<td></td>
<td>(0.892)</td>
<td>(0.962)</td>
<td>(0.955)</td>
<td>(0.957)</td>
<td>(0.957)</td>
<td>(0.957)</td>
<td>(0.957)</td>
</tr>
<tr>
<td>sex ratio</td>
<td>0.057</td>
<td>0.114</td>
<td>0.090</td>
<td>0.108</td>
<td>0.108</td>
<td>0.108</td>
<td>0.108</td>
</tr>
<tr>
<td></td>
<td>(0.272)</td>
<td>(0.263)</td>
<td>(0.264)</td>
<td>(0.266)</td>
<td>(0.266)</td>
<td>(0.266)</td>
<td>(0.266)</td>
</tr>
<tr>
<td>In population squared</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In market potential squared</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>supply shifters</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>province FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>N</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
<td>320</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.627</td>
<td>0.627</td>
<td>0.633</td>
<td>0.633</td>
<td>0.646</td>
<td>0.646</td>
<td>0.646</td>
</tr>
</tbody>
</table>

Note: Supply side controls are the same as in Column 7 of Table 3. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To rule out alternative explanations due to heterogeneity in demand, we supplement the controls in Table 3, Column 7 with a host of demand shifters. Column 1 of Table 4 controls for log per capita income of the city, Column 2 includes log average years of schooling among adults as a proxy for average skill level of city residents, Column 3 includes log urban rate (measured as the share of non-agricultural employment), and Column 4 includes the share of working age population and sex ratio. Because these variables are correlated with covariates already included in the regression, except for log urban rate, none of these variables adds much explanatory power. Column 5 adds all the demand-side shifters included in Columns 1 through 4. According to Column 5, the elasticity of online expenditure share with respect to log population and log market potential is -0.11 and -0.86, respectively. The magnitudes of these coefficients are economically meaningful: based on the estimates, the online expenditure share for a city in the smallest population quintile is about 1.96 percentage points higher than that for a city in the largest population quintile; the online expenditure share for a city in the lowest market potential quintile is 7.35 percentage points.
higher than that for a city in the largest quintile.\textsuperscript{16}

Throughout these columns, the coefficients associated with log population and log market potential remain remarkably stable. Although we cannot control for all the possible demand shifters, the stability of the coefficients is reassuring.\textsuperscript{17}

One remaining concern is that the relationships may not be log linear. Because the two key variables, market size and remoteness, are highly correlated, even if only one truly matters, if the estimation equation is incorrectly specified as log linear, the other may pick up the remaining correlation. To rule out this possibility, Columns 6 and 7 include a quadratic term for each key variable. Neither quadratic term is statistically significant, rejecting a non-linear specification. In both cases, the coefficient associated with the other key variable does not change at all, suggesting that both market size and remoteness matter.

### 3.4 Additional Robustness

We perform some additional robustness tests. First, we use a number of alternative measures for online expenditure share, market size, and market potential. As shown in online appendix C.1, all combinations of these different measures lead to the same conclusion as in our benchmark specification. Since both market size and market potential are functions of population, one concern with our OLS estimates is that, if population is measured with error, the estimated coefficients suffer from attenuation bias. In alternative specifications not reported here, we use market size and remoteness measures constructed from the 2000 census to instrument for the 2010 counterparts. The instruments have a very strong first stage and the IV results are almost identical to the OLS results.

### 3.5 Category-Level Results

To further rule out non-homothetic preference as an alternative explanation, we construct category-specific online expenditure shares, which explicitly take into account differences in consumption compositions. For this exercise, we exploit our product-category-level sales data from Taobao and match them with city-category-level consumption data from the NBS.

There are two data limitations. First, the online sales data are classified in categories defined by Taobao, which are different from the categories in official statistics. We create a crosswalk that maps each of the Taobao-defined categories into one of the seven categories defined by the NBS (see online appendix Table C.2). Second, the coverage of the category-level total consumption data is limited to a few provinces. From various provincial statistical yearbooks, we are able to find 105

\textsuperscript{16}The average value of log population for cities in the smallest population quintile is 13.670, while that for cities in the largest population quintile is 15.926. With the average online share of 0.079, the difference in online shares between the two population quintiles as predicted by the model is $(15.926 - 13.670) \times 0.11 \times 0.079 = 0.0196$. Similarly, the average values of log market potential for the largest and the smallest quintile is 20.518 and 21.597. The difference in online shares between the two market potential quintiles is $(21.597 - 20.518) \times 0.863 \times 0.079 = 0.0735$.

\textsuperscript{17}When we include the full set of demand factors and province fixed effects and add supply factors one-by-one as in Table 3, the coefficients of the two variables of interest also remain remarkably similar. The only exception is that the inclusion of online market potential increases the magnitude of the coefficient associated with log market potential.
### Table 5: City by Category

<table>
<thead>
<tr>
<th></th>
<th>(1) food</th>
<th>(2) cloth</th>
<th>(3) residence</th>
<th>(4) hbd app</th>
<th>(5) health</th>
<th>(6) transport</th>
<th>(7) recreation</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln population</td>
<td>-0.0413</td>
<td>-0.103***</td>
<td>0.0345</td>
<td>-0.0897***</td>
<td>-0.0569</td>
<td>-0.0727**</td>
<td>-0.0678*</td>
</tr>
<tr>
<td></td>
<td>(0.0398)</td>
<td>(0.0339)</td>
<td>(0.116)</td>
<td>(0.0339)</td>
<td>(0.0352)</td>
<td>(0.0333)</td>
<td>(0.0346)</td>
</tr>
<tr>
<td>ln market potential</td>
<td>-0.632**</td>
<td>-0.748***</td>
<td>-1.493**</td>
<td>-0.906***</td>
<td>-0.746***</td>
<td>-0.714***</td>
<td>-0.738***</td>
</tr>
<tr>
<td></td>
<td>(0.274)</td>
<td>(0.269)</td>
<td>(0.607)</td>
<td>(0.248)</td>
<td>(0.266)</td>
<td>(0.243)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>supply shifters</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>demand shifters</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>province FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

N = 318, 318, 317, 318, 318, 318, 318

R² = 0.898, 0.846, 0.572, 0.850, 0.895, 0.727, 0.810

% in category consump = 0.600, 24.60, 0.0018, 24.11, 4.323, 3.721, 3.429

% in total Taobao Sales = 4.98, 43.97, 0.01, 28.90, 5.67, 7.94, 8.53

Note: The dependent variable is the log share of online sales over consumption by NBS category. Supply and demand shifters are the same as in Table 4, Column 5. City-NBS category consumption is imputed. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

cities with city-category level expenditure. We impute the values for the remaining cities.18

We estimate Equation 1 for each NBS category using the same specification as in Column 5 of Table 4. The results are reported in Table 5. Online expenditure shares differ substantially across categories (the second row from the bottom). The categories with the largest online expenditure shares are clothing and household appliances and services. For both categories, e-commerce account for about a quarter of the total sales. These two categories are also the most important for Taobao, accounting for 44% and 29% of total Taobao sales, respectively. In contrast, shares of online sales are negligible for food and residence-related goods and services.

The coefficients associated with population and market potential are overwhelmingly negative. The magnitudes of the coefficients are comparable across categories due to the log-log specification. For clothing and household appliances, the two dominant online-shopping categories, the coefficients are statistically significant and very similar to the baseline estimates. The results in Table 5 thus suggest that non-homotheticity in consumption is unlikely to be driving our results.19

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18To do this, we first regress the category-specific expenditure shares from the small sample on a host of city-level demand and supply shifters. Category-specific expenditure shares for the remaining cities are imputed using the estimated coefficients and the observed city-level demand and supply shifters. We then combine these imputed category-specific expenditure with the category-specific online expenditure consolidated from the Taobao data to obtain category-specific online expenditure shares.

19Online Appendix Table C.3 shows that the same conclusions can be obtained using the small sample of cities for which we directly observe category-specific expenditures. Online Appendix Table C.4 reports coefficients and standard errors from regressions for each Taobao-defined category. There, the similarity among estimated coefficients within the 7 broad NBS categories further rules out non-homothetic preference as a viable alternative explanation.
4 Quantitative Framework

We analyze the impacts of e-commerce on inter-city trade and welfare through the lens of a multi-region general equilibrium model. Because offline trade still makes up 90% of total retail trade in China, we incorporate firms’ decisions to sell through the online and offline channels and allow the availability of the online channel to affect firms’ offline entry decisions. Our model builds on Helpman et al. (2004) which studies the trade-off behind firms’ FDI decisions. This section describes the model setup.

4.1 Environment

There are \( N \) regions, each corresponding to a city in China. We index regions using \( i, j \in \{1, 2, \cdots, N\} \). Region \( i \) is endowed with \( L_i \) units of ‘equipped labor.’\(^{20} \) A worker in region \( i \) supplies one unit of labor inelastically and receives a wage of \( w_i \), which is determined endogenously.

There are two sectors, tradable and non-tradable, indexed by \( T \) and \( NT \), respectively. The preference of the representative consumer in region \( j \) is given by:

\[
U_j = \prod_{h \in \{T, NT\}} (u^h_j)^{\beta^h_j},
\]

in which \( u^h_j \) denotes the sub-utility from consuming goods in sector \( h \), and \( \beta^h_j \) is the share of expenditure on sector \( h \). In the following model description, we do not distinguish between the two sectors, with the understanding that trade costs in the non-tradable sector are infinite.

A good is indexed by a firm \( \omega \) and a variety \( v \). Each firm is affiliated with one sector, and produces a unit measure of varieties in the sector. The sub-utility function of the representative consumer in region \( j \) is

\[
u^h_j = \left( \int_{\Omega^h_j} \int_0^1 q^h_j(\omega, v)(\sigma - 1)/\sigma dv d\omega \right)^{\sigma/(\sigma - 1)}, h \in \{T, NT\},
\]

where \( \Omega^h_j \) is the set of all sector \( h \) firms selling in region \( j \). This definition implies that the elasticity of substitution, \( \sigma \), is the same between any two products within the same sector. Nevertheless, as should be clear shortly, the supply side of the model will generate higher substitutability between online and offline sales within a firm than sales across firms. Lastly, we assume the value of \( \sigma \) to be the same for the two sectors.

4.2 Producers

Firms decide whether to enter based on the expected profit. Let the mass of firms in sector \( h \) be \( M^h_i \). Each firm is infinitesimal and takes aggregate quantities as given. A firm is characterized by

\(^{20}\) In the calibration, we will match per-capita total income for each city, so \( L \) should be interpreted as including other production factors such as capital and equipments.
its region of origin $i$, and its productivity parameter $\phi$, drawn independently from a cumulative distribution function (CDF) specific to region $i$, denoted by $F_i(\phi)$. We assume that $F_i(\phi)$ follows a Pareto distribution, $F_i(\phi) = 1 - \left( \frac{\phi}{\phi_i} \right)^{-\alpha}$, where $\alpha$ is the shape parameter and $\phi_i$ is the technology level of region $i$. The parameter $\phi_i$ captures regional heterogeneity in productivity, and will allow us to match per-capita income of cities.

A firm faces the CES demand for each of its varieties and acts as a monopolist. From consumer optimization, the quantity demanded for variety $v$ supplied by firm $\omega$ at price $p_j(\omega, v)$ is given by

$$q^h_j(\omega, v) = \frac{\beta^h_j Y_j p^h_j(\omega, v)^{-\sigma}}{(p^h_j)^{1-\sigma}},$$

where $Y_j$ is the aggregate expenditure in region $j$ and $P^h_j$ is the aggregate price index for sector $h$, given by

$$p^h_j = \left[ \int_{\Omega} p^h_j(\omega)^{1-\sigma} d\omega \right]^{1/(1-\sigma)}.$$  \hfill (3)

In the above equation, $p^h_j(\omega)$ can be interpreted as the price index for firm $\omega$, and is itself a CES aggregator over the unit measure of varieties produced by the firm:

$$p^h_j(\omega) = \left( \int_0^1 p^h_j(\omega, v)^{1-\sigma} dv \right)^{1/(1-\sigma)}.$$  \hfill (4)

Equations 2 and 4 imply that the total expenditure on goods produced by firm $\omega$ in region $j$ is:

$$s^h_j(\omega) = \beta^h_j Y_j p^h_j(\omega)^{1-\sigma}.$$  

Importantly, since we will introduce quality heterogeneity among varieties produced by a firm, both prices, $p^h_j(\omega, v)$, $p^h_j(\omega)$, and $P^h_j$, and the quantity, $q^h_j(\omega, v)$, should be interpreted as for each quality unit.

4.2.1 Channels and Cost of Distributions

Firms can reach customers in a region through two potential channels, $m \in \{E, P\}$, corresponding to “E-commerce (online)” and “Physical (offline),” respectively. For both online and offline channels, a firm needs to pay an iceberg cost to ship goods to another region. Let $\tau^h_{ij,m}$ denote this iceberg trade cost—the number of goods needed to be shipped by a sector-$h$ firm in region $i$ via channel-$m$, in order to deliver one unit to $j$. The iceberg trade costs capture physical transportation costs, as well as information and other barriers to trade, and are potentially different across online and offline channels. In the quantification, we will parameterize $\tau^h_{ij,E}$ and $\tau^h_{ij,P}$ separately to match the patterns of online and offline trade flows.

In addition to having different iceberg costs, online and offline channels differ in one additional aspect. All firms are able to sell to all regions without incurring any fixed cost through the online
platform. In contrast, to set up a physical store in a market outside the home region, firms need to pay a fixed cost of $f^P$, measured in units of labor at the destination market, before any goods can be sold.\textsuperscript{21} This fixed cost is not product-specific so each firm only needs to pay it once for each destination city. For convenience we assume the value of $f^P$ to be the same across the two sectors, although the exact value of $f^P$ for the non-tradable sector, which has infinite variable trade costs, does not matter in equilibrium.

For each variety $v$, the representative consumer in each region has a pair of random taste shocks ($v^E, v^P$). Each physical unit of a variety produced by a firm translates into $v^E$ quality units in the online marketplace, and $v^P$ quality units through the offline store. Therefore, the marginal cost of bringing one quality unit to the consumers in region $j$ is $\frac{w_i \tau_{ij}^E}{\phi v^E}$ for the online channel, and $\frac{w_i \tau_{ij}^P}{\phi v^P}$ for the offline channel, respectively. When a firm operates in two channels, for each variety, it chooses the channel with the lower cost of delivering one quality unit.\textsuperscript{22}

Our modeling assumption follows Tintelnot (2017) which adopts a similar approach to account for the cannibalization between different establishments of a multinational firm. As in Tintelnot (2017), we assume that the taste shocks are independent across varieties and between channels, and are drawn from the common Fréchet distribution:

$$Pr(v^m_j \leq x) = \exp(-x^{-\theta}).$$

(5)

The combination of zero fixed cost for the online channel and the Fréchet distribution assumption implies that all firms will enter all markets through the online channel. In addition, some firms might find it profitable to establish an offline store. Specifically, when $\tau_{ij}^P < \tau_{ij}^E$, firms can save on shipping cost by opening up a physical store in region $j$. Even if $\tau_{ij}^P > \tau_{ij}^E$, an additional channel provides option values by generating extra draws for the taste shock.

In an equilibrium with e-commerce, firms selling to any destination region fall into two categories in terms of their distributional networks. They may sell to the destination only through the online channel (henceforth referred to as an ONline-only firm and indexed by “ON”), or through both online and offline channels (henceforth referred to as a Two-Channel firm and indexed by “TC”). In the following, we describe the decisions of these two types of firms.

### 4.2.2 Two-Channel Firms

We start with a two-channel firm from region $i$ selling to region $j$. Since the firm will pick the lower-cost channel for any variety, the unit cost of producing and delivering a variety to $j$ is
\[
\min \left( \frac{w_{ij}^p \tau_{ij}^p}{\phi \tau_{ij}^p}, \frac{w_{ij}^E \tau_{ij}^E}{\phi \tau_{ij}^E} \right). \]

With the distributional assumption in Equation 5, for a two-channel firm, the CDF across varieties of the marginal cost of delivery (which is \( \min \left( \frac{w_{ij}^p \tau_{ij}^p}{\phi \tau_{ij}^p}, \frac{w_{ij}^E \tau_{ij}^E}{\phi \tau_{ij}^E} \right) \)) is

\[
C_{ij}^{h,TC}(c) = 1 - \exp \left( - \sum_{m \in \{P, E\}} \left( \frac{\tau_{ij}^m w_i}{\phi} \right)^{-\theta} c^\theta \right).
\]

As is well known, with CES utility and monopolistic competition, the firm charges a constant markup of \( \sigma / (\sigma - 1) \) over the marginal cost for each of its products. The firm-level price index is

\[
p_{ij}^{h,TC}(\phi) = \frac{\kappa^{1-\sigma} w_i}{\phi} \left( \sum_{m \in \{P, E\}} \left( \tau_{ij}^m \right)^{-\theta} \right)^{-\frac{1}{\theta}}, \tag{6}
\]

where \( \kappa = \Gamma \left( \frac{2+1-\sigma}{\theta} \right) \left( \frac{\sigma}{\sigma-1} \right)^{-1-\sigma} \) is a constant. The total sales of this firm are given by:

\[
s_{ij}^{h,TC}(\phi) = \frac{\kappa^{1-\sigma} \beta_j Y_j \omega_1^{1-\sigma}}{(p_i^h)^{1-\sigma}} \left( \sum_{m \in \{P, E\}} \left( \tau_{ij}^m \right)^{-\theta} \right)^{-\frac{1+w}{\theta}} \phi^\sigma - 1, \tag{7}
\]

and the corresponding profit is:

\[
\pi_{ij}^{h,TC}(\phi) = \frac{1}{\sigma} s_{ij}^{h,TC}(\phi).
\]

Equation 7 indicates that, when the e-commerce shipping cost decreases (lower \( \tau_{ij}^E \)), the total sales of a firm in region \( j \) increase. However, some of this increase comes at the expense of lower offline-channel sales—as the online channel becomes more competitive, varieties originally sold through the offline channel are shifted to the online channel. The importance of this crowding-out effect depends on the parameter \( \theta \). To see this, notice that the Fréchet distribution assumption implies that the fraction of sales through the online channel in destination \( j \) for any firm is given by \( \rho = \frac{(\tau_{ij}^h)^{-\theta}}{\sum_m (\tau_{ij}^m)^{-\theta}} \). We therefore have the following:

\[
\log \left( \frac{\rho}{1 - \rho} \right) = -\theta \log \left( \frac{\tau_{ij}^h}{\tau_{ij}^E} \right).
\]

As the above expression makes clear, \( \theta \) determines the elasticity of substitution between the online and offline channels of a firm. Larger values of \( \theta \) correspond to more homogeneous taste shocks, which imply that channel shares react more strongly to shipping cost differences. In the extreme case that taste shocks are the same for all varieties, for any given destination, firms will choose only one channel.
4.2.3 Online-Only Firms

If a firm does not have a physical store in region \( j \), it serves that market through the online channel for its continuum unit of variety. The marginal cost for a variety is \( w_i \tau_{ih}^E \). The CDF of the marginal cost to serve region \( j \) is

\[
G^h_{ON}(c) = 1 - \exp \left( - \left( \frac{\tau_{ij}^E}{\phi} \right)^{-\theta} c^\theta \right),
\]

and the price level of the firm is given by

\[
p^{h,ON}_{ij}(\phi) = \frac{\kappa}{1 - \sigma} \tau_{ij}^h \phi.
\]  

(8)

Total sales of a firm from region \( i \) with productivity \( \phi \) in market \( j \) are

\[
s^{h,ON}_{ij}(\phi) = \frac{\kappa}{1 - \sigma} \tau_{ij}^h \phi \left( \sum_{m \in \{P,E\}} (\tau_{ij}^h)^{-\theta} \right)^{1 - \sigma} \phi^{\sigma - 1},
\]  

(9)

and the profit in market \( j \) is given by \( \pi^{h,ON}_{ij}(\phi) = \frac{1}{\sigma} s^{h,ON}_{ij}(\phi) \).

4.2.4 Channel Choice

For any firm, setting up a physical store in any region would decrease its online sales but increase its total sales in the region. The firm would set up a physical store in region \( j \) only if the additional profit from having the store exceeds the fixed cost, \( \pi^{h,TC}_{ij}(\phi) - \pi^{h,ON}_{ij}(\phi) > w_j f^P \). This is similar to the tradeoff in firms’ FDI decisions in Helpman et al. (2004).

Formally, the necessary and sufficient condition for a firm from \( i \) to set up a physical store in region \( j \) \((j \neq i)\) is given by a productivity cutoff:\(^{23}\)

\[
\phi^*_{ij} = \left( \frac{\kappa Y_j}{\sigma w_j f^P} \right)^{1/\sigma} \left( \sum_{m \in \{P,E\}} \frac{\pi^{h,m}_{ij}(\phi)}{(\tau_{ij}^h)^{-\theta}} \right)^{-1/\sigma} - \left( \tau_{ij}^h \right)^{1 - \sigma} \phi^{\sigma - 1}
\]  

(10)

4.2.5 Entry

Finally, there is a fixed cost of \( F_{Entry} \) units of labor for firm entry. The total mass of firms in each region must be such that the expected profit from entry equals the expected cost:

\[
E(\pi^h) = \sum_{j=1}^{N} \left[ \int_{\phi}^{\phi^*_{ij}} \pi^{h,ON}_{ij}(\phi) dF_i(\phi) + \int_{\phi^*_{ij}}^{\infty} \pi^{h,TC}_{ij}(\phi) - f^P w_j dF_i(\phi) \right] = w_i \cdot F_{Entry}.
\]  

(11)

\(^{23}\)Since we assume that each firm can sell offline to the home region without incurring \( f^P \), we have \( \phi^*_{ii} = \phi_i \).
4.3 The Equilibrium

Given the firm-level decisions, the total demand for labor in region \( i \) from sector \( h \) is:

\[
L^h_i = \sigma M^h_i \sum_{j=1}^{N} \left( \int_{\phi_{ij}}^{\phi_{ij}^s} \frac{\phi_{ij}^{ch} dF_i(\phi)}{w_i} + \int_{\phi_{ij}^s}^{\infty} \frac{\phi_{ij}^{stc} dF_i(\phi)}{w_i} \right) + f^p \sum_{j=1}^{N} M^h_j \int_{\phi_{ji}}^{\infty} dF_i(\phi) + M_i^h F_{\text{Entry}}. \tag{12}
\]

The demand consists of three components. The first component captures the demand arising from the usage of labor as a variable input in production. The second component captures the labor needed in setting up physical stores. The third component captures the labor demand from fixed cost for firm entry. The total demand for labor in region \( j \) is simply:

\[
L_j = \sum_{h} L^h_j. \tag{13}
\]

Finally, given the zero profit condition, the total income of a region is simply the sum of all labor income:

\[
Y_i = w_i L_i. \tag{14}
\]

**Definition 1.** The equilibrium of this economy is defined as a set of prices, quantities, and decision rules, such that given exogenous parameters, the following conditions are satisfied:

1. Consumers and firms optimize (Equations 2 and 6-10).
2. Equilibrium prices are consistent with the decisions of firms (Equations 3 and 4).
3. Free entry and labor market clearing conditions hold; income equals total expenditure in all cities (Equations 11-14).

4.4 The Impact of E-commerce on Welfare

The model incorporates several channels through which e-commerce affects welfare. To fix ideas, consider a technological improvement that makes e-commerce feasible by reducing the retail cost for firm entry. Such a change will affect consumer welfare through both the price index and income.

Focusing first on the price index effect, we can decompose the change in the price index of the tradable sector, defined in Equation 3, into the sum of four components: the variety effect, the price effect, the new entrants effect, and the residual effect. We explain the intuition behind each of these effects below, while Appendix A derives the algebraic expressions for this decomposition exercise.

First, the variety effect is driven by firms which previously do not have offline stores in region \( j \) (firms with productivity lower than \( \phi_{ij}^s \)). The emergence of e-commerce enables these firms to enter region \( j \) without having to establish an offline store. These additional varieties benefit consumers
because they have a love-for-variety preference. Second, for firms that already have entered a region through the physical channel, they now have the option of serving the region through the online channel, leading to a decrease in the firm-level price index (see Equation 6). This is the price effect. Third, the emergence of e-commerce can lead to changes in the masses of firms across regions, which affect the price index. This is the new entrants effect. Finally, there is a residual effect.

In addition to having an impact on the price level, the emergence of e-commerce can also change the income of cities through its impacts on labor demand. We can decompose the increase in labor demand according to the three different uses of labor in the model—as fixed cost in setting up physical stores, as variable input in goods production, or as firm entry cost (see Equation 12). The welfare gains from e-commerce will be the net effects from nominal income and price changes. In the following section, we parameterize the model to quantify the strength of various channels discussed, as well as their joint impacts on consumer welfare.

5 Quantification

We parameterize the model to match the salient features of the Chinese economy. Each region in the model corresponds to a prefecture city in the data. Our calibrated model includes a total of 320 prefecture cities.

5.1 Parameters Assigned Externally

We assign values to a subset of the parameters drawn from the existing literature. Table 6 presents the values for these parameters. We set the elasticity of substitution $\sigma$ for both sectors to 5, which is in the range of values commonly used in the literature. For example, Melitz and Redding (2015) uses a value of 4 while Tintelnot (2017) employs a value of 6. In Section D.2 of the online appendix, we show that our main results are robust to alternative values of $\sigma$.

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24 Since e-commerce sales in the model do not feature extensive-margin adjustments, for changes between non-zero levels of e-commerce, the variety effect is associated with the price changes of the firms who serve region $j$ only through the online channel. In those settings, a more appropriate name would be ‘the price effect from online-only firms.’

25 The residual effect is the sum of two parts. The first part captures the price changes associated with some firms shutting down their offline channel and becoming online-only firms. The second part captures an algebraic residual associated with the covariance between the change in firm entry and the change in the price level.
A key parameter of our model is the dispersion of taste shocks $\theta$. In principle, $\theta$ can be estimated using online sales data and offline sales data at the firm level. Unfortunately, our data do not permit such estimation. Following Tintelnot (2017), we set $\theta = 6$ for both sectors. As a robustness test, in Section D.2 of the online appendix, we repeat our quantification exercise with alternative values for $\theta$ and find that the results do not change.

The Cobb-Douglas preference parameters $\beta_{j}^{NT}$ and $\beta_{j}^{T}$ govern the expenditure shares of the two sectors at the prefecture level. We pick the values for $\beta_{j}^{NT}$ to match the share of services in total household expenditure from the NBS surveys and then set $\beta_{j}^{T} = 1 - \beta_{j}^{NT}$. We also set the exogenous supply of equipped labor in city $i$, $L_i$, to the population of city $i$.

Lastly, the shape parameter of the productivity distribution $\alpha$ governs the firm size distribution. In monopolistic competition settings with the CES preference, the distribution of firms size follows a Pareto distribution with a shape parameter of $\frac{\alpha}{\sigma - 1}$. Using the 2004 data from Annual Survey of Manufacturing, we estimate the shape parameter to be 1.3. Therefore, we set the Pareto shape of productivity to $\alpha = (\sigma - 1) \times 1.3 = 5.2$.

### 5.2 Parameters Determined in Equilibrium

In addition to the parameters discussed above, we have five sets of parameters to be calibrated. These include technology parameter for each city $\phi_{j}$, fixed entry cost for firms $F_{Entry}$, fixed cost of setting up a store $f^p$, offline shipping cost $\tau_{ij}^{h,p}$ and online shipping cost $\tau_{ij}^{h,E}$. The parameters are determined jointly in equilibrium. We set the trade cost in the non-tradable sector to infinity, and henceforth omit the $h$ superscript when referring to trade costs in the tradable sector. We specify the shipping cost for the offline channel to be

$$\ln \tau_{ij}^{p} = \begin{cases} 
\delta_L \ln L_j, & \text{if } i = j \\
\delta_1 + \delta_2 \ln D_{ij} + \delta_L \ln L_j, & \text{if } i \neq j 
\end{cases}$$

(15)

where $\delta_1$, $\delta_L$, and $\delta_2$ are parameters of interest, $D_{ij}$ is bilateral distance between cities $i$ and $j$, and $L_j$ is the population of region $j$. The parameter $\delta_1$ governs the level of between-city shipping cost relative to within-city shipping cost. For $i = j$, we effectively normalize this intercept to 0. The parameter $\delta_2$ is the distance elasticity of offline shipping cost. Intuitively, shipping cost increases with distance. The term $\delta_L \ln L_j$ deserves additional discussion. In the model, firms can reach every consumer in a city once they pay the fixed cost to set up a physical store. In reality, of course, most physical stores only serve consumers living nearby. To capture the idea that the average distance of a store to consumers in a city increases with the size of the market,

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26Our category-level expenditure data covers only around a hundred cities. For these cities we calculate service shares directly. We impute the service shares for the remaining cities. Details of the imputation are described in Section 3.5.

27Specifically, we obtain the slope coefficient with a value of 1.3 from a regression of log rank of firm employment on log firm employment. This slope coefficient corresponds to the shape parameter in the Pareto distribution. See also Di Giovanni and Levchenko (2013) for a recent study using this approach.

28We normalize $L_j$ relative to the smallest city so that the within-city shipping cost $\tau_{ii}^{p} = 1$ for that city.
we introduce $\delta_L \ln L_j$. In our calibration, this term will be positive and it allows us to match the negative relationship between online expenditure share and population.\(^{29}\)

We parameterize the e-commerce shipping cost as

$$\ln \tau_{ij}^E = \begin{cases} 
\gamma_0, & \text{if } i = j \\
\gamma_1 + \gamma_2 \ln D_{ij}, & \text{if } i \neq j,
\end{cases}$$ (16)

where $\gamma_0$ and $\gamma_1$ govern the level of intra-city and inter-city e-commerce shipping costs, respectively, and $\gamma_2$ is the distance elasticity of e-commerce shipping cost. Compared to Equation 15, the existence of $\gamma_0$ allows shipping cost for online trade to be different from that for offline trade. For example, because online purchases are delivered directly to individual consumers, it might be more costly than bulk shipping for offline trade. Lastly, $\gamma_1$ indicates that between-city online sales could be more costly relative to within-city online sales.

We calibrate the parameters as follows. Given an arbitrary set of parameters $\Theta = \{f^P, F_{\text{Entry}}, \delta_1, \delta_2, \delta_L, \gamma_0, \gamma_1, \gamma_2\}$, we first find a set of productivity levels $\phi_i$ to match the nominal income of each city in the model to data (real incomes are not directly observable and will be an output of this calibration exercise). We then use the parameters $\Theta$ and $\phi_i$'s to simulate the model, and calculate a set of $K$ moments, denoted by $\psi_k^{\text{model}}(\Theta)$, based on the simulations. We search over the space of $\Theta$ to minimize an objective function given by

$$\min_{\Theta} \sum_{k=1}^{K} \left( \frac{\psi_k^{\text{model}}(\Theta) - \psi_k^{\text{data}}}{\psi_k^{\text{data}}} \right)^2$$ (17)

where $\psi_k^{\text{data}}$ is the data counterpart of $\psi_k^{\text{model}}(\Theta)$.

Table 7 presents the calibrated parameters and target moments. The target moments are jointly determined by the parameters in equilibrium. Nevertheless, some moments are more informative about certain parameters than others. We discuss the identification of the parameters below. The entry cost $F_{\text{Entry}}$ is pinned down by the average firm size calculated from the 2004 Annual Survey of Manufacturing. The value of the fixed cost of setting up a physical store $f^P$ is pinned down by the percentage of manufacturing firms selling to another city, calculated from the 2004 World Bank Investment Climate survey. To pin down $\delta_1$, which governs the level of offline shipping cost, we use the province offline absorption ratio. This is defined as the share of offline expenditure on offline goods from the same province and calculated from the 2012 Province-level Input-Output Tables.\(^{30}\) To pin down the distance elasticity of offline shipping cost $\delta_2$, we conduct a gravity regression of inter-provincial offline trade flows with origin and destination fixed effects, and

\(^{29}\)However, this term is not essential for the model’s mechanism. In fact, if we omit this term, the model will over-predict (relative to the data) the negative relationship between online expenditure share and population, leading to stronger effects of e-commerce on spatial consumption inequality. Intuitively, this term increases the cost of selling through the offline channel to big cities and makes these cities spend a higher fraction of income online, which works against our main mechanism.

\(^{30}\)The 2012 Province-level Input-Output Tables do not include information on inter-provincial offline trade flows so we do not use it for gravity estimation.
Table 7: Calibrated Parameters and Target Moments

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>fixed costs</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F_{Entry}$</td>
<td>14.3</td>
<td>average firm size (2004)</td>
<td>80</td>
<td>80</td>
</tr>
<tr>
<td>$f^P$</td>
<td>0.076</td>
<td>share of firms selling offline to another city (2004)</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>offline shipping cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>0.712</td>
<td>province absorption ratio</td>
<td>0.54</td>
<td>0.51</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>0.205</td>
<td>distance elasticity in offline gravity (2002)</td>
<td>-1.4</td>
<td>-1.5</td>
</tr>
<tr>
<td>$\delta_L$</td>
<td>0.070</td>
<td>population elasticity of online share</td>
<td>-0.11</td>
<td>-0.11</td>
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<tr>
<td>online shipping cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>0.899</td>
<td>average online share</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>1.653</td>
<td>province online absorption ratio</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>0.101</td>
<td>distance elasticity in online gravity</td>
<td>-0.47</td>
<td>-0.45</td>
</tr>
<tr>
<td>city characteristics</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$\phi^i$</td>
<td></td>
<td>income per capita in city $i$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: calculation based on model simulations. See Equations 15 and 16 for parameterization of the offline and online shipping costs.

obtain the coefficient on log bilateral distance as target moment (Column 1 of Table 1). Recall that $\delta_L$ governs how offline shipping cost varies with destination population size. When $\delta_L$ is positive, offline shipping is more costly for destinations with larger population, so these cities would purchase more from the online platform. To pin down $\delta_L$, we conduct a regression of log online share on log population and log market potential and use the coefficients as target moments (Column 2 of Table 3).

To pin down $\gamma_0$, which governs the intra-city level of e-commerce shipping cost, we use the average online share. To pin down $\gamma_1$ which governs the inter-city level of e-commerce shipping cost, we use the average province online absorption ratio, defined as the average share of online expenditure on goods from the same province. We calculate this statistics from inter-provincial online trade flows from Taobao. Lastly, to pin down the distance elasticity of online shipping cost $\gamma_2$, we conduct a gravity regression of inter-province online trade flows with origin and destination fixed effects, and obtain the coefficient on log bilateral distance as a target moment (Column 2 of Table 1).

Importantly, since some moments are from the pre-e-commerce era (marked with "2002" or "2004" in Table 7), while others are from the e-commerce era, we perform two model simulations to generate moments for any given parameter value. Specifically, for any parameter value, we first simulate the model to obtain moments in the e-commerce era; we then simulate a version of the model with no e-commerce (with infinite $\tau_{ij}^E$) to calculate the moments from 2002 and 2004.

31We use inter-provincial flows as the target moment because we do not have inter-city trade flows for either online or offline.
Figure 1: Calibrated Offline and Online Shipping Costs

Despite having one more moment than parameters, we are able to match all target moments well. As Table 7 shows, the differences between the data and the model moments range from 0 to about 7%.

5.3 Calibrated Online and Offline Shipping Costs

Our calibration reveals significant differences in shipping cost structure between online and offline sales. First, disciplined by the share of firms selling to another city (94%), the fixed cost associated with offline entry is 0.076, which is around 5% of firms’ entry cost. While this number might seem small, the existence of the fixed cost implies that in equilibrium, most firms do not enter most markets, especially not the small ones. As we will show below, this leads to significant inequality in access to consumption goods across cities.

We also find different distance elasticities in trade cost for the two modes of trade: 0.205 for offline trade and 0.101 for online trade. This is the flip side of the reduced-form evidence in Table 1 that shows online trade is much less hindered by distance compared with offline-trade. Figure 1 plots the log of shipping costs $\tau_{ij}^O$ and $\tau_{ij}^E$ against the log of bilateral distance. We plot the $\tau_{ij}^O$ for a destination city with the average population size since $\tau_{ij}^O$ is specified to be a function of destination population $L_j$. Given that offline trade still accounts for the bulk of total trade in the data, it is not surprising that the online shipping cost is higher than the offline cost for all city pairs in Figure 1. On the other hand, since the online shipping cost increases with distance more gradually than the offline shipping cost, the online shipping cost eventually becomes comparable to the offline shipping cost when two cities are very far apart. Consequently, consumers from more remote cities would buy disproportionately more from e-commerce.
5.4 Model Validation

Using our parsimonious specifications of shipping costs, we are able to match the target moments well. To further bolster confidence in using the model to conduct counterfactual experiments, we provide additional evidence that the model generates sensible predictions along dimensions that are not directly targeted.

First, the most important element in this model is online trade. In the calibration, we target the average province online absorption ratio, which measures the extent to which a province sources its online purchase within the province. Our calibration captures this moment with one single parameter, $\delta_1$. We verify whether the model predictions on online absorption ratio for individual provinces and the joint distribution of online and offline absorption ratios are consistent with the data. As the upper panel of Table 8 reports, in the data, the correlation between online and offline absorption ratios at the province level is 0.544—provinces sourcing more from other provinces online also tend to source more from other provinces offline. In the model, this correlation is 0.789, which is reasonably close. The model also generates accurate predictions on the online absorption ratio for individual provinces: as the lower panel of Table 8 shows, the correlation across all provinces between log model-predicted online absorption ratio and its data counterpart is 0.826.

Second, the model attributes differential online purchasing behaviors across cities to the different availability of goods and their prices in the offline market. Therefore, to assess the welfare implications of e-commerce, it is important to check if the offline price index generated by the model matches what we observe in the data. Towards this end, we compare the differences in the ideal price index in our model against the empirical work by Feenstra et al. (2016). Using Nielsen Homescan data for China, Feenstra et al. (2016) document that larger cities in China have more varieties of consumption goods at lower prices. The average slope of the price index against log population is -0.13.\footnote{They construct the price index for each city for four product categories, where they normalize the index in Shanghai to one for each category. They then plot the price index against log population for each product category in separate figures. We retrieve the slope for each product category from their figures and calculate the average. We focus on comparing the slopes because we do not have access to the price index for individual cities.} To obtain the model counterpart, we calculate the price index for the model economy without e-commerce, using the same set of 60 cities in Feenstra et al. (2016). We then

<table>
<thead>
<tr>
<th>Moment Description</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>correlation between online and offline absorption ratio</td>
<td>0.544</td>
<td>0.789</td>
</tr>
<tr>
<td>slope of price index against log population</td>
<td>-0.13</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

Notes: calculation based on model simulations.
regress the price index on log population to obtain a slope of -0.12. Therefore, the price index differences predicted by the model are very close to the empirical estimates.

Third, in the model, one important channel through which the emergence of e-commerce affects welfare is by encouraging new entrants. With an endogenous entry mechanism, the model generates a tight relationship between city size and the number of entrants, which is consistent with the data. However, this mechanism is common to most trade models with endogenous entry. A more demanding test of our model is to examine whether the model-predicted change in the number of firms due to e-commerce is consistent with its data counterpart. Specifically, using the calibrated parameters, we solve for a counterfactual equilibrium without e-commerce. We then calculate the increase in firm mass in different provinces from the emergence of e-commerce. We obtain data on firm counts from the tabulations of the 2013 economic census. The tabulations provide the numbers of firms of different sizes (small/medium/large) entering at different years for each province. With provincial data, we cannot directly estimate the causal impact of e-commerce on firm entry. Instead, we proxy this impact using the fraction of new entrants, defined as those entering after 2005, among active firms covered by the census. The idea is that if a city has a higher fraction of recent entrants, then the mass of firms in that city likely has grown. Figure D.1 in Section D.1 of the online appendix plots the entry rate in the model against the data. As the figure shows, there is a clear positive correlation between the model and the data. The correlation in firm entry between the model and the data is 0.285 (lower panel of Table 8) and increases to 0.455 if the one outlier, Chongqing, is excluded.

Given the intrinsic difficulty in identifying the effects of e-commerce in the data, we also rely on heterogeneous effects. Specifically, we examine the relationship between the growth in firm counts with population and market potential for both the model and the data in Table D.5 in the online appendix. According to the model, a larger population and lower market potential are associated with greater increase in firm entry at the province level after the emergence of e-commerce (Columns 1 and 3 of Table D.5). These model outcomes are corroborated by the regressions using the data counterpart, although the coefficients are less significant (Columns 2 and 4 of Table D.5).

In summary, the model performs reasonably well in terms of non-targeted moments including province online absorption ratio, differences in price index across cities, and changes in firm entry rates associated with e-commerce. We now proceed to analyze the consumption inequality in the model and examine the welfare implications of e-commerce.

33The population elasticity of the number of entrants is close to 1 in both the model and the data.
34To rule out confounding effects from other economic shocks such as reforms to the SOE sector, we focus on the small and medium firms in 2013. More precisely, our measure is the fraction of firms entering after 2005, when e-commerce started to take off, among all small and medium firms active in 2013. We cannot look at individual firms because only the aggregate tabulations are publicly available.
5.5 Spatial Consumption Inequality before E-commerce

The calibrated costs associated with inter-city trade lead to significant spatial inequality in consumption across cities. Panel A of Figure 2 plots the per-capita real wage and the price index in the calibrated economy against population, where we have normalized the real wage and price index in Shanghai to one. As the figure shows, there are substantial differences in real income per capita associated with city population. The average real income per capita of the largest 20% of cities is around 50% higher than the average of the smallest 20% of cities. The population elasticity of real income per capita in our calibrated economy is 0.155. Since we have matched the nominal income of each city to the data in the calibration, the population elasticity of nominal income in the model is exactly the same as the data, which is 0.065. The difference in population elasticity between nominal and real income is explained by the variation in the ideal price index across cities. Put differently, because of the fixed and variable trade costs, residents in smaller cities have access to fewer consumption goods and at higher prices. According to our model, this channel explains more than half of the spatial inequality in living standards across Chinese cities with different population sizes, while nominal income differences account for the remainder.

Panel B of Figure 2 plots the spatial inequality against market potential. We find that there are also substantial differences in both the price index and the real income associated with market potential. The real income per capita of an average city among the top quintile of cities with regard to market potential is around 30% higher than for the lowest quintile.

Figure 2: Spatial Inequality before the Emergence of E-commerce

(a) by Population
(b) by Market Potential

Notes: calculation based on model simulations by the authors. The real wage and price index in Shanghai are normalized to one.

5.6 The Effects of E-commerce on Domestic Trade and Welfare

We examine the impacts of e-commerce on inter-city trade and welfare by considering a move from a counterfactual equilibrium without e-commerce to the calibrated benchmark equilibrium. Table 9 summarizes the changes in the various outcome variables from this move.
Table 9: The Effect of E-commerce on Inter-city Trade and Welfare

### Panel A By Population Quintiles

<table>
<thead>
<tr>
<th>quintile</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
</tr>
</thead>
<tbody>
<tr>
<td>online share</td>
<td>11.07%</td>
<td>9.63%</td>
<td>8.74%</td>
<td>8.24%</td>
<td>7.88%</td>
</tr>
</tbody>
</table>
| change in import ratio (p.p.)
  online (p.p.) | 10.64%    | 9.16%     | 8.17%     | 7.67%     | 7.42%     |
| offline (p.p.) | -8.15%    | -7.72%    | -7.03%    | -6.80%    | -6.76%    |
| change in real income | 2.06%    | 1.67%     | 1.36%     | 1.27%     | 1.23%     |

### Panel B By Market Potential Quintiles

<table>
<thead>
<tr>
<th>quintile</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
</tr>
</thead>
<tbody>
<tr>
<td>online share</td>
<td>10.97%</td>
<td>9.63%</td>
<td>8.96%</td>
<td>8.30%</td>
<td>7.69%</td>
</tr>
</tbody>
</table>
| change in import ratio (p.p.)
  online (p.p.) | 10.77%    | 9.27%     | 8.53%     | 7.75%     | 6.74%     |
| offline (p.p.) | -9.13%    | -7.73%    | -7.26%    | -6.69%    | -5.65%    |
| change in real income | 2.01%    | 1.69%     | 1.50%     | 1.35%     | 1.11%     |

Note: calculation based on model simulations. ‘Online share’ refers to expenditure spent through the e-commerce channel as a share of total expenditure in the tradable sector. ‘Import ratio’ refers to expenditure on goods produced in other cities as a share of total expenditure in the tradable sector. The next two lines break the ‘import ratio’ into the online and offline channels. Both the online share and the import ratio are calculated based on the tradable sector only. Changes in import ratios and real income are calculated relative to the economy without e-commerce. Changes in import ratios are reported in terms of percentage point differences while changes in real income are reported in terms of percentage differences.

Panel A examines these changes along the population dimension. In the calibrated equilibrium, cities in the smallest population quintile spend around 11% of their consumption expenditure online, while for cities in the biggest population quintile, this number is 7.7%. The rise of e-commerce has large effects on the patterns of inter-city trade. Consider the cities in smallest population quintile. The average import ratio for these cities, defined as the fraction of consumption expenditure on goods produced in other cities, increases by 1.64 percentage points from 75.8% to 77.4%. For the city with the medium population, import ratio increases by 1.2 percentage points. This increase masks a much larger shift in the channels of trade: for cities in the smallest quintile, import through the online channel increases from 0 to 10.77% of the total expenditure, while import through the offline channel decreases by 9.13 percentage points from 75.8% to 66.7%. Intuitively, with the reduction of online shipping cost, some firms may find it more profitable to close their offline stores in certain destinations and instead to serve these destinations exclusively through the online channel. Firms keeping offline stores might also shift sales of some of their varieties to the online marketplace, reducing offline sales. Despite this shift, however, e-commerce still increases overall inter-city trade, and the increase is larger for smaller destination cities. Panel B of Table 9 shows that similar patterns are present along the market potential dimension. Together, our results highlight the importance of incorporating firm-level online-offline channel choice for
Table 10: Regression Analysis using Welfare Gains from E-commerce

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pre e-comm</td>
<td>e-comm</td>
<td>gains</td>
</tr>
<tr>
<td>ln population</td>
<td>0.138***</td>
<td>0.135***</td>
<td>-0.00295***</td>
</tr>
<tr>
<td></td>
<td>(0.0381)</td>
<td>(0.0379)</td>
<td>(0.000273)</td>
</tr>
<tr>
<td>ln market potential</td>
<td>0.0684</td>
<td>0.0638</td>
<td>-0.00460***</td>
</tr>
<tr>
<td></td>
<td>(0.0680)</td>
<td>(0.0676)</td>
<td>(0.000496)</td>
</tr>
<tr>
<td>constant</td>
<td>-1.022</td>
<td>-0.896</td>
<td>0.126***</td>
</tr>
<tr>
<td></td>
<td>(0.900)</td>
<td>(0.894)</td>
<td>(0.00700)</td>
</tr>
<tr>
<td>N</td>
<td>320</td>
<td>320</td>
<td>320</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.0941</td>
<td>0.0904</td>
<td>0.678</td>
</tr>
</tbody>
</table>

Note: The dependent variables are calculated from model simulations by the authors. Columns 1 and 2 use the log real wage from the economies without and with e-commerce. Columns 3 uses welfare gains from e-commerce. Robust standard errors in parentheses. * \(p < 0.1\), ** \(p < 0.05\), *** \(p < 0.01\).

our understanding of how e-commerce affects domestic trade.

The increase in domestic trade brought about by e-commerce substantially benefits workers. The average welfare gain from e-commerce for a city in our sample is 1.6%. To put this number into perspective, consider the gains from international trade for the United States. Arkolakis et al. (2012), using the sufficient-statistics formula, finds it to be in the order of 1%. Therefore, the gains from e-commerce for Chinese cities are substantial.

These welfare gains are not evenly distributed across Chinese cities. Along the population dimension, the increase in real income per capita due to e-commerce ranges from an average of 1.1% for the 5th quintile to an average of 2.0% for the 1st quintile. Along the market potential dimension, the increase in real income per capita due to e-commerce ranges from an average of 1.2% for the 5th quintile to an average of 2.1% for the 1st quintile.

To summarize the impacts of e-commerce on spatial consumption inequality succinctly, we adopt a regression approach. The dependent variables in Columns 1 and 2 of Table 10 are log real income in the economies without and with e-commerce, respectively, and the independent variables include log population and log market potential. As Column 1 shows, without e-commerce, the coefficients on log population and log market potential are 0.138 and 0.0684, respectively, indicating spatial income inequality along these two dimensions. The arrival of e-commerce reduces inequality along both dimensions. In Column 2, the coefficients on log population and log market potential are reduced to 0.135 and 0.0638, respectively. The dependent variable in Column 3 is welfare gains from e-commerce, which are equal to the difference between the dependent variables in Columns 1 and 2. According to Column 3, a 10% decrease in population is associated with greater welfare gains of 0.0295 percentage points, while a 10% decrease in market potential is associated with greater welfare gains of 0.0460 percentage points. Taking the ratios of the coefficients from Column 3 and Column 1, we can obtain two measures of the effects of e-commerce...
on spatial inequality—according to the quantification exercise, the arrival of e-commerce reduces the inequality associated with population size by 2.1% and the inequality associated with market potential by 6.7%.\textsuperscript{35}

Projecting from the current rate of growth, industry analysts forecast the importance of e-commerce to be increasing over time (Dobbs et al., 2013). In Appendix B, we use the model to analyze the effects of further e-commerce development. Specifying future development as a uniform decrease in online shipping costs, we find that when online sales reach 24% of total retail sales, a typical city will enjoy a 4.9% welfare gain from e-commerce. Moreover, the welfare gains accrue disproportionately to residents from small and remote cities. The development of e-commerce thus remains a powerful tool for improving welfare and reducing spatial inequality in living standards in the foreseeable future.

5.7 Decomposing the Welfare Gains

To understand the channels of the welfare gains from e-commerce and how such channels differ across cities, we decompose the change in real wage into changes in the nominal income and the price index in Figure 3.\textsuperscript{36}

![Figure 3: Nominal Wage and Price Index in General Equilibrium](image)

Notes: calculation based on model simulations by the authors.

As the figure makes clear, smaller cities experience both larger increases in the nominal wage and greater decreases in the price index than larger cities. Since the slopes of the fitted lines in Figure 3a and 3b are comparable in absolute value, changes in the nominal wage and the ideal price index contribute about equally to the differential changes in real wages across cities.

\textsuperscript{35}Specifically, $-0.00295 = -2.1\%$ and $-0.00460 = -6.7\%$.

\textsuperscript{36}In considering nominal wages, we need to choose a normalization for each equilibrium. We normalize the aggregate nominal GDP to one for each equilibrium.
We further examine specific mechanisms underlying the changes in each component, starting with the nominal wage. In the model, the nominal wage in a city is determined by the labor market clearing condition. Since the labor supply is fixed, the change in nominal wages is entirely driven by shifts in labor demand. We therefore consider different labor demand components, focusing on the tradable sector as it is where the initial shocks take place. As Equation 12 shows, labor is used either as fixed cost in setting up physical stores, as variable input in goods production, or as firm entry cost. We plot the percentage changes in these three components in Figure 4a.

In the figure, the blue diamonds indicate the changes in labor demand related to fixed cost of market entry. With e-commerce, firms have less incentive to set up physical stores. As a result, all cities experience a decrease in labor demand from this channel. Quantitatively, this decrease is larger for smaller cities. Red circles indicate the labor demand change associated with the use of labor as a variable input in production. As the figure shows, the change in this component is more negative for smaller cities, but the magnitude is small compared to the changes in other components. Finally, black crosses indicate the change in labor demand associated with fixed cost of firm entry. The change in this component is positive for all cities. Intuitively, since firms can now reach consumers in all cities more cheaply, e-commerce leads to an increase in firm entry. As the home market accounts for a smaller share of profit for firms in smaller cities, the increase in market access brought about by e-commerce is especially important for small cities. As a result, the change in the third component of labor demand is larger in magnitude for smaller cities. Overall, our decomposition exercise indicates that the increase in the nominal wage is primarily a result of the increase in firm entry, which is especially significant for small cities.

We decompose the change in the price index of the tradable sector into four components according to Equation 22 in the appendix. The results are presented in Figure 4b. As shown in
the figure, the composition of the change in $P_{i}^T$ varies across market size. The variety effect is the biggest component of the four, suggesting important welfare gains from increased access to varieties. The variety effect is smaller in magnitude (less negative) for larger cities. This is not surprising as larger cities have more varieties to begin with and therefore have smaller room to improve. The price effect is another important component of the reduction in the price index—the option to serve a market through the online channel leads to a decrease in firm-level price index (see Equation 6). We find the price effect to be more significant for larger cities. Lastly, we find that the new entrants effect tends to reduce the price index, while the residual effect tends to work in the opposite direction. As Figure 4b shows, relative to the first two components, the last two components are more similar across cities of different sizes, so they play an insignificant role for reducing spatial consumption inequality.

The results from our decomposition exercise are supported by survey evidence. In a McKinsey survey, when asked about what attracts them to buy online, 55 percent of the respondents in tier-3 cities cited ‘access to varieties’ as a main reason, compared with 31 percent in tier-1 cities, and 44 percent in tier-2 cities (Ali Research, 2015). In contrast, 32 percent of the respondents in tier-3 cities cited ‘lower prices’ as a main reason, compared with 44 percent in tier-1 cities, and 42 percent in tier-2 cities. Together, these survey responses suggest that the variety effect is more important for small and medium cities while the price effect is more important for big cities, in line with our decomposition results.

5.8 Comparison to the ACR formula

It is instructive to compare our findings on welfare to alternative approaches based on the simple ACR formula (Arkolakis et al., 2012). The first alternative is to simply view the emergence of e-commerce as a reduction in the cost of communication, which makes offline trade less costly. In this setting, the welfare gains from e-commerce can be calculated from changes in import penetration ratio due to e-commerce. We cannot directly observe the changes in total import (online and offline combined), but in Section 5.6, we show that because of the crowding out effect on offline trade, e-commerce only leads to around 1.2 percentage points increase in the import ratio. Viewed through the ACR formula, this change will lead to negligible welfare gains.

The second alternative is to treat e-commerce as introducing a new ‘online good’ that adds to the existing ‘offline good’ which is produced and sold only locally in each city, ignoring the offline trade between cities. In other words, this approach assumes e-commerce to be the only means of inter-city trade. With tradable and non-tradable sectors, the ACR formula in this context is given by:

$$Gains \text{ from e-commerce} = (1 - \lambda) \frac{\beta^T}{\sigma} - 1,$$

where $\beta^T$ is the expenditure share of the tradable sector, $\lambda$ is the online expenditure share and $\sigma$ is the elasticity of substitution between the online good and the offline good. The main difference between the model underlying this formula and our model is that our model allows for the possi-
bility that the increase in online sales crowds out the sales of similar or identical products. Because of this substitution effect, the welfare gains from our baseline model may be smaller than those predicted by Equation 18.

Figure 5: Online Expenditure Share and Welfare Gains

Indeed, with $\sigma = 5$, the application of the above formula gives an average of 1.8% as the welfare gains from e-commerce, which is larger than the number of 1.6% in our baseline calibration. In Figure 5, we plot the gains from e-commerce in our model and those according to Equation 18 against log population. We find that Equation 18 tends to over-predict the gains from e-commerce for large cities (low online expenditure share) and slightly under-predicts the gains for smaller cities (high online expenditure share). This can be explained by the differences in the composition of online sales between smaller and larger cities. For smaller cities, the online sales revenue are mostly from goods which were previously unavailable in those markets and consumers derive large welfare gains from these new varieties. On the other hand, for larger cities, the online sales revenue may be from previously-offline-only goods expanding into the online channel. As a result, consumers in larger cities enjoy smaller welfare gains relative to Equation 18. This explanation is also consistent with our finding in the decomposition exercise in Section 5.7 that new varieties contribute the most to the decrease in the price index for smaller cities.

In summary, while the second alternative is much better than the first one, it still generates biased estimates of the welfare gains from e-commerce. Perhaps more importantly, neither alternatives are able to speak to how e-commerce affects domestic trade, which highlights the advantage of using our benchmark model that incorporates firm’s online-offline channel choice.

\[37\] The average gains from the ACR formula varies with the value for $\sigma$. A different way of conducting the comparison with ACR gains is to choose $\sigma$ so that the average gains are equal between our baseline numbers and the ACR gains. This different way of choosing $\sigma$ also gives the patterns that Equation 18 over-predicts the gains from e-commerce for large cities and under-predicts the gains for smaller cities.
5.9 Further Discussions

In the benchmark quantitative framework, we assume that consumers have the CES preference, and that firms compete monopolistically. Together, these two assumptions imply constant markups and rule out the pro-competitive effect of e-commerce, which might be empirically relevant. This channel might be more important for residents from smaller cities, where retail markups tend to be higher (Hottman, 2014). This section discusses our model’s implications for price levels and summarizes the results when we deviate from constant markups.

As shown in the model section, our benchmark model allows marginal costs to be affected by e-commerce. This enables us to separate the change in price index into four components, including a price effect, a variety effect, a new entrants effect, and a residual. Consistent with the survey evidence, we find that the variety effect is stronger than the price effect for small cities, while the opposite is true for big cities (Section 5.7). In addition, as we discuss in Section 5.4, our calibrated model also generates a relationship between price index and city size that is comparable to its empirical counterpart, constructed from bar-code level data. Our framework therefore captures important effects of e-commerce through price.

How would explicitly modeling variable markups affect our main conclusion? If e-commerce were the only means of inter-city trade, then the result from Arkolakis et al. (forthcoming) applies directly to our setting. Relating to our results on spatial consumption inequality, because the welfare formula in Arkolakis et al. (forthcoming) simply augments the ACR formula by a model constant, which is common to all cities, the model prediction that smaller cities benefit more from e-commerce will not be affected.

Less straightforward is how our results would change if we introduce variable markups in a setting with both online and offline trade. We perform such an exercise as a robustness test in Section E of the online appendix. Specifically, we use the specification of preference from Simonovska (2015), which offers the advantage of generating analytical pricing decisions while allowing for the pro-competitive effect. For analytical tractability and computational feasibility, the model abstract away from the between-channel cannibalization within firms, and is calibrated to a sample of 50 cities. The numerical exercise further confirms that e-commerce disproportionately benefits residents from smaller and more remote cities.

6 Concluding Remarks

This paper studies how e-commerce as a new trade technology affects inter-city trade and welfare. In contrast to traditional trade, e-commerce eliminates the fixed costs needed when entering a city, and alleviates the negative impacts of distance on trade. Because of these two features, while beneficial to all, e-commerce disproportionately increases imports by small and remote cities, and

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38Arkolakis et al. (forthcoming) shows that under monopolistic competition with non-CES preference (hence variable markups) and a set of standard assumptions, the gains from trade are given by a simple formula that depends only on a few sufficient statistics.
benefits residents from these cities. Using data from the dominant e-commerce platform in China, we show that indeed online trade flows respond less negatively to distance compared to offline trade flows. Moreover, consistent with e-commerce bringing larger welfare gains to smaller and more remote cities, we find that residents from these cities spend a larger share of their expenditure online.

We then develop a general equilibrium model to quantify the effects of e-commerce on trade and welfare. We find the emergence of e-commerce increases inter-city trade substantially, but this increase comes at the expense of reduced offline trade. The average welfare gains from e-commerce are around 1.6 percent, and much larger for smaller and more remote cities. With its rapid growth, e-commerce promises to further reduce this inequality in the coming years.

Limited by the data, this paper has focused on the distribution of welfare gains across cities. In reality, online consumption intensity varies greatly over the socio-economic spectrum, and the welfare gains from e-commerce might have an important within-city dimension. Incorporating this within-city dimension is an important direction for future research.

References


Clay, Karen, Ramayya Krishnan, Eric Wolff, and Danny Fernandes, “Retail Strategies on the Web: Price and Non-price Competition in the Online Book Industry,” Journal of Industrial Economics,


A Deriving the Equation for the Decomposition of Price Index Changes

We derive the analytical expressions used in the decomposition of changes in the price index of the tradable sector below. From the definition of price index, we have

\[
(P_T^T)^{1-\sigma} = \sum_{i=1}^{N} M_{iT}^T \left( \int_{\phi}^{\Phi_i} (P_{ij}^{ON}(\phi))^{1-\sigma} dF(\phi) + \int_{\Phi_i}^{\infty} (P_{ij}^{TC}(\phi))^{1-\sigma} dF(\phi) \right) 
\]

(19)

where \( \Psi_{ij} = \left( \int_{\phi}^{\Phi_i} (P_{ij}^{ON}(\phi))^{1-\sigma} dF(\phi) + \int_{\Phi_i}^{\infty} (P_{ij}^{TC}(\phi))^{1-\sigma} dF(\phi) \right) \).

Using \( X' \) to denote the new-equilibrium value of variable \( X \), we can decompose the change in...
\((P^T_j)^{1-\sigma}\) into the following terms.

\[
\Delta (P^T_j)^{1-\sigma} = \sum_{i=1}^{N} M^T_i \int_{\phi}^{\phi_{ij}^T} (p^ON_{ij}(\phi))^{1-\sigma} \phi_{ij} dF(\phi) + \sum_{i=1}^{N} M^T_i \int_{\phi}^{\phi_{ij}^T} (p^TC_{ij}(\phi))^{1-\sigma} \phi_{ij} dF(\phi) \\
+ \sum_{i=1}^{N} (M^T_i - M^T_i) \bar{\Psi}_{ij} + \sum_{i=1}^{N} M^T_i \left( \int_{\phi}^{\phi_{ij}^T} (p^ON_{ij}(\phi))^{1-\sigma} - p^TC_{ij}(\phi))^{1-\sigma} \phi_{ij} dF(\phi) + \sum_{i=1}^{N} (M^T_i - M^T_i) (\bar{\Psi}_{ij} - \bar{\Psi}_{ij}) \right)
\]

Finally, since \(d \ln (P^T_j) = \frac{1}{1-\sigma} d \ln ((P^T_j)^{1-\sigma})\), we have

\[
\frac{\Delta P^T_j}{P^T_j} \approx \frac{1}{1-\sigma} \frac{\Delta (P^T_j)^{1-\sigma}}{(P^T_j)^{1-\sigma}}
\]

Combining Equation 20 and Equation 21, we have

\[
\frac{\Delta P^T_j}{P^T_j} \approx \frac{1}{1-\sigma} \left[ \frac{A}{(P^T_j)^{1-\sigma}} + \frac{B}{(P^T_j)^{1-\sigma}} + \frac{C}{(P^T_j)^{1-\sigma}} + \frac{D}{(P^T_j)^{1-\sigma}} \right]
\]

where the terms A, B, C and D are defined in Equation 20. We have decomposed the change in price index of the tradable sector into a variety component, a price component, a new entrants component, and a residual component. We present the numerical results of this decomposition in Section 5.7.

\section*{B The Effect of Further Development in E-commerce}

In the main text, we have quantified the realized gains from e-commerce. However, the rapid development of e-commerce in China is likely to continue at a fast pace in the near future. Indeed, the total revenue of e-commerce in China is projected to increase by as much as 225% between 2012 to 2020. Assuming that total consumption is increasing at an annual rate of 7%, the share of total expenditure spent online would increase by 88.9% over the eight-year period (Dobbs et al., 2013), reaching a level of 20%.

To understand the scope for e-commerce to further improve consumer welfare and reduce spatial consumption inequality, we further lower the e-commerce shipping cost \(\tau_{ij}^E\) from the calibrated level. Specifically, we decrease the e-commerce cost according to \(\tau_{ij}^{E'} = k \tau_{ij}^E\), where \(k\) is a common factor. We pick \(k\) so that the overall online expenditure share for the economy is about 24.0%, three times its 2013 value, which is well within reach based on the projected growth in e-commerce.

We compare the outcomes under this experiment to the economy without e-commerce to obtain the cumulative effects of e-commerce. Figures 6a and 6b plot the cumulative welfare gains
against population and market potential, respectively. As a result of the further reduction in online shipping cost, the cumulative percentage increase in real income for an average city is 4.9%. Moreover, as Figure 6 shows, the cumulative welfare gains from e-commerce are negatively correlated with population and with market potential. The slopes for the economy with higher levels of e-commerce in Figure 6 are much more negative than for the benchmark e-commerce economy. Therefore, further development of e-commerce in China would be able to substantially reduce the inequality in real wage between cities, while increasing the average real wage.

Figure 6: Cumulative Welfare Gains with Further Development of e-commerce

(a) By Population

(b) By Market Potential

Notes: calculation based on model simulations by the authors. ‘Benchmark’ refers to the realized gains from e-commerce under our benchmark calibration. ‘Further Development’ refers to future cumulative gains when the online expenditure share is three times its 2013 level.