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***From Street Stalls to Screens: The Price
Integration of China's Cities***

Marina Glushenkova and Marios Zachariadis

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Marina Glushenkova ^{*} Marios Zachariadis [†]

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Abstract

We investigate the extent to which the substantial decline in price dispersion across Chinese cities can be attributed to the emergence and expansion of e-commerce. We find that online trade exerted a strong negative effect on bilateral price differences across Chinese cities over time for the period from 2006 to 2021. Furthermore, we find that the impact of online trade on price integration was even more pronounced for cities located farther apart geographically. As a result of this mechanism, price dispersion declined significantly over the study period, reaching levels comparable to those observed among core euro-area economies by the end of the sample period.

JEL Classification Codes: E3, F4, H54, O5, R4

Keywords: market segmentation, price convergence, e-commerce, road infrastructure, welfare.

^{*}Nottingham University Business School China, 199 Taikang East Road, 315100 Ningbo, China, email: marina.glushenkova@nottingham.edu.cn

[†]Department of Economics, University of Cyprus, 1678 Nicosia, Cyprus. E-mail: zachariadis@ucy.ac.cy

1 Introduction

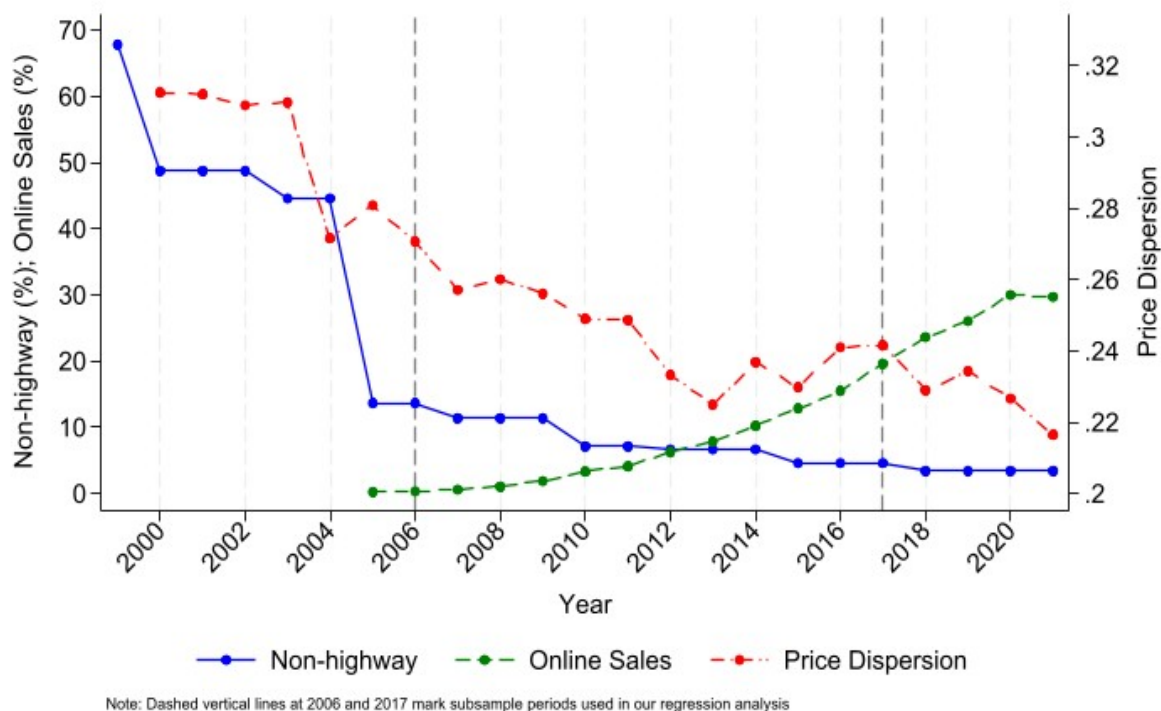
Market segmentation inhibits competition and reduces overall economic welfare. Consequently, measuring and understanding its evolution over time is important for assessing the degree of inefficiency associated with an economy or group of regions. A natural way to measure market segmentation and, conversely, the extent of economic integration, is to examine price level differences across locations over time. In the present paper, we follow this approach using city-level microeconomic price level data, together with variation in e-commerce penetration across cities and products, and a time-varying measure of actual travel time between cities that captures ongoing highway infrastructure development, to assess the role of the rise of e-commerce in integrating markets across China.

A large literature in international economics has utilized price level microdata to understand the determinants of market segmentation and its evolution over time. Crucini et al. (2005) consider law-of-one-price deviations across European Union economies and document an average price dispersion of 28 percent during the period from 1975 to 1990. Glushenkova and Zachariadis (2016) show that average price dispersion falls to about 23 percent by 2010, after the introduction of the euro. By comparison, according to our microeconomic price levels data, the average price dispersion was near 31 percent across China's cities in the early 2000's and fell to less than 22 percent by the end of our sample in 2021.

This significant reduction in the degree of price dispersion across China's cities during these two decades suggests, by this metric, a level of integration close to that among core euro area economies. Such an improvement in arbitrage across locations is consistent with substantial efficiency gains and corresponding increases in economic welfare. We try to understand the forces behind this increase in integration across China's cities, focusing on the rise of e-commerce as a potential explanation for this phenomenon during the period under study.

The development of transport infrastructure is another potentially important factor that has contributed to the integration of China's cities in the past. The important role of highway infrastructure in lowering internal trade costs and raising welfare is well understood (see, e.g., Allen and Arkolakis (2014) and Allen and Arkolakis (2022)). Using data for 50

Figure 1: Price Dispersion, Highway Construction, and E-commerce



goods in 29 capital cities in China for the period 1993-1998, Li and Chen (2013) show, for example, that inter-regional price differences declined by approximately 30 percent following the expansion of the railway network. Similarly, Fan et al. (2023) found that expressway construction in China between 1999 and 2010 increased domestic trade by 14%, contributing to price convergence. Moreover, Kaboski et al. (2026) show that, beyond facilitating trade, improved connectivity in China spurred broader structural changes including a shift out of agriculture and a surge in business starts.

However, while the expansion of transport infrastructure played a dominant role in domestic market integration in the late 1990s and early 2000s, its direct impact likely diminished as the network matured and a new and powerful force emerged in the following decade: the rise of e-commerce. As shown in Figure 1, the share of e-commerce in overall trade increased by more than a hundredfold during the period under study, from less than 0.3% in 2006 to nearly 30% by 2021. By contrast, the highway network was largely completed by the beginning of the sample, with the non-highway share dropping from 68 percent to 14 percent between 1999 and 2006. As a result, average travel time between China's cities had fallen

from 42 hours in 1999 to 27 hours by 2006. Thus, whereas transport infrastructure might well have played the central direct role in the price integration of China’s cities in the early 2000s, it appears plausible based on Figure 1, that e-commerce may be the main driving force after 2006. Given the period under study, we will focus on the role of e-commerce.

Our analysis contributes to the literature along several important dimensions. First, unlike much of the existing research that relies on aggregated price indices or limited city samples, we employ a detailed disaggregate dataset of retail prices covering a large number of Chinese cities. This allows us to examine bilateral price differences at a granular level, capturing the rich variation in price dispersion across products and regions that aggregate measures inevitably obscure. Second, we go beyond conventional time-invariant distance measures based on simple straight-line or as “the crow flies” calculations. Instead, we employ a time-varying Geographic Information System (GIS) measure of actual travel time along the shortest road routes between city centers. Unlike conventional straight-line distance measures, this approach captures changes in highway infrastructure between cities over time rather than assuming constant distance, thereby capturing time-varying trade frictions rather than imposing static travel costs. Third, we construct city-specific and product-category-specific online share measures. This granularity matters because e-commerce reduces price differences for particular products in particular cities - not just on average across all products or all cities. These novel data and measurement strategies allow us to identify the effect of e-commerce from variation across city pairs, products, and time, while controlling for product and city-pair fixed effects, providing credible evidence on whether, and under what conditions, e-commerce brought prices closer across China.

We find that online trade had a strong negative effect on bilateral price differences across China’s cities over time. Cities that experienced the largest growth in online commerce during the period under study (those in the top 5% of the distribution) saw their online trade share rise by 0.48 percentage points with an associated reduction in bilateral price differences of about 0.95% in the baseline model (1.03% in the more complete model in the third column of Table 3). By contrast, cities with very small increases in online activity (the bottom 5%)

experienced an increase in online share of only 0.018 percentage points corresponding to a negligible reduction in price differences of merely 0.03% to 0.04%. These results suggest that e-commerce substantially improves market integration in locations where online trade becomes widely adopted, but has little effect where online penetration remains low. As a result of this mechanism, by the end of the sample period price dispersion across China's cities had fallen to levels comparable to that among core euro-area economies. Importantly, this price-converging effect is particularly pronounced for more distant city-pairs, consistent with e-commerce alleviating the traditional trade frictions associated with distance.

Theory suggests that e-commerce should reduce search costs and increase price transparency, expanding consumer access to sellers outside local markets and intensifying competition, while also enlarging market size for firms so that their production and distribution costs fall.¹ It is thus no surprise that previous work, e.g. Gorodnichenko and Talavera (2017), has anticipated that as retail shifts to the internet "price differentials are going to be smaller and less persistent, bringing the law of one price closer to reality." We examine this prediction for the case China. As the world's largest e-commerce market, where digital platforms now account for nearly half of all retail transactions, China represents a critical case for understanding whether the internet delivered on its promise of frictionless arbitrage and spatial price equalization. This, and the availability of appropriate disaggregate retail price data across space and time, along with information regarding highway infrastructure between cities, and variation in e-commerce penetration across space and products, make China an especially valuable setting for studying this issue.

In related work, the seminal early contribution by Brown and Goolsbee (2002), focusing on the life insurance market, showed how the rise of the internet brought prices closer and increased competition and consumer surplus in the United States. The more recent literature on the effects of online trade on retail prices mostly focuses on the comparison of the degree of price stickiness and the estimation of price convergence rates in online and traditional markets. For example, Gorodnichenko et al. (2018), based on an analysis of daily price data for more than 50,000 goods in the US and the UK, find that prices are similarly sticky in

¹For example, online retailers often have centralized warehouses and nationwide logistics.

online and physical markets, while Duch-Brown et al. (2021) show that the convergence rate is equally fast for online and offline channels for consumer electronics product categories in the EU.

Fan et al. (2018) use a multi-region general equilibrium model to consider the welfare gains from e-commerce in China as a new technology that reduces trade costs and the fixed cost of market entry. They show that welfare gains from e-commerce were on average 1.6 percent and 30 percent bigger for smaller cities with limited market potential. Our analysis is complementary to this earlier work in that we attempt to link online trade to price differences across cities as a measure of welfare-reducing market segmentation. Using city-level disaggregate price levels, a time-varying measure of actual travel time between cities, and product-region-specific e-commerce, we find that the gains in terms of falling price dispersion arising from e-commerce were indeed greater for more distant cities, consistent with greater welfare gains for such locations as predicted by the Fan et al. (2018) model.

The next section presents our data and some preliminary analysis. Following that, we present our estimation exercises and results, before briefly concluding.

2 Data construction and preliminary analysis

2.1 Retail Prices

We use a monthly panel of retail prices obtained from the China Price Information Centre, the primary source for China’s official Consumer and Producer Price Indices. This extensive dataset is characterized by a high standard of reliability and covers over 180 products and services in 165 cities from January 2000 to June 2021. Fan and Wei (2006) use an early version of this to study the law of one price in China for 36 cities from 1990 to 2003. Here, we consider the recent period from 2000 to 2021 while expanding the sample to more than 100 cities.²

²As the data are not uniformly available across this entire period, we apply a set of restrictions to ensure comparability over time and across goods and locations.

Using this panel of prices, we first explore the geographical dimension of the data. In Section 3, we study the effect of online trade on bilateral price differences. For this purpose, we calculate bilateral price differences as

$$q_{ijkt} = p_{ijt} - p_{ikt}, \quad (1)$$

where p_{ijt} is the logarithm of the price for item i in city j at time t , $p_{ijt} = \ln(P_{ijt})$. Bilateral price differences are informative about the degree of domestic price integration, with larger differences indicating a higher degree of market segmentation. Figure 2 plots the densities of q_{ijkt} for 2000, 2006, 2017, and 2021 to show how price differences have changed over time.³ The density function becomes more highly peaked at zero over time, suggesting smaller price differences and thus a higher degree of market integration. Notably, the major changes took place between 2000 and 2006, and then between 2017 and 2021, while during the period from 2006 to 2017 the adjustments were relatively small. This, along with the fact that the road network was largely completed by 2006 and certainly before 2017, supports our hypothesis that while transport infrastructure was the key driver of integration in the early 2000s, a subsequent force - the rise of e-commerce - is a more likely candidate to have played the more dominant role in recent years. We test this hypothesis in the next section.

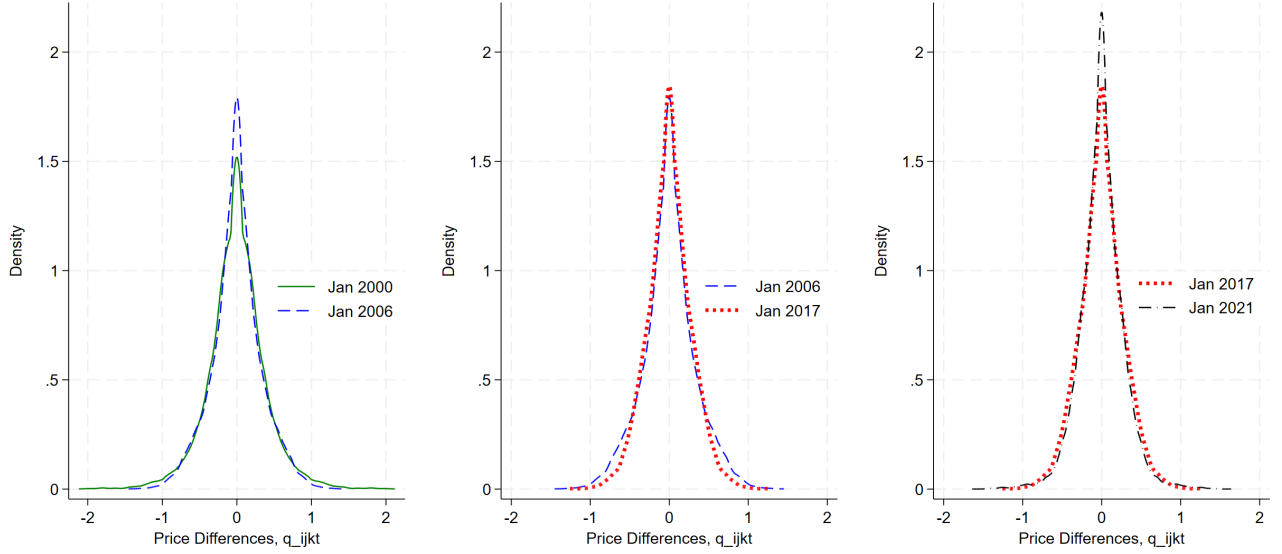
For the purposes of our bilateral price differences analysis, we convert absolute monthly price differences to annual by taking the average over the year. This is deemed necessary due to the non-availability of bilateral explanatory variables at a higher frequency.⁴ To ensure comparability over time, we keep a price if the good is available in at least 80% of cities. We construct a balanced panel by ensuring that the product is available for a city pair in each period, leaving us with 97 cities and 54 items for our analysis.

2.2 Online Retail Shares

Aggregate category-specific online retail sales used in section 3.2.1 are obtained from the aggregate industry-level data in the China Digital Economy Research database, provided by

³This figure utilizes a balanced panel sub-sample of 59 cities and 19 goods available in every single period.

⁴We note that the computational demands of using monthly bilateral price differences would be excessive.

Figure 2: **Empirical Distribution of Bilateral Price Differences**

the China Stock Market & Accounting Research Database (CSMAR). These data, sourced from the Chinese Ministry of Commerce, are available starting in the first quarter of 2017 for the seven aggregate product categories shown in Table 1. For each product category g and year s , we define onlineness ($Onlineness_{gs}$) as the share of that category's online retail sales in total online retail sales for the year.⁵

Second, as a robustness check, in section 3.2.2, we use more disaggregated data from Statista eCommerce Market Insights, which offers product-category-level e-commerce data.⁶ For each product category g' and year s , we calculate onlineness ($Onlineness_{g's}$) as the category's business-to-consumer (B2C) online revenue divided by total B2C online revenue across all categories. Using CSMAR restricts our analysis to seven product categories, whereas Statista data allows us to match our products to the twenty-two disaggregated categories shown in Table A1.

We are particularly interested in a category's online share in total retail sales since this can capture the potentially increasing importance of online trade over time in addition to the good's tendency to be traded online. However, this measure is not readily available. We thus

⁵CSMAR data are available at a quarterly frequency. We temporally aggregate the quarterly measures to the annual level by taking the mean onlineness for each category and year.

⁶Available at <https://www.statista.com/outlook/ecommerce-outlook>

have to construct it by utilizing the available data on the goods' onlineness along with the overall online retail share. We obtain the data on province-level online and total retail sales from China Digital Economy Research database, provided by CSMAR, a comprehensive source covering China's finance and economy. Since we aim to capture the effect of e-commerce on cross-city price differences, we ideally want to have city-level variation in online sales. We thus proxy for city-level e-commerce activity using per capita post volumes, $PerCapPostVolume_{js}$.⁷ Consequently, we construct a product-specific city-level measure of online shares as

$$OnlineShare_{gjs} = Onlineness_{gs} \times (\omega_{j \in p, s} \times \frac{OnlineRetailSales_{ps}}{TotalRetailSales_{ps}}) \quad (2)$$

where $\omega_{js} = \frac{PerCapPostVolume_{js}}{\sum_{j \in p} PerCapPostVolume_{js}}$ is a proxy for city j 's weight in province p 's e-commerce volume in year s , while $OnlineRetailSales_{ps}$ and $TotalRetailSales_{ps}$ are the online and total retail sales of province p in year s , respectively.

Table 1 presents the values of onlineness and online shares for each of the seven aggregate product category for 2017, 2019, and 2021.⁸ As we can see there, whereas the degree of online presence increased for some product categories (e.g., articles of daily use) and fell for others (notably, clothing and household appliances), the online share increased for all product categories (except household appliances, for which it stayed stable), consistent with an increasing importance of online trade over this time period. Table A2 presents the values of onlineness and online shares for the 22 disaggregate product categories.

The timeframe of our disaggregate and aggregate categories online shares analyses is 2017 to 2021. This is dictated by data availability, as the data required to measure onlineness at the product level, and province-level retail sales do not exist prior to 2017.

To be able to utilize the entire 2006-2021 period for which we have price data in our baseline

⁷This follows Wei et al. (2025), who use express delivery volumes to proxy for city-level e-commerce activity in China, since online orders are delivered via post.

⁸The sum of the onlineness measures across categories does not equal one because the table reports only the categories that can be matched with our price data.

Table 1: Onlineness and Online Shares

Product Category	Onlineness			Online Share		
	2017	2019	2021	2017	2019	2021
Articles of daily use	0.065	0.157	0.159	0.013	0.041	0.047
Beverage	0.005	0.012	0.012	0.001	0.003	0.003
Clothing	0.290	0.239	0.223	0.057	0.062	0.066
Communication Equipment	0.090	0.063	0.075	0.018	0.016	0.022
Grain and Oil, Food	0.041	0.072	0.072	0.008	0.019	0.021
Household Appliances	0.169	0.123	0.104	0.033	0.032	0.031
Tobacco and Liquor	0.002	0.008	0.010	0.000	0.002	0.003

Note: Online Share is calculated using total national online sales and national retail sales, i.e. $OnlineShare_{gs} = Onlineness_{gs} * (OnlineRetailSales_s / TotalRetailSales_s)$

analysis in section 3.1, we abstract from the product dimension and consider the following:

$$OnlineShare_{js} = \omega_{js} \times \frac{OnlineSales_s}{TotalRetailSales_s}, \quad (3)$$

where $\omega_{js} = \frac{PerCapPostVolume_{js}}{\sum_j PerCapPostVolume_{js}}$ is a proxy for city j 's weight in national e-commerce volume in year s , and $OnlineSales_s$ and $TotalRetailSales_s$ are national online and total retail sales in year s , respectively. The evolution of the online share for each city over time is shown in Table A3 of the Appendix for selected years.

2.3 Transport Infrastructure

To understand the forces behind the observed price convergence over the period under study, we utilize transport infrastructure data in addition to e-commerce data.

We collect data on the least-cost road paths between city pairs from 1998 to 2018. These paths are constructed using digitized maps of China's road network. The data for 1998, 2001, 2003, 2005 and 2007 are sourced from Yang (2018), who calculated them using digital maps provided by the Australian Consortium for the Asian Spatial Information and Analysis Network (ACASIAN). The data for recent years, i.e. 2010, 2012, 2015, and 2018, are obtained from NanInfo⁹, a Chinese listed company providing high-resolution maps.

Importantly, we construct a measure of travel time as a proxy for the travel cost that needs to be incurred for trade to occur between two cities. This measure accounts for road

⁹<https://www.seeway.ai/about-us>

quality (e.g., highways versus non-highways) in addition to the physical distance between cities. Using travel time rather than road length allows us to better capture changes in road quality and is therefore more closely related to trade costs. In contrast to previous work, our ‘distance’ measure thus exhibits variation over time, allowing us to account for changes in bilateral transportation costs between Chinese cities reflected in improvements in the quality of the road network over time.

To calculate travel time, we apply average freight transport speeds of 90 km/h on highways and 40 km/h on non-highway roads, based on China Automotive Technology and Research Centre estimations for actual average speed for freight vehicles. Travel time, TT_{jkt} , is calculated as $TT_{jkt} = (HighwayDistance_{jkt}/90) + (NonHighwayDistance_{jkt}/40)$.

Table 2 shows the evolution of average price dispersion, travel time, and online share between 2000 and 2021, along with the earliest available road network data (from 1998). Average price dispersion declines from 0.313 in 2000 to 0.257 in 2007 and 0.216 in 2021, comparable to core euro-area economies from Glushenkova and Zachariadis (2016), for example. Our data indicate that the most substantial road quality enhancements occurred between 1998 and 2006, as evidenced by the dramatic drop in travel time from 41.6 hours to 26.8 hours, and that changes in average travel time during more recent periods have been marginal. This suggests that factors beyond transport infrastructure development have contributed to the ongoing price integration after 2006. Notably, the last column of Table 2 reveals a substantial increase in the share of e-commerce in overall trade in recent years, rising by more than a hundredfold from about 0.2% in 2005 to about 1% in 2008 and to nearly 30% by 2021. This evidence suggests a potential change in the main driver of market integration, where transport infrastructure drove initial price convergence in the early 2000s, and e-commerce likely becoming the primary engine of continued price integration in more recent years, as shown by its rapid expansion alongside stable travel times but declining price dispersion in Table 2.

Table 2: Evolution of Price Dispersion, Travel Times, and Online Share

year	Mean $SD_{it}(p_{ijt})$	Med $SD_{it}(p_{ijt})$	Mean $(TravelTime_{jkt})$	Med $(TravelTime_{jkt})$	$OnlineShare_t$
1998	-	-	41.6	37.2	-
2000	0.313	0.311	37.6	33.0	-
2001	0.312	0.315	37.6	33.0	-
2002	0.309	0.309	37.6	33.0	-
2003	0.310	0.312	36.3	31.6	-
2004	0.272	0.276	36.3	31.6	-
2005	0.281	0.284	26.8	22.3	0.23%
2006	0.271	0.265	26.8	22.3	0.34%
2007	0.257	0.244	26.1	22.0	0.61%
2008	0.260	0.250	26.1	22.0	1.05%
2009	0.256	0.255	26.1	22.0	1.88%
2010	0.249	0.238	23.2	19.6	3.33%
2011	0.249	0.236	23.2	19.6	4.11%
2012	0.233	0.221	23.1	19.5	6.23%
2013	0.225	0.220	23.1	19.5	7.84%
2014	0.237	0.229	23.1	19.5	10.26%
2015	0.230	0.229	22.2	18.8	12.88%
2016	0.241	0.238	22.2	18.8	15.51%
2017	0.242	0.240	22.2	18.8	19.59%
2018	0.229	0.220	21.4	18.2	23.64%
2019	0.234	0.230	21.4	18.2	26.06%
2020	0.227	0.226	21.4	18.2	30.00%
2021	0.216	0.218	21.4	18.2	29.69%

Notes: $SD_{it}(p_{ijt})$ is described in equation (2) and captures price dispersion across cities. In the first and second columns, we calculate annual price dispersion measures using a two-step procedure. First, for each period, t , we compute the standard deviation and median of prices across products, i . Second, we average these dispersion measures across months to obtain year-level estimates. Columns 3 and 4 report the average and median (MED) travel times across all city pairs, respectively. The travel time is constructed using digitized maps of China's road network for the years 1998, 2000, 2003, 2005, 2007, 2010, 2012, 2015, and 2018. The last column reports the national online share, defined as total online sales divided by total retail sales.

2.4 Other Explanatory Variables

Following Fan et al. (2018), we calculate market potential as $MP_{js} = \sum_{k \neq j}^N \frac{pop_{ks}}{dist_{jks}}$, where pop_{ks} is the population of city k in year s , and $dist_{jks}$ is the shortest road distance between cities j and k in year s . Different from previous studies, we use the actual road distance between cities instead of Euclidean distance, thus our distance measure varies over time with the development of road infrastructure. We use this to account for the potentially moderating effect of physical market potential on the role of online trade.

Finally, to assess the importance of non-traded input costs on price differences, we construct wage differences between city pair, jk , in year s as $WageDif_{jks} = \ln(W_{js}) - \ln(W_{ks})$ using EPS data.¹⁰

¹⁰Available at <https://www.epschinadata.com/>

3 Estimation and empirical results

3.1 Analysis based on aggregate online shares

In order to consider the entire 2006-2021 period, essential for understanding the evolving role of e-commerce, in our baseline specification we initially abstract from the product dimension in online shares and focus on city-specific variation.¹¹

We estimate the following baseline regression:

$$|q_{ijks}| = \beta_0 + \beta_1 \text{OnlineShare}_{js} + \beta_2 \text{WageDiff}_{jks} + \beta_3 \text{SameProv}_{jk} + \delta_i + \delta_j + \delta_k + \text{Trend}_s + \varepsilon_{it}, \quad (4)$$

where $|q_{ijks}|$ stands for the average absolute log price difference for product i between cities j and k in year s , OnlineShare_{js} is the online share of city j in year s , calculated as described in equation (3), WageDiff_{jks} captures wage differences between any two cities j and k in year s , SameProv_{jk} is a same-province dummy which takes the value 1 if two cities belong to the same province and 0 otherwise, and δ_i , δ_j , δ_k , are good i , city j and city k dummies respectively, and Trend_s is a common linear time trend capturing secular economy-wide developments common to all products and city pairs. The results are shown in Table 3.

The estimated magnitude for the impact of e-commerce on price differences is -1.988 in column (1) of Table 3. This estimated effect implies that the 1.6% and 1.2% respective increases in online shares observed during the period under study for the two cities with the highest online shares in 2021, Shenzhen and Guangzhou (presented in Table A3 of the Appendix) are associated with 3.2% and 2.4% declines in bilateral price differences.¹² However, the effects vary considerably across the distribution of online share changes. The 0.48% increase in online share observed for cities at the top 5 percentile is associated with a 0.95% (1.03%) decline in bilateral price differences, whereas the 0.018% increase for cities at the bottom 5 percentile is associated with a negligible decline of only 0.03% (0.04%) in our

¹¹As described at the end of subsection 2.2, this is deemed necessary due to data availability constraints for product-specific online shares that restrict the disaggregate online shares analysis to the 2017-2021 period.

¹²The change in price differences associated with a change in online share of 0.0163 (0.0124) for Shenzhen (Guangzhou), is calculated as $e^{\beta \times \Delta X} - 1 = e^{-1.988 \times 0.0163} - 1 \approx -0.0318$ (-0.0243), which amounts to a 3.18% (2.43%) decline.

Table 3: Effect of Online Share on Bilateral Price Differences (2006-2021)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Online Share	-1.988*** (0.111)	-2.136*** (0.111)	-2.151*** (0.112)	0.334 (0.406)	76.840*** (2.260)	81.820*** (2.327)
Wage Diff.	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
Same Province	-0.058*** (0.003)	-0.006* (0.003)	-0.006* (0.003)	-0.006* (0.003)	-0.006 (0.003)	-0.006 (0.003)
Travel Time		0.033*** (0.001)	0.033*** (0.001)	0.034*** (0.001)	0.033*** (0.001)	0.034*** (0.001)
Market Poten.			-0.004 (0.003)	-0.003 (0.003)	-0.004 (0.003)	-0.004 (0.003)
Interactions terms:						
Travel Time*Online				-0.918*** (0.144)		-1.293*** (0.144)
Market Poten.*Online					-6.685*** (0.191)	-6.810*** (0.192)
Total effects:						
Online share				-2.179***	-1.178***	-1.200***
Travel time				0.033***		0.033***
Market potential					-0.009***	-0.008**
Constant	0.258*** (0.025)	0.156*** (0.025)	0.177*** (0.031)	0.173*** (0.031)	0.169*** (0.031)	0.163*** (0.031)
Trend	yes	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes	yes
City j FE	yes	yes	yes	yes	yes	yes
City k FE	yes	yes	yes	yes	yes	yes
Obs.	2,541,050	2,541,050	2,541,050	2,541,050	2,541,050	2,541,050
R-squared	0.500	0.503	0.503	0.503	0.503	0.503

Notes: Robust standard errors are presented in parentheses. Asterisks indicate a significance level of the coefficients ***1%, **2.5%, and *5%. The total effect of X is $\frac{\partial E[Y]}{\partial X} = \hat{\beta}_X + \hat{\beta}_{X \times Z} \cdot \bar{Z}$, where $\hat{\beta}_X$ is the coefficient on X , $\hat{\beta}_{X \times Z}$ is the coefficient on the interaction term between X and Z , and $\bar{Z}$ is the sample mean of variable Z .

baseline model in column 1 of Table 3 (in the more comprehensive model in column (3)). Similarly, cities at the top quintile of the online share distribution experienced an increase of 0.20% in online shares associated with a decline in price differences of 0.39% to 0.42% depending on the model specification, whereas cities at the bottom quintile experienced an increase of 0.04% in online shares associated with a minute 0.07% to 0.08% decline in price differences. This stark contrast demonstrates that the growth of e-commerce was conducive in facilitating price convergence across Chinese cities in cities with high online penetration expansion but did not do much for cities where online shares remained low.

As already alluded to in the previous paragraph, the direct effect of online shares is even larger in columns (2) and (3) of Table 3 where we consider the effect of trade-related factors such as travel distance (measured by the logarithm of travel time between cities) and physical market potential on bilateral price differences, as compared to the baseline model of column (1), and is now estimated at -2.136 and -2.151 respectively for these two more

comprehensive specifications. In line with the predictions of arbitrage theory, travel distance between cities as captured by actual travel time, which is introduced in column (2) of Table 3, has a positive direct effect on price differences equal to 0.033 in both columns (2) and (3), acting as a barrier to market integration. At the same time, we do not find a significant direct effect of market potential on price differences when we introduce this in column (3). In column (4), we allow for an interaction of online shares with travel time. This tests whether the effect of online trade is stronger for more distant cities, following Fan et al. (2018). Then, in column (5), we also introduce an interaction term between market potential and online shares, which tests whether the effect of online trade is stronger for cities with smaller market potential for physical trade, following, again, Fan et al. (2018).

The negative sign of the interaction term of travel time and online share (-0.918 and -1.293, respectively, in columns (4) and (6)) supports the hypothesis that the effect of e-commerce is stronger for more distant cities. At the same time, the negative interaction term between market potential and online share (-6.685 and -6.810, respectively, in columns (5) and (6)) that we estimate here does not support the hypothesis that the effect of e-commerce is stronger in cities with lower market potential. The opposite appears to be the case. Reassuringly, we document a significant positive (negative) total effect of travel time (market potential) in columns (4) and (6) ((5) and (6)) of Table 3.

Finally, the total effect of the online share in columns (4) to (6) of Table 3, which includes the interaction between travel-related factors and online share, varies between -2.179 and -1.178.¹³

3.2 Analysis based on category-level online shares

In this section, we go beyond aggregate online shares to utilize category-level ones. To do so, we now sacrifice the long-period dimension of the previous section and necessarily focus on the subperiod from 2017 to 2021.

¹³We note that the large positive *direct* effect we estimate for the online share in columns (5) and (6), is attributable to the hypothetical unrealistic (non-existent in the data) case of zero market potential, and is not relevant to consider on its own. As interpreting this coefficient in isolation can be misleading, we also report the total effect of online share.

3.2.1 Short sample analysis based on category-level online shares

Here, we assess the impact of e-commerce penetration on bilateral price differences using the seven aggregate category online shares shown in Table 1. This exploits both the product and geographic dimensions of our price data, allowing us to examine how bilateral price differences are affected by the online share ($OnlineShare_{gjs}$) characterizing different types of products in different cities in a given year. The analysis based on category-level online shares is limited to the recent period 2017-2021 due to data availability constraints for category-specific online shares.

We estimate our baseline equation (4) using as the key explanatory variable the online share of product category g in city j in year s , $OnlineShare_{gjs}$, calculated as in equation (2).

Table 4 presents the estimation results. As shown in the first row of estimates in columns (1) to (3), the effect of the online share on price differences is negative, varying between -0.578 and -0.589 . This implies that a one-percentage-point increase in the online share leads to about 0.58% decrease in bilateral price differences.

The finding regarding the impact of travel time on price differences persists in this shorter time period analysis and is comparable in magnitude to the effect estimated for the longer sample (0.029 in column (2) of Table 4 versus 0.033 in column (2) of Table 3), in line with arbitrage theory.

Moreover, we now find a significant negative direct effect of market potential on bilateral price differences in column (3) of Table 4, which persists in columns (4) to (6). This suggests that cities with higher market potential, and thus easier access to physical markets, tend to have smaller price differences, in line with the predictions of arbitrage theory.

The estimated coefficient on the interaction term between travel time and online share in column (4) of Table 4 is -0.302 and significant at the 5% level, suggesting that indeed the effect of online trade in bringing prices closer is stronger for more distant cities. The total effect of the online share is -0.586 in column (4), which is similar in size to the direct effect estimated in columns (1) to (3) for the models without the interaction term of travel time

Table 4: Effect of Aggregate Categories Online Share on Bilateral Price Differences

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Online Share	-0.578*** (0.122)	-0.589*** (0.122)	-0.586*** (0.122)	0.223 (0.371)	-5.148** (2.208)	-3.630 (2.477)
Wage Dif	0.006*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Same Province	-0.059*** (0.003)	-0.013*** (0.004)	-0.013*** (0.004)	-0.013*** (0.004)	-0.013*** (0.004)	-0.013*** (0.004)
Travel Time		0.029*** (0.001)	0.029*** (0.001)	0.030*** (0.001)	0.029*** (0.001)	0.030*** (0.001)
Market Potential			-0.036*** (0.006)	-0.035*** (0.006)	-0.036*** (0.006)	-0.036*** (0.006)
Interaction Terms:						
Travel time*Online				-0.302* (0.135)		-0.248! (0.144)
Market Potential*Online					0.380* (0.183)	0.309 (0.193)
Total effects:						
Online share				-0.586***	-0.637***	-0.627***
Travel time				0.029***		0.029***
Market potential					-0.035***	-0.035***
Constant	0.256*** (0.031)	0.167*** (0.032)	0.360*** (0.047)	0.354*** (0.047)	0.365*** (0.047)	0.359*** (0.047)
Trend	yes	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes	yes
City j FE	yes	yes	yes	yes	yes	yes
City k FE	yes	yes	yes	yes	yes	yes
Observations	827,024	827,024	827,024	827,024	827,024	827,024
Number of id	172,885	172,885	172,885	172,885	172,885	172,885
Between R-squared	0.337	0.339	0.339	0.339	0.339	0.339

Notes: Robust standard errors are presented in parenthesis. Asterisks indicate a significance level of the coefficients ***1%, **2.5%, and *5%. ! p-value equals 0.085. The total effect of X is $\frac{\partial E[Y]}{\partial X} = \hat{\beta}X + \hat{\beta}_{X \times Z} \cdot \bar{Z}$, where $\hat{\beta}X$ is the coefficient on X , $\hat{\beta}_{X \times Z}$ is the coefficient on the interaction term between X and Z , and $\bar{Z}$ is the sample mean of variable Z .

with the online share.

We also test for the moderating effect of physical market potential on the importance of online trade. To do so, in column (5) of Table 4, we add market potential and its interaction term with online shares to our regressions. We find that the coefficient on this interaction term is positive, indicating that e-commerce appears to be most effective for integrating cities with limited physical market access in this case. However, when we additionally include travel time and its interaction with online share in column (6), the interaction term with market potential becomes insignificant, while the interaction with travel time is significant at the 10% level. This suggests, again, that market potential was not a key moderating factor in the relationship between e-commerce and price differences for our sample.

Finally, the total effect of the online share in columns (5) and (6), having added the interaction terms with travel distance and market potential, is respectively -0.637 and -0.627 ,

larger but comparable in size to the direct effect estimated in columns (1) to (3) for the models without the interaction term of travel time with the online share.

3.2.2 Short sample analysis based on disaggregate online shares

Finally, we refine our analysis by re-estimating equation (4) using the twenty-two disaggregate categories' online shares from Statista shown in Table A2 in place of the aggregate category shares employed in the previous sub-section. This allows us to examine whether the effects observed at the aggregate categories level hold at a finer level of product detail. The results are in Table 5.

Table 5: Effect of Disaggregate Online Share on Bilateral Price Differences

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Online Share	-0.585*** (0.168)	-0.611*** (0.168)	-0.622*** (0.168)	1.311** (0.541)	12.972*** (3.140)	18.878*** (3.395)
Wage Dif	0.006*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Same Province	-0.059*** (0.003)	-0.013*** (0.004)	-0.013*** (0.004)	-0.013*** (0.004)	-0.014*** (0.004)	-0.013*** (0.004)
Travel Time		0.029*** (0.001)	0.029*** (0.001)	0.030*** (0.001)	0.029*** (0.001)	0.030*** (0.001)
Market Potential			-0.036*** (0.006)	-0.036*** (0.006)	-0.035*** (0.006)	-0.035*** (0.006)
Interaction terms:						
Travel Time*Online				-0.722*** (0.195)		-0.974*** (0.202)
Market Poten.*Online					-1.134*** (0.260)	-1.409*** (0.267)
Total effects:						
Online Share				-0.624***	-0.483***	-0.452***
Travel Time				0.029***		0.029***
Market Potential					-0.037***	-0.036***
Constant	0.255*** (0.031)	0.167*** (0.032)	0.363*** (0.047)	0.358*** (0.047)	0.358*** (0.047)	0.350*** (0.047)
Good FE	yes	yes	yes	yes	yes	yes
City i FE	yes	yes	yes	yes	yes	yes
City j FE	yes	yes	yes	yes	yes	yes
Time trend	yes	yes	yes	yes	yes	yes
Observations	827,024	827,024	827,024	827,024	827,024	827,024
Number of id	172,885	172,885	172,885	172,885	172,885	172,885
Between R-squared	0.337	0.339	0.339	0.339	0.339	0.339

Notes: Robust standard errors are presented in parenthesis. Asterisks indicate a significance level of the coefficients ***1%, **2.5%, and *5%. †- p-value equals 0.052. The total effect of X is $\frac{\partial E[Y]}{\partial X} = \hat{\beta}_X + \hat{\beta}_{X \times Z} \cdot \bar{Z}$, where $\hat{\beta}_X$ is the coefficient on X , $\hat{\beta}_{X \times Z}$ is the coefficient on the interaction term between X and Z , and $\bar{Z}$ is the sample mean of variable Z .

These results confirm the findings from the previous subsection. The direct effect of online share on price differences remains negative and statistically significant, ranging between -0.585 and -0.622 in columns (1) - (3). This implies that a one-percentage-point increase in product-level online share reduces bilateral price differences by approximately 0.6% - a

magnitude similar to the aggregate categories-based estimates. This consistency suggests that both measures capture the same underlying price-reducing effect of e-commerce, reinforcing our conclusion that the development of online trade has been conducive to domestic price integration. The total effect of online share when we introduce its interaction with travel time and market potential, is comparable in size with the direct effect reported in columns (1) to (3), estimated at -0.624 , -0.483 , and -0.452 in columns (4) to (6).¹⁴

Similar to the results presented in Table 4, travel time exerts a positive direct effect on price differences, confirming its role as a barrier to physical arbitrage. More importantly, the interaction between travel time and online share is negative in both specifications, indicating once again that e-commerce is particularly effective at reducing price differences for distant city-pairs. However, the magnitude of this moderating effect is substantially larger in the disaggregate analysis - the interaction coefficient is -0.722 in the disaggregate online share specification, compared to -0.302 in the aggregate specification, with the former significant at the 1% level. This suggests that product-level data reveal a stronger distance-shrinking effect of e-commerce than aggregate category averages would imply. In other words, when we measure online shares at the disaggregate product level, we find that e-commerce does more to integrate far-flung markets than when we rely on broader category-level measures.

Finally, the coefficient on market potential is comparable across Tables 4 and 5, equal to -0.036 in column (3) of each table for instance, indicating a stable direct effect. Yet, the interaction term between market potential and online share differs markedly. It is positive and only marginally significant in Table 4, but negative and strongly significant in Table 5, where we use disaggregated online shares. This difference may arise because the former specification uses aggregate category-level online shares, which smooths over product-specific variation in e-commerce penetration, potentially attenuating or reversing the true estimated effect of market potential.

¹⁴The direct effect of the online share in columns (4) - (6) is positive. This is because the direct effect of online share represents its effect when travel time and/or market potential is zero, which is a hypothetical non-existent scenario. Interpreting this coefficient in isolation can be misleading, therefore, we report the total effect of online share.

Distinguishing between category- and city-level effect of online shares

Our primary measure, $OnlineShare_{gjs}$, embeds variation along both the product and city dimensions. This aggregation conflates two potentially distinct mechanisms: product-specific online competition and city-level e-commerce intensity (e.g., delivery infrastructure or broadband access). To distinguish between these channels, we construct separate city- and product-specific measures of e-commerce and include them jointly in the regression.

Table 6: Effect of Disaggregate Online Share on Bilateral Price Differences: category- vs city-level effects

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Online Share_{city}	-0.002* (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.010** (0.004)	-0.007 (0.027)	-0.031 (0.029)
Online Share_{category}	-0.010*** (0.002)	-0.010*** (0.002)	-0.011*** (0.002)	0.008 (0.004)	0.060*** (0.020)	0.105*** (0.021)
wageDif	0.011*** (0.001)	0.010*** (0.001)	0.010*** (0.001)	0.009*** (0.001)	0.010*** (0.001)	0.009*** (0.001)
sameProvince	-0.058*** (0.004)	-0.012*** (0.004)	-0.012*** (0.004)	-0.013*** (0.004)	-0.012*** (0.004)	-0.013*** (0.004)
ltime		0.030*** (0.002)	0.030*** (0.002)	0.029*** (0.002)	0.030*** (0.002)	0.029*** (0.002)
lnMP			-0.034*** (0.011)	-0.033*** (0.011)	-0.034*** (0.011)	-0.034*** (0.011)
Interaction terms						
Online Share _{city} *Travel Time				0.002 (0.001)		0.003 (0.002)
Online Share _{category} *Travel Time				-0.007*** (0.002)		-0.009*** (0.002)
Online Share _{city} *Market Potential					0.000 (0.002)	0.002 (0.002)
Online Share _{category} *Market Potential					-0.006*** (0.002)	-0.008*** (0.002)
Total Effects						
Online Share _{city}				-0.004***	-0.003***	-0.004***
Online Share _{category}				-0.010***	-0.010***	-0.010***
Travel Time				0.029***		0.030***
Market Potential					-0.034***	-0.034***
Constant	0.293*** (0.006)	0.210*** (0.007)	0.593*** (0.124)	0.587*** (0.124)	0.603*** (0.124)	0.596*** (0.124)
Good FE	yes	yes	yes	yes	yes	yes
City i FE	yes	yes	yes	yes	yes	yes
City j FE	yes	yes	yes	yes	yes	yes
Time trend	yes	yes	yes	yes	yes	yes
Obs	810,820	810,820	810,820	810,820	810,820	810,820
R-squared	0.297	0.299	0.299	0.299	0.299	0.299

Notes: Online share measures are standardized to ensure comparability using the z-score formula: $z = (x - \mu)/\sigma$, where x is the online share measure, μ is the mean of the online shares, and σ is its standard deviation. Robust standard errors are presented in parenthesis. Asterisks indicate a significance level of the coefficients ***1%, **2.5%, and *5%. The total effect of X is $\frac{\partial E[Y]}{\partial X} = \hat{\beta}X + \hat{\beta}_{X \times Z} \cdot \bar{Z}$, where $\hat{\beta}X$ is the coefficient on X , $\hat{\beta}_{X \times Z}$ is the coefficient on the interaction term between X and Z , and $\bar{Z}$ is the sample mean of variable Z .

First, we construct an aggregate city-level measure of online shares as $OnlineShare_{js} = \omega_{j \in p, s} \times \frac{OnlineRetailSales_{ps}}{TotalRetailSales_{ps}}$, where $\omega_{js} = \frac{PerCapPostVolume_{js}}{\sum_{j \in p} PerCapPostVolume_{js}}$ is a proxy for city j 's weight in province p 's e-commerce volume in year s , $OnlineRetailSales_{ps}$, and $TotalRetailSales_{ps}$ are

the online and total retail sales of province p in year s , respectively. Second, we calculate the product-category measure of e-commerce $OnlineShare_{gs} = Onlineness_{gs} \times \frac{OnlineRetailSales_s}{TotalRetailSales_s}$, where $OnlineRetailSales_s$ and $TotalRetailSales_s$ denote national online and total retail sales in year s , respectively. Including both measures in our regressions simultaneously allows us to assess whether one channel dominates.¹⁵

As shown in Table 6, both mechanisms are present in the data, exhibiting strong statistical significance. The standardized coefficient estimates for the direct effect of city-level online shares varies between -0.002 and -0.003 in columns (1) to (3) and the associated total effect ranges from -0.003 to -0.004 in columns (4) to (6), indicating that a higher involvement of a city in online trade is associated with a reduction in cross-city bilateral price differences. At the same time, the standardized coefficient estimates for the direct effect of category-specific online shares varies between -0.010 and -0.011 in columns (1) to (3), and the associated total effect is -0.010 in columns (4) to (6), implying that product categories with a greater online presence tend to exhibit smaller cross-city price differences.

Notably, the magnitude of the estimated coefficient for the direct effect of the category-specific measure is five times larger than that for the city-level measure in column (1), indicating that product-specific online exposure plays a more important role in reducing cross-city price differences than city-level e-commerce activity. Therefore, price differences shrink more for cities that are more involved in e-commerce in general, but also, and more importantly, for products that are traded more intensively online. Our findings suggest that the convergence mechanism operates predominantly at the product level, i.e., products that are more widely sold via digital platforms face stronger price competition and transparency, which reduces price dispersion across locations.

4 Conclusion

There have long been high expectations (see, e.g. Gorodnichenko and Talavera (2017)) that the shift of retail activity to the internet would bring down spatial price dispersion, moving

¹⁵For comparability purposes, we standardize these measures.

us closer to the theoretical ideal of the law of one price and the welfare-enhancing efficiencies associated with it. China, the world's largest e-commerce market with online trade amounting to about half of all retail transactions, provides an ideal setting for examining whether the internet can fulfill its promise of frictionless arbitrage and spatial price equalization. Against this backdrop, we set out to understand the evolution of market integration across Chinese cities over recent decades to assess the role played by the rise of e-commerce.

The fact that the observed decline in price differences across China's cities continued even after the highway network had been largely completed suggests that another force emerged as the primary driver of market integration following that point in time. The rapid expansion of e-commerce after 2006, which closely followed the completion of the highway network, makes it a natural candidate for explaining this continued reduction in market segmentation. Using city-level disaggregated retail price data over time, together with variation in e-commerce penetration across cities and products, and a time-varying GIS measure of actual travel time between cities capturing ongoing highway infrastructure, we provide formal empirical evidence that supports this hypothesis.

Drawing on three distinct sets of data: a long sample covering 2006-2021, and two shorter ones spanning 2017-2021 and employing aggregate and disaggregate category-level measures of online market shares respectively, we find that the total effect of online shares on bilateral price differences is qualitatively identical across datasets and empirical specifications. The robustness of this result, regardless of the sample period or level of product aggregation, provides strong evidence that e-commerce has become an important force promoting market integration and, by extension, economic efficiency and consumer welfare.

Importantly, we also show that the effect was substantially stronger for geographically distant city pairs, implying greater efficiency and welfare gains for remote locations, consistent with the theoretical predictions of Fan et al. (2018). The finding that remote locations benefited more from this integrative force than economically connected core locations that already engaged in intensive trade between them, suggests that online trade may generate especially large gains in developing or other less connected economies.

At the same time, our analysis suggests that investments in public infrastructure, particularly efficient transportation networks, are crucial for allowing e-commerce to realize its full welfare-enhancing potential: had it not been for the near-completion of the highway system by 2006 with the highway share rising from 32 to 86 percent between 1999 and 2006 and average travel time falling from 42 to 27 hours over the same period, it is difficult to imagine that online trade could have emerged as the powerful integration force that it turned out to be. This points to an important and previously underappreciated complementarity between digital commerce and physical infrastructure, highlighting a new channel through which public infrastructure generates positive economic spillovers in the internet era, adding further credence to the premise regarding the transformative power of physical connectivity enabled by major highway programs (see Kaboski et al. (2026)).¹⁶

¹⁶This improved connectivity plausibly also laid the foundation for e-commerce by enabling faster, more reliable logistics and, as Kaboski et al. (2026) show, by spurring broader structural changes including a shift out of agriculture and a surge in business starts, might have created the entrepreneurial and broader commercial ecosystem on which e-commerce could later thrive.

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Data Appendix

Table A1: Data Matching

Product Name	Statista category
Beer, Local main sales 630ml	Beer
Beer, Canned around 350ml	Beer
Domestic cigarette, Local main sales, mid,low-end	Cigarettes
Domestic cigarette, Local main sales, high-end	Cigarettes
Brown sugar, Local main sales (packaged)	Confectionery
White granulated sugar, Local main sales (packaged)	Confectionery
Peanut oil, barreled single squeeze	Edible Oils
Eggs, fresh whole	Eggs
Fish, grass carp, live, about 1000 grams each	Fresh Fish
Fish, carp, live, over 500 grams each	Fresh Fish
Watermelon, Local main sales, grade I	Fresh Fruits
Bananas, domestically produced, grade I	Fresh Fruits
Apple, red Fuji, grade I	Fresh Fruits
Chicken, white, gutted	Fresh Meat
Fresh pork, rib without bones	Fresh Meat
Fresh pork, lean	Fresh Meat
Cole, fresh, grade I	Fresh Vegetables
Hot pepper, fresh, grade I	Fresh Vegetables
Eggplant, fresh, grade I	Fresh Vegetables
Cabbage, fresh, grade I	Fresh Vegetables
Garlic moss, fresh, grade I	Fresh Vegetables
Chinese cabbage, fresh, grade I	Fresh Vegetables
Leek, fresh, grade I	Fresh Vegetables
Carrot, fresh, grade I	Fresh Vegetables
Cucumber, fresh, grade I	Fresh Vegetables
Radish, fresh, grade I	Fresh Vegetables
Potato, fresh, grade I	Fresh Vegetables
Tomato, fresh, grade I	Fresh Vegetables
Celery, fresh, grade I	Fresh Vegetables
Beans, fresh, grade I	Fresh Vegetables
Green pepper, fresh, grade I	Fresh Vegetables
Gas stove, Local main sales	Major Appliances
Range hood, Local main sales, Direct suction	Major Appliances
Washing machine, Local main sales, pulsator(5kg)	Major Appliances
Electric hot water heater, Local main sales, 50L	Major Appliances
Microwave oven, Galanz 900w	Major Appliances
Air conditioner, Chunlan, 1.5 horse power	Major Appliances
Gas water heater, Local main sales 8L	Major Appliances
Refrigerator, Local main sales, 210-250 cubic decimeter	Major Appliances
Washing machine, Local main sales, tumbling-box (5kg)	Major Appliances
Men's shirt, Local main sales, Cotton	Men's Apparel
Milk, Local main sales (packaged)	Milk
Flour, First class	Other Cereal Products
Hairtail, frozen, about 250 grams each	Processed Fish & Seafood
Polished round-grained rice, second class	Rice
Soy sauce, bottled 500ml	Sauces
Vinegar, bottled 500ml	Sauces
Salt, iodized	Spices & Culinary Herbs
Chinese spirit, high-end	Spirits
Chinese spirit, low-end	Spirits
Cell phone, Local main sales	Telephony
Color TV, Local main sales, Liquid crystal 32 inch	TV, Radio & Multimedia
Wine, Dry red, 750ml 12% volume mid, low-end	Wine
Women's underwear, Local main sales, Cotton	Women's Apparel

Table A2: Product Onlineness

Product Category	Onlineness					Average Online Share				
	2017	2018	2019	2020	2021	2017	2018	2019	2020	2021
Beer	0.0014	0.0006	0.0006	0.0007	0.0007	0.00003	0.00002	0.00002	0.00003	0.00002
Cigarettes	0.2564	0.2083	0.1978	0.1970	0.1750	0.00641	0.00667	0.00845	0.00912	0.00967
Confectionery	0.0083	0.0115	0.0143	0.0212	0.0275	0.00025	0.00030	0.00050	0.00094	0.00119
Edible Oils	0.0016	0.0022	0.0027	0.0039	0.0050	0.00005	0.00007	0.00014	0.00015	0.00025
Eggs	0.0026	0.0036	0.0044	0.0064	0.0083	0.00007	0.00014	0.00017	0.00025	0.00032
Fresh Fish	0.0072	0.0100	0.0123	0.0179	0.0232	0.00018	0.00031	0.00049	0.00086	0.00110
Fresh Fruits	0.0133	0.0184	0.0228	0.0333	0.0431	0.00037	0.00085	0.00094	0.00145	0.00185
Fresh Meat	0.0124	0.0171	0.0211	0.0307	0.0397	0.00045	0.00061	0.00085	0.00122	0.00202
Fresh Vegetables	0.0125	0.0173	0.0214	0.0312	0.0404	0.00042	0.00055	0.00093	0.00157	0.00177
Major Appliances	0.0364	0.0383	0.0418	0.0456	0.0511	0.00112	0.00140	0.00137	0.00176	0.00239
Men's Apparel	0.0349	0.0299	0.0277	0.0231	0.0243	0.00116	0.00137	0.00093	0.00099	0.00104
Milk	0.0081	0.0113	0.0140	0.0201	0.0260	0.00016	0.00035	0.00054	0.00078	0.00113
Other Cereal Products	0.0061	0.0053	0.0058	0.0070	0.0078	0.00015	0.00016	0.00024	0.00034	0.00038
Processed Fish & Seafood	0.0039	0.0053	0.0066	0.0097	0.0125	0.00011	0.00018	0.00028	0.00047	0.00047
Rice	0.0153	0.0235	0.0298	0.0475	0.0606	0.00045	0.00083	0.00094	0.00238	0.00268
Sauces	0.0147	0.0125	0.0144	0.0178	0.0206	0.00046	0.00049	0.00053	0.00071	0.00117
Spices & Culinary Herbs	0.0002	0.0002	0.0003	0.0003	0.0004	0.00001	0.00001	0.00001	0.00002	0.00002
Spirits	0.0049	0.0019	0.0020	0.0024	0.0025	0.00013	0.00007	0.00008	0.00009	0.00010
TV, Radio & Multimedia	0.0046	0.0053	0.0056	0.0058	0.0070	0.00014	0.00017	0.00024	0.00026	0.00023
Telephony	0.0222	0.0270	0.0254	0.0281	0.0310	0.00065	0.00082	0.00118	0.00151	0.00124
Wine	0.0004	0.0002	0.0002	0.0002	0.0002	0.00001	0.00001	0.00001	0.00001	0.00001
Women's Apparel	0.0680	0.0580	0.0534	0.0443	0.0469	0.00158	0.00185	0.00235	0.00257	0.00196

Table A3: Evolution of Online Share Over Time

city	2006	2011	2016	2021	city	2006	2011	2016	2021
Shenzhen	0.000154	0.002622	NA	0.016420	Tangshan	0.000009	0.000083	0.000347	0.000610
Guangzhou	0.000038	0.000529	0.007738	0.012422	Yichang	0.000007	0.000088	0.000203	0.000601
Hangzhou	0.000024	0.000261	0.006410	0.009252	Daqing	0.000021	0.000212	0.000359	0.000589
Suzhou	0.000031	0.000990	0.004338	0.005536	Baotou	0.000014	0.000096	0.000207	0.000576
Xiamen	0.000063	0.002070	0.004581	0.004871	Chuzhou	0.000006	0.000052	0.000128	0.000575
Beijing	0.000065	0.000744	0.001161	0.004140	Tonghua	0.000012	0.000127	0.000406	0.000567
Ningbo	0.000022	0.000284	0.002528	0.003837	Anshan	0.000011	0.000133	0.000356	0.000564
Shantou	0.000009	0.000077	0.000846	0.003031	Sanming	0.000014	0.000161	0.000447	0.000562
Quanzhou	0.000015	0.000142	0.001595	0.002854	Taian	0.000006	0.000073	0.000323	0.000554
Wuhan	0.000015	0.000166	0.001935	0.002784	Huangshi	0.000008	0.000130	0.000462	0.000553
Nanjing	0.000026	0.000232	0.002606	0.002624	Jingmen	0.000007	0.000095	0.000353	0.000539
Zhengzhou	0.000017	0.000145	0.001702	0.002524	Jilin	0.000013	0.000101	0.000375	0.000516
Changsha	0.000012	0.000173	0.001162	0.002270	Tongling	0.000014	0.000157	0.000250	0.000516
Tianjin	0.000032	0.000401	0.001737	0.002164	Zaozhuang	0.000006	0.000073	0.000270	0.000507
Hefei	0.000013	0.000102	0.001166	0.002092	Ganzhou	0.000009	0.000070	0.000160	0.000497
Nanchang	0.000018	0.000286	0.001316	0.002046	Heze	0.000004	0.000062	0.000200	0.000495
Qingdao	0.000016	0.000145	0.000690	0.001994	Xining	0.000012	0.000088	0.000320	0.000495
Nantong	0.000014	0.000196	0.001069	0.001934	Yuncheng	0.000010	0.000075	0.000264	0.000485
Chengdu	0.000011	0.000149	0.001278	0.001865	Shaoxing	0.000016	0.000159	0.000289	0.000477
Jinan	0.000015	0.000161	0.001434	0.001850	Hanzhong	0.000009	0.000123	0.000299	0.000447
Taiyuan	0.000021	0.000253	0.000419	0.001843	Jinzhou	0.000007	0.000092	0.000276	0.000429
Fuzhou	0.000023	0.000163	0.001288	0.001789	Tieling	0.000009	0.000093	0.000256	0.000422
Shijiazhuang	0.000013	0.000132	0.000605	0.001711	Huainan	0.000008	0.000092	0.000264	0.000397
Shenyang	0.000016	0.000119	0.000942	0.001697	Hengyang	0.000005	0.000067	0.000182	0.000395
Kunming	0.000012	0.000118	0.001004	0.001575	Beihai	0.000007	0.000075	0.000258	0.000393
Xian	0.000016	0.000190	0.001169	0.001548	Jiuquan	0.000013	0.000091	0.000249	0.000388
Lhasa	NA	0.000135	0.000353	0.001321	Jiujiang	0.000010	0.000069	0.000133	0.000385
Nanning	0.000009	0.000138	0.000205	0.001309	Yanan	0.000010	0.000103	0.000142	0.000380
Yangzhou	0.000018	0.000184	0.000913	0.001290	Changde	0.000005	0.000074	0.000168	0.000359
Yinchuan	0.000017	0.000082	0.000244	0.001215	Zunyi	0.000005	0.000058	0.000223	0.000346
Dalian	0.000019	0.000290	0.000863	0.001158	Leshan	0.000007	0.000078	0.000246	0.000345
Guiyang	0.000015	0.000125	0.000263	0.001150	Shizuishan	0.000018	0.000097	0.000148	0.000335
Harbin	0.000015	0.000134	0.000312	0.001146	Jincheng	0.000012	0.000098	0.000131	0.000319
Changchun	0.000013	0.000112	0.000667	0.001096	Weinan	0.000007	0.000075	0.000162	0.000317
Hohhot	0.000017	0.000170	0.000917	0.000977	Yantai	0.000014	0.000139	0.000216	0.000231
Shanghai	0.000071	0.000662	0.001025	0.000917	Anshun	0.000003	0.000042	0.000148	0.000223
Xuzhou	0.000007	0.000118	0.000501	0.000864	Pingliang	0.000003	0.000031	0.000072	0.000199
Chongqing	0.000007	0.000137	0.000496	0.000751	Lanzhou	0.000014	0.000123	0.000285	0.000186
Wuhai	0.000021	0.000141	0.000520	0.000702	Mianyang	0.000005	0.000090	0.000182	0.000180
Liuzhou	0.000007	0.000075	0.000259	0.000662	Qujing	0.000003	0.000030	0.000072	0.000160
Xingtai	0.000004	0.000042	0.000246	0.000649	Zhaotong	0.000002	0.000025	0.000060	0.000156
Quzhou	0.000008	0.000076	0.000159	0.000620	Mudanjiang	0.000021	0.000262	0.000274	0.000058
Datong	0.000012	0.000129	0.000229	0.000614	Urumqi	0.000027	0.000244	0.000396	NA