Regional Poverty Alleviation Partnership and E-Commerce Trade

Zemin (Zachary) Zhong * Wenyu Zhou † Jiewei Li ‡ Peng Li §

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Abstract

Regional inequalities are prevalent in all major economies. What are the effects of inclusive growth policies targeting economically disadvantaged regions? In this study, we examine how the East-West Poverty Alleviation Partnership, which pairs rich cities in East China with economically disadvantaged cities in West China, affects e-commerce trade. Using proprietary trade-flow data from Alibaba, we find that the partnership boosts e-commerce trade between partnered cities. This effect is asymmetric, as it increases exports from West China to East China, but not the other way around. The effect is also particularly strong for product categories in which the West has a comparative advantage and for Western regions with the largest economic and development disparities. Additionally, the results indicate that the partnership benefits both big and small sellers equally. In exploring the underlying mechanisms, we find partnership-driven migration as well as consumer awareness can partially explain the effect.

JEL classification: I38, L81, O12, O18, P25, P36

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*Rotman School of Management, University of Toronto, zachary.zhong@rotman.utoronto.ca.
†International Business School, Zhejiang University, wenyuzhou@intl.zju.edu.cn, corresponding author.
‡HEC Lausanne, jiewei.li@unil.ch.
§Alibaba Research, marx.lp@alibaba-inc.com.

1 Introduction

Regional inequalities are prevalent in all major economies, including the economic gap between the heartland and coast regions in the US, East and West Europe, as well as East and West China. In response, governments have introduced various place-based policies aimed at promoting inclusive growth, reducing inequalities, and alleviating poverty. E-commerce platforms, by offering businesses access to markets and reducing barriers to entrepreneurship, have the potential to contribute to these inclusive growth policies. This is particularly relevant in remote areas and among ethnic minorities, where physical and cultural distances can pose substantial hurdles. In this paper, we empirically examine the impact of one of China's most extensive poverty-alleviation policies on e-commerce.

Despite China's miraculous economic growth, poverty remains a prevalent issue in West China, home to most of the country's ethnic minorities. As of 2012, over 50 million people, representing 17.6% of the local population in this region, lived in poverty. In stark contrast, poverty was virtually eliminated in the eastern provinces, where GDP per capita was 87% higher than in West China in 2012. Even in 2021, this gap remained significant, at 68%. To address regional inequality and poverty, the Chinese central government established the East-West Poverty Alleviation Partnership, which pairs Western regions with their Eastern counterparts. Eastern local governments are charged with providing financial aid and other forms of support, such as governance expertise, technology, market access, and labor exports, to their partnered cities in the West. Over the past few years, this partnership has facilitated the migration of millions of people from West to East and prompted billions of investments that created hundreds of thousands of local jobs in West China. These initiatives have played a significant role in lifting tens of millions of West China residents out of poverty. Yet, despite the importance and scale of this partnership, to the best of our knowledge, there has been no study on its economic effects.

We evaluate the economic impact of the regional partnership plan through e-commerce trade. Unlike financial aid, which typically involves zero-sum transfers between regions, trade often generates surpluses. E-commerce, constituting about one-fourth of all consumption in China, is particularly relevant in this context, as e-commerce can potentially reduce transportation costs and trade barriers for cities between East and West China, which are often more than a thousand miles apart

(Goldfarb and Tucker, 2019). Consequently, this has the potential to help businesses in economically disadvantaged West China access the vast East China market. Our analysis is based on trade flow data derived from all transactions on Alibaba, the leading e-commerce platform in China. The data, aggregated on a monthly basis at the prefecture-city pair level from 2017 to 2021, totals 1.15 million observations.

We first present empirical patterns using the classic gravity model. We document that being city partners is associated with a 5.6% increase in e-commerce trade. Notably, this association is only significant for West-to-East trade (11.9%). However, this pattern should not be interpreted as causal due to potential systematic differences between partnered city pairs and non-partnered ones. We thus further use a spatial regression discontinuity (RD) design for causal identification. This design is implemented by comparing partnership pairs with control pairs in close proximity, which should share similar unobserved demand for goods produced in the other cities, as well as similar unobserved trade barriers. We verify that within close proximity, partnership and control pairs are balanced in terms of observables.

We find that the partnership caused a 4.8% increase in e-commerce trade flow, which translates to an increase of 2-3 billion Chinese Yuan in trade. The effect is asymmetric: from east to west, the impact is minimal and statistically insignificant, while from west to east, it is substantial (10.0%) and statistically significant. The effects on the number of transactions are qualitatively similar. The results are robust across various specifications and bandwidth choices, different types of control city pairs, and as well as under alternative implementations of spatial RD.

We also investigate the heterogeneous effects on different sellers by examining the impact on the sellers' concentration ratio for each city-pair-month cell. Our findings indicate that the partnership does not influence the sellers' concentration ratio, suggesting that the policy equally benefits large and small sellers in the West. Among different product categories, the effect is notably strong for food and beverage, clothing, and household goods, with exports from West to East increasing by 12% to 9.6% due to the partnership. These sectors are comparative advantages of the West and priority investments by the policy to create local jobs.

We further examine how the effects vary across cities with different characteristics. Our findings reveal that pairs with larger GDP gaps or Western cities with worse physical and digital infrastructure exhibit stronger effects. Western cities with higher proportions of ethnic minorities, more Geographical Indication (GI) products, and more e-commerce firms benefit more from the partnership, suggesting that the policy can help overcome cultural barriers as well as unlock the supply-side potential in e-commerce. Dynamically, while the overall effects decreased following the COVID-19 pandemic, the effect from West to East remained consistent as before.

In testing the mechanism, we find that migration between partnered cities partially explains the effect. Thus, the partnership addresses inequality in two ways: it assists migrant workers from the West in securing jobs in Eastern cities, who in turn support sellers in their hometowns through e-commerce. Consumer awareness, as measured by online search, also partially mediates the effect. We find no evidence supporting the effect being driven by targeted public-sector spending, typically observed at the end of the year or during the Chinese New Year, nor by reduced transportation costs between partnered cities as measured by direct flight routes.

This study carries broad and significant implications for both policymakers and platforms. Our results suggest that the partnership plan boosts e-commerce trade between regional pairs, particularly from economically disadvantaged regions to more developed ones. The benefits are equitably distributed among both large and small sellers. This experience from the world's largest e-commerce platform also holds implications for other economies where the debate on whether digitization exacerbates or alleviates inequality remains active and ongoing.

We are the first to examine the economic effects of the regional cooperation plan, thereby contributing to the literature on inequality, local economic development, and e-commerce trade. The primary policy we explore addresses the issue of regional inequality in China (Montalvo and Ravallion, 2010; Zhang and Zou, 2012; Lemoine et al., 2015; Liu et al., 2017; Fan, 2019; Kanbur et al., 2021; Zhang, 2021). The plan also bears some similarity to the partnership plan in disaster relief (Bulte et al., 2018) and social entitlement exchange (Luo and Zhang, 2009), based on the incentive role of personnel control (Li and Zhou, 2005). However, it operates on a much larger scale, targeting persistent regional inequality.

Broadly, our study also relates to aid-for-trade in the fields of international and development economics (Cali and Te Velde, 2011; Rajan and Subramanian, 2011; Vijil and Wagner, 2012; Hühne et al., 2014; Lee and Ries, 2016; Martínez-Zarzoso et al., 2017; Kim, 2019; Gnangnon, 2019). The distinction lies in our focus on large-scale intranational aid and e-commerce trade. More generally, we contribute to the literature on place-based policies (Kline and Moretti, 2014; Neumark and Simpson, 2015; Duranton and Venables, 2018; Austin et al., 2018; Ehrlich and Overman, 2020). Within the context of China, existing literature has so far concentrated on special economic zones (Lu et al., 2019), high-tech zones (Tian and Xu, 2022), and the Western Development Program (Jia et al., 2020). We are the first to specifically study the East-West Partnership Program and the first to examine the effect of place-based policy on e-commerce trade in general.

The literature on the geography of e-commerce trade finds that e-commerce reduces transportation costs, thereby diminishing the role of distance in trade (Blum and Goldfarb, 2006; Hortaçsu et al., 2009; Chen et al., 2015; Lendle et al., 2016; Brynjolfsson et al., 2019; Zhao et al., 2019; Hui, 2020; Chintagunta and Chu, 2021; Carballo et al., 2022; Elfenbein et al., 2023). In particular, Fan et al. (2018) also studied the geographic pattern of intranational trade on Alibaba. We build on this literature by bridging this body of work with regional inequality and the effect of regional partnerships. As such, we also contribute to the literature on online platforms and poverty (Couture et al., 2021), and more broadly, to the literature on the impact of the digital economy in rural and remote areas (Forman et al., 2005; Goyal, 2010; Aker and Mbiti, 2010; Parker et al., 2016; Luo et al., 2019). We demonstrate how the policy utilizes an e-commerce platform to assist disadvantaged regions and test for its rich heterogeneous effects and mechanisms.

2 Background

2.1 Regional Income Inequality in China

As China's economy grew in the past decades, so did the regional inequality. From 1978 to 2000, the ratio of GDP per capita in East China to that in West China increased from 1.85 to 2.42. Since then, regional inequality has been declining, but it remains considerable (Kanbur et al., 2021; Zhang, 2021). In 2012, the GDP per capita in the East was 87% higher than that in the West, a gap which had narrowed to 68% by 2021.

Concurrent with the decline in regional inequality, there has been significant progress in reducing poverty in Western China. As of 2012, 50.86 million people in the West (17.6% of the local population) lived in poverty, a number reduced to only 3.23 million by 2019. This reduction in poverty enabled the central government to declare its elimination in 2021, marking a significant milestone in the centennial celebration of the founding of the Chinese Communist Party.

2.2 East-West Poverty Alleviation Partnership

The East-West Poverty Alleviation Partnership has been a central policy toward reducing regional inequality and poverty. Initiated by the State Council in May 1996, the program started as a province-to-province partnership that included six provinces and seven provincial cities (such as Beijing, Tianjin, and Shanghai) in East China paired with ten provinces in West China. Most of the partnerships have remained the same, with only minor reshuffling at the end of 2016. In 2017, the central government further formalized the partnerships between counties and cities and published the full list of "prosperity-together" pairs, based on which we construct the partnership treatment.[1]

The partnership encompasses multiple policies. It calls on local governments in the East to provide fiscal aid to the West through their budgets. It encourages government officials to visit the West and exchange officials between partnered cities, with the goal of sharing governance and development expertise. Firms in the East are encouraged to invest in the aided West regions. The governments in the West have also organized training sessions and labor exports to their partnered cities in the East. Between 2015 and 2020, local governments in the East sent 78 billion Chinese Yuan in aid to the West. Government officials made 148,642 visits and facilitated 16,198 exchanges. 22,683 firms invested over 1 trillion Chinese Yuan, creating 313,750 local jobs. The partnership also provided 3,429,408 training opportunities and over 4 million jobs through labor exports. All of these efforts are Key Performance Indicators (KPIs) that the central government tracks.

The partnership plan also encourages societal participation, including philanthropy and "poverty

[1] Before 2017, while some city-level partnership pairs existed, there was no systematic policy to organize city-level partnerships.

alleviation through consumption," in which e-commerce has been playing a vital role. The idea that the digital economy can benefit geographically isolated regions has been well established (Forman et al., 2005; Luo et al., 2019). The partnership can promote intercity e-commerce trade through various mechanisms. On the supply side, the partnership plan often includes investments in the supply chain, infrastructure, shipping services, and training for sellers to host online storefronts or live-stream e-commerce sessions. While many of these investments may increase the aided regions' overall exports, some may specifically increase exports to the paired eastern regions. For example, the product categories that eastern firms invest in may correlate with their local preferences. Shipping routes, such as new airline networks, may reduce the specific transportation costs between partnership pairs. On the demand side, local governments in the East can promote products from their paired regions through advertising, channel support, coupons, and consumer subsidies. Other policy initiatives, such as labor exports, may also indirectly increase trade flow.

3 Data

Our study utilizes data from several sources. The key variation is the East-West Poverty Alleviation Partnership from the Yearbook of China's Poverty Alleviation and Development. The outcome variable is the trade flow data from Alibaba Group, the largest e-commerce company in China. We supplement these two datasets with city-pair characteristics, migration, and Baidu search index data.

3.1 City Partnerships

We collect the list of city partnerships (Online Appendix Table A.1) reported in the 2018 Yearbook of China's Poverty Alleviation and Development, published by the State Council Leading Group of Poverty Alleviation and Development.[2] Within all 87 Eastern cities and 110 Western cities, there are 19,140 ($2 \times 87 \times 110$) directed city pairs.[3] There are 56 Eastern cities and 81 Western cities

[2]See pages 768-777 in the 2018 Yearbook of China's Poverty Alleviation and Development.

[3]The 87 Eastern cities belong to 6 provinces and 3 municipalities, including Beijing, Shanghai, Tianjin, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong, and the 110 Western cities belong to 9 provinces and 1 municipality, including Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, and Yunnan; see Table A.1 for more details.

Table 1. Summary Statistics

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: city partnerships								
Partnership pair	19,140	0.013	0.115	0.00	0.00	0.00	0.00	1.00
Panel B: e-commerce trade flows (full sample)								
Trade amount	1,148,400	6,710,610.75	35,489,376.75	0.00	81,174.18	455,479.42	1,298,604.85	3,330,035,240.52
Deal volume	1,148,400	37,620.12	246,761.85	0.00	767.21	3,622.76	19,610.40	19,812,880.78
Seller concentration ratio	1,148,400	88.56	13.77	18.51	80.74	89.22	97.47	99.99
Buyer concentration ratio	1,148,400	82.32	14.64	14.69	72.88	82.55	91.79	99.99
Panel C: e-commerce trade flows (east-to-west sample)								
Trade amount	574,200	9,062,917.15	57,932,763.85	0.00	300,124.01	892,274.52	5,339,022.40	2,920,621,699.07
Deal volume	574,200	115,145.46	589,621.79	0.00	2,975.83	12,983.27	34,234.36	25,296,946.13
Seller concentration ratio	574,134	88.08	11.87	20.65	81.21	88.27	95.55	99.98
Buyer concentration ratio	574,135	81.76	12.77	19.32	73.25	81.67	89.91	99.98
Panel D: e-commerce trade flows (west-to-east sample)								
Trade amount	574,200	1,177,110.25	8,953,320.35	0.00	36,360.83	93,751.99	583,916.55	508,782,865.30
Deal volume	574,200	12,109.87	68,299.08	0.00	317.92	1,523.43	4,256.68	3,420,159.12
Seller concentration ratio	568,458	89.07	15.44	18.51	80.03	90.52	98.00	99.99
Buyer concentration ratio	562,293	82.88	16.33	14.69	72.31	83.68	93.71	99.99
Panel E: city-pair characteristics								
Distance	9,570	1,565.36	492.86	113.10	1,254.59	1,542.96	1,895.36	3,237.34
GDP difference	9,570	1.71	4.73	-12.75	0.28	1.27	2.48	15.56
Panel F: intercity migration flows								
Pre-CNY traffic ratio (mean)	9,570	0.154	0.661	0.000	0.001	0.011	0.068	15.681
Post-CNY traffic ratio (mean)	9,570	0.129	0.579	0.000	0.001	0.010	0.053	15.938
Panel G: Baidu search index								
Baidu search index	19,140	38.52	60.97	0.00	3.00	16.00	55.00	1224.00

Note: This table reports the summary statistics of the full sample, including the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max), for the key variables used in our study. The sample covers the period from January 2017 through December 2021. To satisfy the data privacy requirements of Alibaba Group, the summary statistics for the e-commerce trade flows shown in Panels B, C, and D are obtained by transforming the original values using a linear model with randomly generated coefficients, which preserves the rank of the data. Partnership pair is a dummy variable that equals one if two cities form a partnership pair. Trade amount, deal volume, seller concentration ratio, and buyer concentration ratio are monthly variables of e-commerce trade flows as detailed in Section 3.2. Distance and GDP difference are city-pair characteristics defined in Section 3.3. Pre-CNY traffic ratio (mean) and Post-CNY traffic ratio (mean) are two intercity migration ratios as detailed in Section 3.4. The Baidu search index is detailed in Section 3.4.

in the program, forming 256 directed partnership pairs, based on which we define the treatment indicator $Partnership\_pair_{ij}$ that equals 1 if city i and j are "partner cities" under the framework of the East-West Poverty Alleviation Partnership. Panel A of Table 1 reports the summary statistics of this variable for the full sample. These city partnerships were first announced at the beginning of 2017 by the central government and remain the same throughout our sample period.[4] Figure 1 illustrates the pairs on a map. The rest are potential control pairs, out of which we can further classify them into four types: 1) Neither Eastern city i nor Western city j is in the program (1,798 pairs); 2) Only Eastern city i is in the program (3,248 pairs); 3) Only Western city j is in the program (5,022 pairs); and 4) Both i and j are in the program, but they are not in a partnership pair with each other (8,816 pairs). We will show our results are robust to various combinations of control pairs.

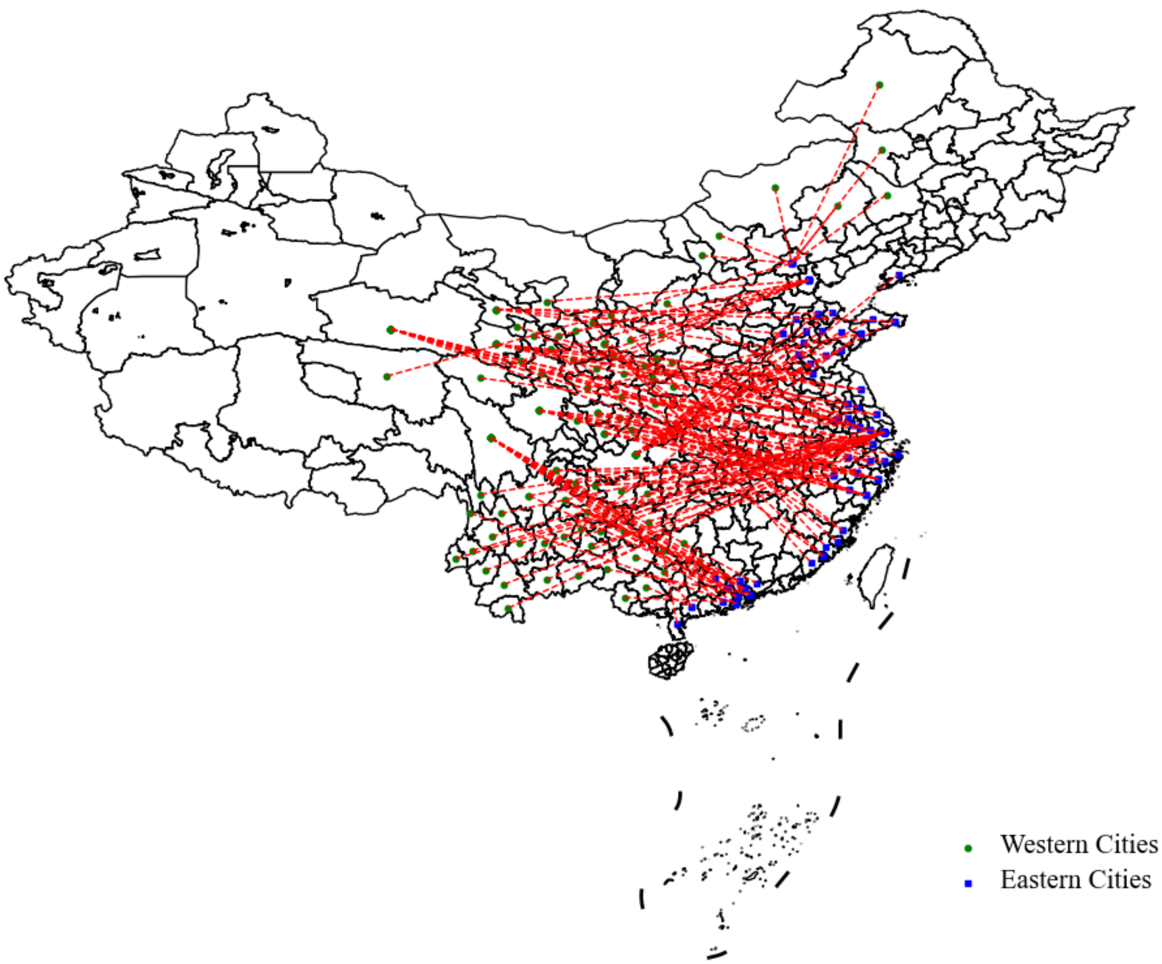
3.2 E-commerce Trade Flows

The e-commerce trade flow data used in our study consists of four key outcome variables, including trade amount in Chinese Yuan (*trade*), the number of deals or transactions (*deal*), seller concentration ratio, and buyer concentration ratio, for each directed city pair on a monthly basis. These variables are constructed using transaction-level data from Taobao and Tmall, the most popular online retail platforms in China, which are owned by the Alibaba Group. Specifically, for the trade flow from city i to city j, the seller (resp. buyer) concentration ratio is defined as the share of the trade amount of the top 10% largest sellers (resp. buyers), measured by transaction amount in city i (resp. city j), relative to the total monthly trade flow between these two cities.

Panels B, C, and D of Table 1 report the summary statistics of the outcome variables for the full, east-to-west, and west-to-east samples, respectively. The final dataset consists of the e-commerce trade flows of 19,140 directed city pairs from January 2017 to December 2021, resulting in a sample size of 1,148,400 ($19,140 \times 60$ months). The East-to-West e-commerce trade flows are an order of magnitude larger than those in the other direction, as the e-commerce industry is much more developed in the eastern region of China. There are a few missing data points in the two concentration ratios due to zero trade in these city pair-month cells. In Online Appendix Table A.2, we further

[4]See http://www.gov.cn/xinwen/2017-01/06/content_5157037.htm.

Figure 1. Graphical Illustration for the City Partnerships



Note: This figure displays the city partnerships, represented by red dashed lines, between the targeted western cities (green circles) and their corresponding eastern partner cities (blue squares).

show the summary statistics of the share of partnered cities relative to the overall East-West trade. On average, the trade between partnered cities is about 4.78% of the overall East-West trade, while Western cities' exports to partnered cities constitute 5% of their overall export to all East cities.

3.3 City and Pair Characteristics

We supplement the data with the following city and city-pair level characteristics. We calculate the distances based on the longitudes and latitudes of city centers, which we obtain from the Baidu Map. For our heterogenous effect analysis, we collect city-level GDP statistics in 2018 from the China City Statistical Yearbook. Panel E of Table 1 shows the summary statistics of these city-pair characteristics. We further include the e-commerce infrastructure in West China by the number of newly entered e-commerce companies in Western cities, constructed from the registration information of industrial and commercial enterprises based on industry classification.[5] We also collect data on the share of ethnic minorities in the population of each western city from the 2020 census. In addition, we compile the number of products with Geographical Indication (GI) as of 2022 for every city.[6] To measure offline trade, we use the standard Input-Output Table for the years 2012 and 2017, the most recent data available.[7]

3.4 Intercity Migration Flows and Baidu Search Index

We collect migration and Baidu search index data for testing the mechanism. Due to China's rapid industrialization and urbanization, millions of the working-age population have migrated from rural areas to urban centers in search of employment opportunities. These migrants often leave their families behind in their rural hometowns. Before the Chinese New Year (CNY) - China's most important holiday season - they travel from urban areas back to rural ones to reunite with their families. After the festivities, they return to the urban centers. This migration, known as

[5] We used the numbers of companies registered in the categories of digital services. See `http://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902784.html` (in Chinese) for the codes.

[6] Published by China National Intellectual Property Administration. See `https://www.cnipa.gov.cn/col/col1388/index.html` (in Chinese)

[7] We obtain the data from Carbon Emission Accounts & Datasets (Zheng et al., 2022). Other studies using similar data include Yuan et al. (2019); Chen and Zhao (2023) and Wang et al. (2024).

Chunyun (the Chinese New Year travel rush), represents one of the largest annual human migrations worldwide.

Utilizing the migration flow patterns before and after the CNY, we construct measures of migration between city pairs as follows. We use the migration data based on the GPS data of hundreds of millions of actual users of Baidu Map, the equivalent of Google Maps in China.[8] The data is available at a daily level between Jan 1, 2019, and Dec 31, 2021. Each entry records the percentage of migration flows from one city to another, for both inflow and outflow, defined as the number of migrants relative to the total number of migrants from the origin or destination city. We further normalize the migration percentage by the population of the destination city (for outflow) or origin city (for inflow).[9] We then take the days during the official Chunyun periods[10] and split them into pre-CNY and post-CNY periods. We calculate the average daily East-to-West inflow pre-CNY traffic and the average daily West-to-East outflow traffic post-CNY for each of the holiday seasons of 2019, 2020, and 2021.[11] Additionally, we calculate the mean of both pre-CNY traffic and post-CNY traffic, averaged across these three years. Thus, we have eight measures (three years plus the mean for both pre-CNY and post-CNY traffic) representing the same underlying migrant population - those migrating from their hometowns in Western China to work in Eastern China. Online Appendix Table A.3 shows that all eight measures are highly correlated with each other. We thus focus on the result using the pre-CNY traffic averaged across the three years in the paper, and show the results are consistent when we use other measures.

We also gather the following Baidu Search Index data, the equivalent of Google Trends, from Baidu's API. The original data shows the search index of one city (e.g. the keyword "Leshan", a

[8]Census data such as the sample from the 2015 China 1% Population Census is too sparse for city pair-level migration.

[9]For example, the inflow data shows that on Jan 19, 2020 (before CNY), of all migrants arriving in the Western city of Leshan, 1.45% originated from the Eastern city of Shenzhen and 0.40% from Foshan. The outflow data shows that on Jan 29, 2020 (after CNY), of all migrants departing from Leshan, 1.01% went to the Eastern city of Shenzhen and 0.19% to Foshan. However, much of this difference is attributable to the population disparity between Shenzhen (17.63 million) and Foshan (9.52 million). Therefore, calculating the ratio based on the origin cities (here, Shenzhen and Foshan) helps to account for this difference in scale.

[10]It is determined by the Chinese Ministry of Transport as 15 days before CNY and 25 days after CNY: Jan 21 to Mar 1, 2019; Jan 28 to Mar 8, 2021. For 2020, due to the COVID outbreak around the CNY of Jan 25, 2020, we use the days between Jan 1 and Mar 31.

[11]We can also calculate the corresponding East-to-West outflow pre-CNY traffic and West-to-East inflow post-CNY traffic. These measures are theoretically equivalent to the ones we use. However, this approach encounters more measurement challenges due to the larger total migration population to and from Eastern cities, resulting in many observations falling below the minimum threshold of 0.01% due to a larger denominator.

city in West China) by residents of another city (e.g. Shenzhen in East China) at a monthly level between Jan 2017 and Dec 2021. We match the data with the trade-flow data for the city-pair month in the opposite direction. For instance, for the West-to-East trade (e.g. Leshan to Shenzhen), we match the search from the East for keywords of Western cities (e.g. Shenzhen residents searching for the keyword of "Leshan") to measure the demand-side awareness on the location of the supply side.

Panel F of Table 1 reports the summary statistics of the intercity migration flows, including East-to-West outflow pre-CNY and West-to-East inflow post-CNY. Panel G reports the summary statistics of the Baidu Search Index data.

4 Methodology

We use the canonical gravity model as our baseline:

$$\log\left(trade_{ij,m}\right) = \gamma Partnership\_pair_{ij} + \beta \log\left(distance_{ij}\right) + \delta_{im} + \eta_{jm} + \epsilon_{ij,m} \tag{1}$$

where $trade_{ij,m}$ represents the directed trade amount from city i to city j in month m. $Partnership\_pair_{ij}$ is the treatment indicator, denoting whether i and j form a partnership pair, and γ is the key coefficient of interest. $\log\left(distance_{ij}\right)$ is the standard log distance between i and j in the gravity model. We control for δ_{im} and η_{jm}, which are the export and import city-month fixed effects, respectively. These fixed effects fully absorb characteristics that may influence a city's overall e-commerce export or import in any given month, including the size and growth rate of local economies, seasonality patterns in supply and demand, as well as variations in e-commerce penetration rates. $\epsilon_{ij,m}$ is the error term, for which we account for serial correlation by clustering the standard errors at the city-pair level.

If $\mathrm{E}[\epsilon_{ij,m}|Partnership\_pair_{ij}, \log\left(distance_{ij}\right), \delta_{im}, \eta_{jm}] = 0$, that is, the unobserved error terms driving trades between city pairs are not systematically correlated with the treatment, then the coefficient γ can be interpreted as a causal effect of the partnership. In the baseline model, we find significant differences in distances and economic statistics between the partnered city pairs and the control pairs: The last column of Online Appendix Table A.6 shows that the treatment status is significantly correlated with longer distances and larger GDP gaps between city pairs. Consequently, the identification assumption may not hold: Consumers in city i might systematically prefer products sold by sellers in their partnered city j even in the absence of the partnership. This motivates us to use spatial regression discontinuity for causal identification.

The premise of spatial RD is that cities in close proximity should share similar unobserved characteristics potentially affecting the outcome, thereby allowing the separation of the treatment effect. In our context, when evaluating the outcome of partnered city pair ij, we intend to compare it with a control pair kj. In this pair, city k and city i are close in proximity, and hence, should share similar preferences for products sold by city j's sellers, as well as face similar trade barriers and transaction costs. Therefore, the comparison of trade flows between pair ij and kj serves as a natural experiment. Formally, the pair-level spatial RD relies on the assumption that $\log(trade_{ij,m}) = \gamma Partnership\_pair_{ij} + \delta_{im} + \eta_{jm} + f(lat_i, lng_i, lat_j, lng_j) + \epsilon_{ij,m}$, where $f(\cdot)$ is a flexible continuous function of the latitude and longitude of city i and j, with the condition that $\mathrm{E}[\epsilon_{ij,m}|Partnership\_pair_{ij}, \delta_{im}, \eta_{jm}, f(lat_i, lng_i, lat_j, lng_j)] = 0$. Our segment-segment fixed effect model replaces $f(lat_i, lng_i, lat_j, lng_j)$ with the fixed effects of segment-segment pairs, denoted as θ_{IJ}. This approximation remains consistent as the segments get arbitrarily small.

We implement the spatial RD using the spatial fixed effect. We first construct segments through spatial clustering, ensuring that the distance between any two cities in the same segment is within a small bandwidth d. We then estimate the following model:

$$\log(trade_{ij,m}) = \gamma Partnership\_pair_{ij} + \beta \log(distance_{ij}) + \delta_{im} + \eta_{jm} + \theta_{IJ} + \epsilon_{ij,m} \tag{2}$$

where θ_{IJ} denotes the segment-segment fixed effect, and I and J are the segments to which cities i and j belong, respectively. This approach echoes the boundary segment fixed effects in Dell (2010). In the marketing literature, several well-established studies employ the Border-DMA (Designated Market Area) fixed effect in their spatial RD design to identify the causal effect of advertising (Shapiro, 2018; Tuchman, 2019). We extend the segment fixed effects model to control for the segment-segment pair fixed effect because the outcome we focus on is at the city-pair level. The bandwidth we use in our context is comparable to the average distance between two adjacent counties (about 30 miles) in the Border-DMA studies. In our spatial RD, we restrict the segment such that the largest distance between any two cities is within the bandwidth d. We use $d = 100$km (62 miles) as our primary model and test its robustness over a wide range of bandwidths as low as 50km (31 miles).[12] We also restrict the segments to be within the same province due to potential policy discontinuities at provincial borders, e.g., local protectionism (Barwick et al., 2021).

The identification assumption now becomes $\mathrm{E}[\epsilon_{ij,m}|Partnership\_pair_{ij}, \log(distance_{ij}), \delta_{im}, \eta_{jm}, \theta_{IJ}] = 0$, i.e., within the same segment pair, where all Eastern (Western) cities are in close proximity, unobserved error terms driving trades are not systematically different between a treated city pair and a control pair. We confirm that within the same segment pair, there are no observable differences between treated and control pairs, and the results are robust to a wide range of bandwidths in spatial clustering.[13]

We also show that our results are robust to two alternative implementations of spatial RD: spatial matching and regular RD. In spatial matching, we only include samples of treated city pairs and their corresponding control pairs that are within a certain distance. In the regular RD method, for every treated pair ij, we find neighboring cities of i, such as city k, and collapse the locations of i and k into a single dimension of $distance_{ik}$ as the running variable. This variable has a negative sign for the control pair kj and a positive sign for the treated pair ij. We then use a standard local linear regression to estimate the treatment effects. The details of these two alternative methods are provided in the Online Appendix D. Both methods yield consistent results.

[12] Table A.4 in the Online Appendix shows the distribution of segment size for different bandwidth choices, and Figure A.1 illustrates the segments on the map. Table A.6 further shows that as long as the bandwidth is no greater than 100km, the observable characteristics are balanced such that they can no longer predict the treatment status.

[13] Additionally, in the Online Appendix Table A.20, we present the summary statistics for the consumption shares for each category both for the full sample and within segments. The results demonstrate that within a segment, the absolute difference between treated and control cities is small compared to the variation in the full sample. For example, the absolute difference in the share of Food and Beverage within segments has a mean of 0.84, which is one order of magnitude smaller than the standard deviation of 8.74 of the full sample. This indicates that cities within the same segment indeed exhibit similar patterns in terms of online consumption. In Online Appendix Table A.25, we show that treated and control pairs had similar offline trades in 2012 and 2017.

5 Results

5.1 Main Results

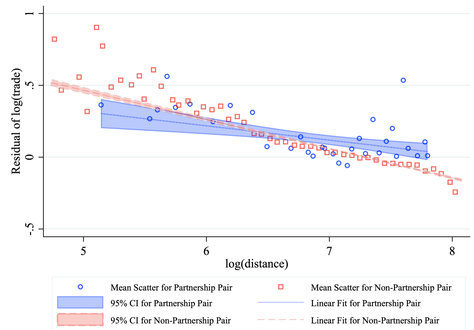
We first visualize online trade between Western and Eastern cities in partnership pairs and non-partnership pairs in Figure 2. The pattern shows that while overall log trade and log distance display a linear relationship as the gravity model predicts, partnered cities trade more than non-partnered cities (top panel), especially West-to-East (bottom panel).

Table 2 presents the estimates of the baseline gravity model. We find that the partnership is associated with a 5.6% increase in e-commerce trade, driven solely by West-to-East trade (11.9%). Consistent with the literature on online trade (Lendle et al., 2016; Fan et al., 2018), the coefficients on log distance are around -0.33. The estimates on deals (the number of transactions) are similar. We find no correlation between the concentration ratios and the partnership. Taken together, the gravity model shows a strong correlation between partnership and e-commerce trade, and the correlation only exists for West-to-East trade. Table A.5 in the Online Appendix further shows that the results are similar when we control for import and export province pair fixed effects.

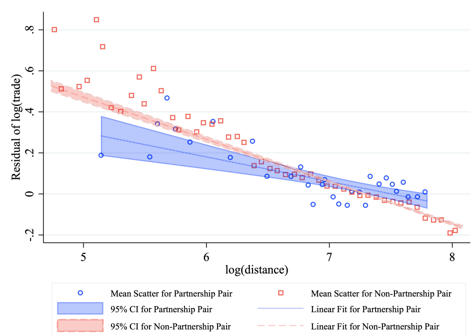
Table 3 displays our main results based on the spatial RD, where partnership pairs and control pairs are in close proximity and balanced in all observable characteristics. Consistent with the gravity model, we find that the partnership causes a 4.8% increase in the overall e-commerce trade amount, and the effect is asymmetric in direction. For West-to-East trade, the effect is 10.0%, while for East-to-West trade, it is negligible and not statistically significant. The effects on the number of deals are similar (3.1% overall and 6.0% West-to-East), suggesting the effects are driven by more goods sold rather than the composition of transactions across different price tiers. Overall, the regional partnership promotes trade between partnered city pairs, notably helping sellers from economically disadvantaged regions in the West tap into the market in the East.

The main effects are economically significant. The partnership effect is equivalent to reducing the distance between city pairs by 14.4% overall or by 30% West-to-East. A simple back-of-the-envelope calculation implies that the partnership increases trade between all 128 partnership pairs over the five years by an amount in the range of 2 to 3 billion Chinese Yuan (0.30 to 0.45 billion USD).

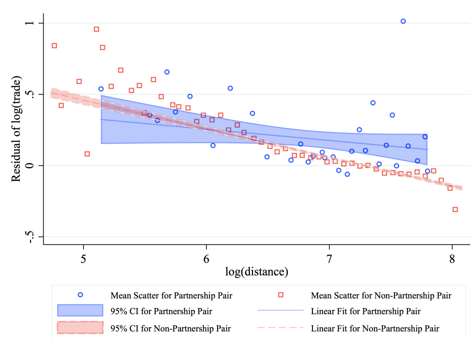
Figure 2. Gravity Model for E-commerce Trade Amount



(a) Full Sample



(b) East-to-West Trade



(c) West-to-East Trade

Note: This figure illustrates the relationship between the residuals of the logarithm of e-commerce trade, denoted as log(trade), and the distance between city centers, represented by log(distance). The residuals of the logarithm of e-commerce trade are obtained by regressing the monthly e-commerce trade amount on the city-month fixed effects. The blue circles and red squares display the residuals of log(trade) averaged over fifty evenly spaced distance bins. The blue and pink shaded areas represent the 95% confidence intervals for the linear fits of the relationship for partnership and non-partnership pairs, respectively.

Table 2. Gravity Regression: Main Results

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.056***	-0.008	0.119***	0.036***	-0.005	0.076***
	(0.018)	(0.012)	(0.034)	(0.009)	(0.008)	(0.014)
log(distance)	-0.334***	-0.339***	-0.329***	-0.316***	-0.332***	-0.300***
	(0.005)	(0.006)	(0.007)	(0.004)	(0.006)	(0.005)
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.963	0.986	0.929	0.991	0.994	0.984
F-statistic	2653.68	1595.11	1133.80	3399.44	1655.63	1776.52
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	-0.124	-0.115	-0.133	-0.006	0.053	-0.065
	(0.202)	(0.214)	(0.345)	(0.162)	(0.183)	(0.267)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.504	0.646	0.418	0.515	0.659	0.424
F-statistic	22.17	49.71	0.26	92.64	35.91	56.93
Observations	1,136,426	574,134	562,292	1,137,650	574,135	563,515

Note: This table reports the regression results of the baseline gravity model. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount, deal volume (total number of transactions), seller concentration ratio, and buyer concentration ratio, as detailed in Section 3.2. The independent variable of interest is the partnership pair. All columns control for the export city-month and import city-month fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

How are the benefits of the partnership distributed across different buyers and sellers? We find the effects are not driven by large sellers or buyers disproportionately benefiting from the partnership. The lower panel of Table 3 shows that the partnership effect on the seller concentration ratio is small and overall not statistically significant. The West-to-East effect on the seller concentration ratio is a precise zero: -0.007 with a standard error of 0.357, relative to the disguised sample average of 89.07 (the true value is of a similar magnitude), suggesting that the city partnership benefits both major and small sellers equally. Similarly, the effect on the buyer concentration ratio has an estimated coefficient of 0.024 (s.e. 0.289) relative to the disguised sample average of 82.88 (the true value is of a similar magnitude), suggesting that major buyers alone do not drive the increase in e-commerce trade from West to East.

5.2 Robustness Checks

5.2.1 The Main Identification Strategy

First, we note that our spatial RD strategy balances the treated and control city pairs. Table A.6 in the Online Appendix shows that within the bandwidth of $d = 100$km or smaller, the observable characteristics of city pairs in 2017 are not correlated with the treatment status. Table A.25 in the Online Appendix shows that the treatment has no effect on offline overall or West-to-East trade using the standard input-output table in the year 2012 when e-commerce was still relatively nascent (6.3% of total consumption), suggesting that the treatment is not systematically correlated with offline trade barriers.

The main result of the partnership effect on trade is robust across a wide range of alternative regression specifications. Table A.9 and Table A.10 in the Online Appendix show that the estimates remain consistent when we include either Export Segment–Import Segment–Month fixed effects, or city and month fixed effects.

The spatial RD is also robust across a wide range of bandwidths. Table A.11 in the Online Appendix presents the spatial RD estimates for distances of 50km, 75km, 125km, and 150km. All results are robust. Furthermore, we address potential cultural differences between the treatment and

Table 3. Spatial RD: Main Results

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.048***	-0.004	0.100***	0.031***	0.002	0.060***
	(0.016)	(0.015)	(0.028)	(0.010)	(0.010)	(0.017)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.967	0.988	0.935	0.993	0.996	0.987
F-statistic	4.91	10.16	19.68	5.71	3.13	13.76
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.048	0.101	-0.007	0.108	0.191	0.024
	(0.214)	(0.236)	(0.357)	(0.189)	(0.244)	(0.289)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.528	0.669	0.442	0.549	0.683	0.444
F-statistic	1.11	4.61	9.19	0.474	3.899	5.641
Observations	1,136,426	574,134	562,292	1,137,650	574,135	563,515

Note: This table reports the regression results of the spatial RD model. The distance threshold is set at 100km. The unit of observation is city-pair-month. The dependent variables are the logarithms of e-commerce trade amount, deal volume (total number of transactions), seller concentration ratio, and buyer concentration ratio, as detailed in Section 3.2. The independent variable of interest is the partnership pair. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

control pairs by restricting the treated cities and control cities to be in the same dialect district. The estimates reported in Table A.12 in the Online Appendix indicate that the main results remain robust.

We further test whether the results are consistent when we use different control groups. Specifically, in our main model, we have four types of control groups: (1) neither the Eastern city nor the Western city is in the program; (2) only the Eastern city is in the program; (3) only the Western city is in the program; and (4) both cities are in the program but are not partnered with each other. Online Appendix Table A.21 to Table A.24 shows that if we exclude any of the four types of control groups the results remain consistent not only for our main bandwidth of 100km, but also for 75km and 125km.

Some segment pairs contain more than one treated city pair, which may lead to complications as the control pairs within these segment pairs are compared with multiple treated pairs. We exclude all those segment pairs and estimate the main model in Online Appendix Table A.13, which shows that the results remain consistent.

5.2.2 Alternative Spatial RD Implementation

The main results are robust to two alternative spatial RD design implementations. First, in spatial matching (see Online Appendix Section D.1 for details), for every treated pair, we match control pairs that are in close proximity and only include the spatially matched sample in the regression. In doing so, the same city pair may appear multiple times in the spatial matching, and it does not control for the segment pair fixed effect and is thus less flexible than the main model. We report the summary statistics (Online Appendix Table A.26 and Table A.27), and find that the spatially matched sample is balanced with respect to a set of economic indicators (Online Appendix Table A.28). The estimation results (Online Appendix Table A.29) are similar to the main results: overall partnership significantly increases trade and the effect is asymmetric in its direction (only West-to-East).

Second, we consider a regular RD design (see Online Appendix Section D.2 for details). In essence, it is similar to spatial matching but places more weight on treated and control city pairs that are closer to each other. The results from the regular RD design are similar to the main results based on segment-segment fixed effects. In Online Appendix Table A.30, we find the RD estimates of the partnership effects on trade show a consistent effect both for e-commerce trade amount (3-4%) and deal volume (3-4%) across a wide range of bandwidth from 60km to 130km. Moreover, these effects are also significant only in the West-to-East e-commerce trade (6-7%). Online Appendix Figure A.2 visualizes the pattern using regular RD plots. Furthermore, Online Appendix Table A.31 reveals that city partnerships do not significantly influence the seller and buyer concentration ratios, suggesting that both large and small sellers equally benefit, which is again consistent with our main model.

5.3 Heterogeneity Analyses

In this section, we test the heterogeneous effect across product categories, regional and pair characteristics, as well as across time. We focus on West-to-East trade as the overall effect is solely driven by West-to-East trade.

5.3.1 Different Categories

We break down the trade amount into six categories: Clothing, Food and Beverage, Household Goods, Electronics, Healthcare, and Others, and separately estimate the spatially matched sample for each category. Table 4 shows that the partnership effects on West-to-East trade are present in Clothing, Food and Beverage, as well as Household Goods. The most substantial effect is in the Food and Beverage category (12%). This finding aligns with the policy's intention – to aid rural areas in the West where there are comparative advantages in agricultural products, particularly for households in poverty. The impact on Clothing (which also includes shoes, leather, and accessories) is similar in magnitude, which is consistent with the observation that the West has rich supplies of leather, wool, and cotton, and the textile industry is one of the largest investments for creating local job opportunities in West China. The third category, Household Goods, encompasses a wide range of products such as furniture, toys, kitchen, and beauty items, which also shows a significant effect. The remaining three categories – Electronics, Healthcare, and Others – show no effect as expected:

These categories are neither the comparative advantage of the West nor the priority areas of policy investment.

Table 4. Spatial RD: Categorical Analysis on West-to-East E-commerce Trade Amount

	log(trade)		
Category	Clothing	Food and Beverage	Household Goods
Partnership pair	0.118***	0.120***	0.096**
	(0.040)	(0.045)	(0.047)
log(distance)	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes
Adj. R^2	0.892	0.941	0.906
F-statistic	4.52	3.99	13.75
Observations	574,200	574,200	574,200
	log(trade)		
Category	Electronics	Healthcare	Others
Partnership pair	-0.041	-0.025	0.035
	(0.051)	(0.076)	(0.053)
log(distance)	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes
Adj. R^2	0.855	0.810	0.843
F-statistic	2.03	0.35	4.99
Observations	574,200	574,200	574,200

Note: This table reports the regression results of the spatial RD model for six categories: Clothing, Food and Beverage, Household Goods, Electronics, Healthcare, and Others. The distance threshold is set at 100km. The unit of observation is city-pair-month. The dependent variable is the logarithm of the West-to-East e-commerce trade amount. The independent variable of interest is the partnership pair. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

5.3.2 Minority and GI products in Western Cities

West China is also home to the majority of China's ethnic minorities, while the majority Han population predominantly inhabits Central and East China. Thus, the partnership potentially integrates ethnic minorities into the national market for inclusive growth. E-commerce, in particular, has the potential to overcome cultural and language barriers (Brynjolfsson et al., 2019). We collect the share of minorities in the overall population for all Western cities and use a median split to create the dummy variable $\mathbb{I}$(High minority share), then estimate the model that further includes its interaction with the partnership pair indicator. The result in Table 5 Column 1 shows that the partnership effects are not only stronger but, in fact, solely driven by Western cities that have high minority shares. While this result apparently contrasts with the finding in Elfenbein et al. (2023), which documents that online trade is positively associated with cultural similarities, it could be explained by the migration mechanism discussed in Section 5.4.1 as follows: Migrants from Western ethnic regions to their partnered Eastern cities tend to purchase culturally specific products from their hometown sellers, items that are often scarce in offline markets.

We formally test the idea that regions with more ethnic minorities may have a larger treatment effect due to more unique or exotic products.[14] We use the number of GI products - products with specific geographical origin - as the measure of exotic products (see details in Section 3.3). We then use a similar median split to indicate regions with more GI products. We find that the number of GI products is indeed significantly correlated with the share of the minority population (Online Appendix Table A.8 Panel A). Table 5 Column 2 shows that the partnership effect is also significantly larger for Western cities with more GI products. Thus, we believe the number of GI products can be interpreted as a measure of e-commerce supply-side potentials unlocked by the partnership. Below we will also discuss how these are related to the supply-side of e-commerce infrastructure measured by the number of e-commerce firms.

5.3.3 Economic Disparities

We also explore how economic disparities and infrastructures affect the magnitude of the partnership effect. Specifically, we consider the following measures: (1) the difference in GDP of partnered cities; (2) Internet and mobile phone penetration rates in West China; (3) measures of physical infrastructure: high-speed rail, freeway density, and road densities. The latter two categories of measures, while related to e-commerce, are also strongly correlated with GDP per capita (Online

[14] We thank an anonymous reviewer for this suggestion.

Table 5. Heterogeneity Analyses for West-to-East E-commerce Trade

Panel A	log(trade)					
	(1)	(2)	(3)	(4)	(5)	(6)
Partnership pair	-0.015	0.051*	0.026	0.017	-0.032*	-0.019
	(0.020)	(0.029)	(0.022)	(0.016)	(0.017)	(0.029)
Partnership pair × $\mathbb{I}$(High minority share)	0.174***					
	(0.044)					
Partnership pair × $\mathbb{I}$(More GI products)		0.168***				
		(0.057)				
Partnership pair × $\mathbb{I}$(High GDP difference)			0.108***			
			(0.041)			
Partnership pair × $\mathbb{I}$(Late high-speed rail commencement)				0.194***		
				(0.052)		
Partnership pair × $\mathbb{I}$(Low freeway density)					0.241***	
					(0.045)	
Partnership pair × $\mathbb{I}$(Low road density)						0.228***
						(0.053)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.935	0.935	0.935	0.937	0.937	0.935
F-statistic	14.67	14.98	13.44	16.81	18.74	17.14
Observations	574,200	574,200	574,200	574,200	574,200	574,200

Panel B	log(trade)				
	(7)	(8)	(9)	(10)	(11)
Partnership pair	-0.017	-0.021	0.040	0.009	0.112***
	(0.027)	(0.026)	(0.040)	(0.043)	(0.031)
Partnership pair × $\mathbb{I}$(Better e-commerce infrastructure)	0.217***				
	(0.050)				
Partnership pair × $\mathbb{I}$(Better cumulative e-commerce infrastructure)		0.188***			
		(0.045)			
Partnership pair × $\mathbb{I}$(Low internet penetration rate)			0.105**		
			(0.053)		
Partnership pair × $\mathbb{I}$(Low mobile phone penetration rate)				0.147***	
				(0.052)	
Partnership pair × $\mathbb{I}$(COVID-19 pandemic)					-0.031
					(0.019)
log(distance)	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.935	0.934	0.935	0.935	0.935
F-statistic	17.30	17.05	14.43	16.45	13.23
Observations	574,200	574,200	574,200	574,200	574,200

Note: This table reports the regression results of the spatial RD model, testing the heterogeneity in the main effect. The distance threshold is set to be 100km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the West-to-East e-commerce trade amount. The independent variables of interest are the interaction terms of the partnership pair and the corresponding subgroup indicators. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Appendix Table A.8 Panel B).

Our findings are consistent: the partnership effect is more pronounced in Western cities that are relatively less developed (Table 5 Column 3), have poorer physical infrastructure (Table 5 Columns 4-6), and are less connected to the Internet and mobile networks (Table 5 Columns 9-10). These results uniformly suggest that the policy is most effective in regions with the largest income gaps relative to East China, and in areas with poorer digital and physical infrastructure. The fact that the policy's greatest impact is seen in areas most in need of assistance indicates that it has indeed achieved its objective of targeting poverty, particularly absolute poverty.

We then consider whether the number of e-commerce firms that captures the supply side of online trade plays a role in taking advantage of the partnership. We measure the number of newly entered firms related to the e-commerce industry in 2018 as well as cumulative to 2021 and test the heterogeneous effects. We find that the magnitude of the partnership effect is strongly associated with the number of e-commerce firms in Western cities (Table 5 Columns 7-8), implying that Western cities with superior e-commerce supply-side benefit more from the partnership. To alleviate the reverse causality concern, we test the HTE using the lagged number of e-commerce firms and find similar results (Online Appendix Table A.7 Columns 4-5). This result is consistent with the HTE of GI products, which also shows regions with more supply-side potentials benefit more from the partnership.

As an additional observation, we note that the distance between city pairs does not significantly moderate the effect (Online Appendix Table A.7 Column 3). This indicates that although the pattern observed in Figure 2 might suggest a larger impact within the gravity model, such an implication does not extend to the causal spatial RD design.

5.3.4 Dynamic Effects: The COVID-19 Pandemic

The COVID-19 pandemic, which emerged at the start of 2020, has significantly impacted the e-commerce industry in both China and globally (Alcedo et al., 2022; Han et al., 2022; Alipour et al., 2022). However, its impact on the effectiveness of the partnership policy remains unclear. On one hand, the pandemic might have shifted consumer shopping behaviors across online and offline channels, potentially amplifying the policy's effects as observed in online trade. On the other hand, the pandemic may have negatively impacted offline exchanges, visits, and migrations.

In Table 5 Column 11, we report the estimates of the partnership effects before and after the outbreak of the COVID-19 pandemic (defined as January 2020). We find that there are no significant changes in the West-to-East e-commerce trade. This could be attributed to the limited disruption in offline interactions, owing to China's zero-COVID policies, at least before 2022.

5.4 Mechanisms

In this section, we further explore the underlying mechanisms of the city partnership effect on e-commerce trade. Again, we focus on the West-to-East trade in the main paper.

5.4.1 Migration

One potential explanation for the partnership effects is China's internal migration, which has been well documented in the literature (Chan, 2013). Specifically, a key policy within the partnership framework encourages residents from Western cities to find jobs in their partnered cities (labor export), which may help to remove frictions such as liquidity constraints in migration (Cai, 2020). Once settled, these migrants might buy goods from their hometowns online (related to the literature on brand preferences of migrating consumers, e.g. Bronnenberg et al. (2012)), leading to an increase in e-commerce trade between partnered cities, from West to East.

To test this hypothesis, we first show that the partnership increases West-to-East migration using the migration flow data described in Section 3.4 and the same spatial-RD model as the main specification. Panel A, Column 1 of Table 6 shows that the migration ratio between partnered cities is indeed significantly higher than neighboring control city pairs. We then include the migration flows in the benchmark spatial-RD model on trade. Panel B, Column 3 in Table 6 shows that (1) migration has a significantly positive effect on trade and (2) the partnership effect decreases in magnitude but still remains statistically significant. We further test whether the mediating role of migration is significant by testing whether the inclusion of migration flows in the specification leads to a statistically significant change in the estimated partnership effect.[15] We find that this change is significant at the 1% level for e-commerce trade, indicating that migration significantly (but also only partially) mediates the partnership effect.

The results prove robust across various migration measures, including data from any of the years between 2019 and 2021, and both pre-CNY and post-CNY traffic (Online Appendix Table A.15) - this is expected since both pre-CNY and post-CNY traffic measure the same underlying West-to-East migration population who go back to their hometown in West China before CNY and return to East China afterward. We also test the effects of the reverse East-to-West migration. Although the partnership increases migration in this direction, it has negligible effects on trade (Online Appendix Table A.16) which is expected given the majority of migrations in China go from rural to urban areas - in this context overwhelmingly West-to-East.

5.4.2 Awareness of Partnered Cities

We also test whether the partnership increases Eastern consumers' awareness of and interest in their partnered regions in West China, thus increasing the West-to-East online trade between partnered cities. To measure consumer awareness, we use the Baidu Search Index data as described in Section 3.4, which we match with the main trade flow data in the opposite direction; for example, for trade from city i to city j, we match the search index of keyword city i from residents in city j, to capture the demand-side awareness. We then test the mediating role of consumer awareness as follows.

First, we test whether the partnership increases Baidu Search using the same spatial-RD specification as the main model. Panel A, Column 2 in Table 6 shows that partnership indeed causes more Baidu searches in both directions: on average, the treatment increases the search index by around 12%. Panel B, Column 4 shows that more Baidu searches lead to more West-to-East trade. The direct effect, however, remains statistically significant albeit smaller in magnitude. We also test the significance of the change in the estimated partnership effect after including Baidu searches. We find

[15]Other standard mediation tests, such as the Sobel test, do not apply in our setting for two reasons. First, while all our models are linear, they include multiple high-dimensional fixed effects that may be different across the models. Second, the mediator (migration) is measured at the city pair level, while our main model is at the city pair-month level.

Table 6. Mechanisms: Intercity Migration and Awareness of Partnered Cities

Panel A	Pre-CNY traffic ratio	log(Baidu search index)	
	(1)	(2)	
Partnership pair	0.528**	0.121***	
	(0.162)	(0.020)	
log(distance)	Yes	Yes	
Exp. City FEs	Yes	No	
Imp. City FEs	Yes	No	
Exp. City-Month FEs	No	Yes	
Imp. City-Month FEs	No	Yes	
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	
Adj. R^2	0.762	0.850	
F-statistic	13.26	17.81	
Observations	19,140	1,148,400	
Panel B	log(trade)		
	(3)	(4)	(5)
Partnership pair	0.055***	0.066***	0.052***
	(0.019)	(0.019)	(0.019)
Pre-CNY traffic ratio	0.009***		0.008***
	(0.001)		(0.001)
log(Baidu search index)		0.027***	0.026***
		(0.004)	(0.004)
log(distance)	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes
Adj. R^2	0.949	0.951	0.949
F-statistic	24.71	26.78	29.71
Observations	574,200	574,200	574,200

Note: This table reports the regression results of the spatial RD model, testing the mechanisms of intercity migration and awareness of partnered cities. The distance threshold is set at 100km. The unit of observation is by city-pair-month. The dependent variable is the logarithm of the West-to-East e-commerce trade amount. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

that this change is statistically significant at the 1% level, showing a partial mediating role of Baidu searches.

We further jointly test the two mechanisms of migration and awareness by including both mediators in the main model. As Panel B, Colum 5 in Table 6 shows, both migration and Baidu search still have significant effects on online trade, with point estimates close to independently estimating their mediation. The direct effect remains statistically significant. Thus, the evidence suggests both mechanisms co-exist and together they only partially explain the main effect. Finally, as a side note, we find that both migration and awareness also affect East-to-West trade, despite the partnership having no direct effect (Online Appendix Table A.17). This suggests that migration and consumer awareness, independent of the partnership, also correlate with online trade, which is consistent with our approach of using these two measures as mediators.

5.4.3 Alternative Mechanisms

We also explore several alternative mechanisms of the partnership effect. The first is purchases from the public sector, including local governments and state-owned enterprises that may deliberately purchase goods from the partnered city to fulfill the requirements of poverty alleviation. Although there is no data available on public spending on e-commerce, these spendings typically occur at the end of the year[16] or during the Chinese New Year since the governments tend to spend all budgets before the new fiscal year starts. Motivated by this observation, we test whether the partnership effects vary during these periods. The results reported in Table 7 show that the partnership effects on the West-to-East e-commerce trade do not change significantly at the end of the year or during the Chinese New Year, which indicates that the partnership effects are unlikely to result from public sector spending. Furthermore, the precisely estimated zero effect on the buyer concentration ratio (Table 3) suggests the effects are not driven by a few main buyers as we would expect from public sector spending.

[16] According to Chinese law (http://www.npc.gov.cn/zgrdw/englishnpc/Law/2007-12/12/content_1383623.htm), a budgetary year begins on January 1 and ends on December 31 in a calendar year. Because of the use-it-or-lose-it budget, year-end crash expenditure is well-known. For example, see http://www.jryj.org.cn/EN/abstract/abstract588.shtml (in Chinese). In the US context, similar wasteful year-end spending has also been well-documented (e.g. Liebman and Mahoney, 2017).

Table 7. Mechanisms: Targeted Subsidies

Dependent Variable	log(trade)	
	(1)	(2)
Partnership pair	0.100***	0.100***
	(0.028)	(0.028)
Partnership pair × $\mathbb{I}$(December)	-0.004	
	(0.017)	
Partnership pair × $\mathbb{I}$(Spring Festival month)		0.002
		(0.022)
log(distance)	Yes	Yes
Exp. City-Month FEs	Yes	Yes
Imp. City-Month FEs	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes
Adj. R^2	0.934	0.935
F-statistic	13.16	13.18
Observations	574,200	574,200

Note: This table reports the regression results of the spatial RD model, testing the mechanism of targeted subsidies. The unit of observation is city-pair-month. The dependent variable is the logarithm of the West-to-East e-commerce trade amount. The independent variables of interest are the interaction terms between the partnership pair and the time period indicators. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, Additionally, we test whether the effect is driven by reduced transportation costs. We collect data on flight routes between all city pairs in China in 2019. We find that the partnership has no significant impact on the number of direct flights between city pairs (Online Appendix Table A.18), and controlling for the flights does not alter the main effect (Online Appendix Table A.19). We thus conclude this mechanism is unlikely.

5.5 Implications and Discussions

In line with standard gravity models used in trade studies, in our research design the overall export growth attributed to e-commerce development is fully captured by the Export City-Time fixed effects. Thus, the empirical strategy does not allow a direct test of whether the policy promoted overall e-commerce growth in West China. Nevertheless, we can analyze the correlation between the heterogeneous effects and the overall growth of e-commerce. To do so, we split the Western regions by their GDP and e-commerce growth rates during the sample period, respectively. The results show that Western regions with larger treatment effects also exhibit stronger economic growth (Online Appendix Table A.7 Column 1) and overall e-commerce export growth (Online Appendix Table A.7 Column 2). Additionally, we find a significant correlation between overall e-commerce exports and both overall GDP growth and the GDP of the primary and tertiary sectors (Online Appendix Table A.35).

All HTE results can be interpreted in two ways. First, the heterogeneity of the effect may be correlated with the treatment intensity. Second, they may indicate different responses to the policy. In the case of economic and e-commerce growth, these results can be interpreted as indicative of the policy's role in promoting overall economic growth and, specifically, e-commerce exports. Alternatively, they may also indicate that Western regions with more growth potential could have benefited more from the partnership. These two interpretations have different policy implications, with the former indicating the role of the partnership policy in promoting growth, and the latter pointing out potentially effective targeting of partnership. The same caution applies to other HTE results including the e-commerce infrastructure. Separately identifying the interpretations is beyond the scope of the current paper.

The migration mechanism also has important policy implications: the West-to-East migration, including organized labor export under the partnership framework, not only helps migrants find jobs but also indirectly benefits the businesses and residents who remain in Western China through e-commerce trade.

There are two potential counterfactual scenarios related to the implication of this result. Firstly, there are reasons to believe that the partnership reduces migration frictions, leading to a more efficient spatial distribution of labor and capital. This likely implies an increase in the productivity and income of the migrants, ultimately enhancing their purchasing power.[17] Consequently, their e-commerce purchases may exceed what their offline purchases would have been had they not migrated.[18]

Second, given the partnership-driven migration, without e-commerce, migrants could not have bought many products from their hometowns through offline channels. Thus, the increase in e-commerce trade among partnership pairs with more migration may reflect new trade that would not have happened without e-commerce. In other words, migrants may be more than substituting offline purchases (of goods from their hometowns, for example in supermarkets) for online purchases. If this were not the case, one would expect to see a negative effect of the partnership on offline trade. We test the idea using offline trade-flow data and find no such effect. Specifically, we use the input-output tables for 2017 (the most recent data available) between all city pairs in China. Using the same spatial RD model, we find no effect on offline trades (Online Appendix Table A.25). Thus, the results do not support such pure online-offline substitution. Relative to this counterfactual, we believe the results show that e-commerce can potentially alleviate the aforementioned negative effect of migration, i.e., shrinking the demand in the local product market, on the population that remains in the West. E-commerce thus complements migration in alleviating poverty in the West by keeping some of their purchasing power in the West.

[17] The literature on exogenous migration typically finds an increase in earnings after migration due to natural disasters or policies aiming to promote migration (e.g. Bryan et al., 2014; Bryan and Morten, 2019; Deryugina et al., 2018; Nakamura et al., 2022). There are studies showing similar effects for migrants from rural to urban areas in China (e.g. Du et al., 2005). In our context, the increase in earnings will likely be more pronounced due to the large wage gap between West and East China than the settings in the literature.

[18] There could also be secondary effects, such as information spillover from migrants to local consumers in their destination cities as well as remunerations sent by migrants to their family members in their hometowns. A formal analysis of this mechanism requires us to go beyond the reduced form approach to analyze the dynamic general spatial equilibrium on the allocation of capital, labor, and consumption, which is an active and understudied area of research (see Jia et al. (2023) for a recent review).

The awareness mechanism shows that the partnership generates consumer interest in the paired Western cities, which translates to higher demand for products sold by sellers in these partnership cities. The fact that neither migration nor consumer awareness completely accounts for the result indicates that additional mechanisms are contributing. This is to be expected due to the scale and complexity of the partnership policy. For example, there may be supply-side mechanisms that help Western cities develop and market products that consumers in their partnered Eastern cities prefer. These mechanisms may be related to the positive moderating roles of the number of GI products and e-commerce firms, which may be correlated with the positive HTE on the share of the minority population. The government official visits and exchanges or the investment amounts promoted through the partnership may also be relevant. However, due to the data limitation in measuring these mechanisms, we leave their detailed exploration for future research.

6 Concluding Remarks

Despite the potential of online platforms to connect remote regions, it remains unclear how they may contribute to alleviating regional inequality. This study focuses on how e-commerce interacts with a significant inclusive growth policy that pairs prosperous and fast-growing regions in East China with low-income regions in West China. We test whether the policy promotes e-commerce trade, how benefits are distributed across sectors, regions, and different sellers, and what the mechanisms are. We find that the partnership policy indeed increases e-commerce trade, and the increase is driven by more exports from low-income regions to high-income ones. By exploring the rich heterogeneities of the effects, we find that they are mostly driven by categories that abound in West China, between regional pairs with large economic gaps, and from regions in West China with better e-commerce infrastructure. We also find that policy-driven migration as well as consumer awareness can partially explain the increase in trade.

These findings have important policy implications. We are the first study to document the economic effects of the East-West Partnership, a major policy that contributed to the largest reduction of poverty in human history to date. We find that the policy significantly promotes e-commerce trade by a magnitude of billions of Chinese Yuan over the past few years. The findings also highlight conditions under which the policy is most effective, for example, low-income regions with superior e-commerce infrastructure as well as more GI products, which underlines the importance of the supply side in promoting e-commerce trade from underdeveloped regions. The migration mechanism implies an unintended consequence of migration, which benefits their hometowns through e-commerce. The consumer awareness mechanism highlights the potential of the policy to "market" the cities in West China.

Several insights from this study may apply to contexts beyond China. The main effect shows that policies targeting regional inequalities can be mutually beneficial instead of mere redistribution. By leveraging e-commerce and digital platforms, policymakers in other countries can potentially replicate these benefits to address economic disparities and help small businesses. The heterogeneous effects show that such policies will be most successful in least-developed regions, with supply-side characteristics such as e-commerce infrastructure and GI products. The mechanisms of migration and consumer awareness can also work in other contexts. In many developing countries such as India, rural-to-urban migration is still ongoing. The results thus suggest such migration can benefit the originating regions of the migrants through e-commerce trade. Other initiatives, such as sister cities, can also promote e-commerce trade through cultural exchanges and raising awareness.[19]

Our study has a few limitations. We estimate the effect on trade between city pairs. Because most regions are treated (but with different pairs), any region-level overall increases in trade are absorbed by the fixed effects and cannot be estimated within the current framework. The effects are partial equilibrium results that cannot be easily aggregated. While some results suggest that the effect is not solely driven by redistribution (the effect remains robust for only using city pairs of a focal export city and the neighboring cities of its partnered import city as control, while redistribution is more likely between neighboring export cities), formal tests for redistribution remain outside of the scope of this study.

All these limitations lead to future areas of research. In addition, we believe that testing how e-commerce interacts with other inclusive policies will be important. It will also be interesting to estimate how the partnership policy affects other significant outcomes, such as education and

[19] For example, see https://cities-today.com/how-sister-city-partnerships-can-play-a-new-role-in-a-global-economy/

gender/ethnic inequalities.

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Online Appendix to Regional Poverty Alleviation Partnership and E-Commerce Trade

A Data Description

Table A.1. China's East-West Poverty Alleviation Partnership

No.	East Province	East City	West Province	West City
1	Beijing	Beijing	Inner Mongolia	Chifeng
2	Beijing	Beijing	Inner Mongolia	Ulanqab
3	Beijing	Beijing	Inner Mongolia	Hinggan
4	Beijing	Beijing	Inner Mongolia	Hulun Buir
5	Beijing	Beijing	Inner Mongolia	Xilingol
6	Beijing	Beijing	Inner Mongolia	Huhhot
7	Beijing	Beijing	Inner Mongolia	Tongliao
8	Beijing	Beijing	Qinghai	Yushu
9	Tianjin	Tianjin	Qinghai	Huangnan
10	Shanghai	Shanghai	Qinghai	Golog
11	Jiangsu	Nanjing	Qinghai	Xining
12	Jiangsu	Wuxi	Qinghai	Haidong
13	Jiangsu	Changzhou	Qinghai	Hainan
14	Jiangsu	Yancheng	Qinghai	Hainan
15	Jiangsu	Nantong	Qinghai	Hainan
16	Jiangsu	Xuzhou	Qinghai	Hainan
17	Jiangsu	Yangzhou	Qinghai	Hainan
18	Zhejiang	Wenzhou	Qinghai	Haixi
19	Zhejiang	Hangzhou	Qinghai	Haixi
20	Zhejiang	Huzhou	Qinghai	Haixi
21	Zhejiang	Jiaxing	Qinghai	Haixi
22	Zhejiang	Ningbo	Qinghai	Haixi
23	Zhejiang	Jinhua	Qinghai	Haixi
24	Zhejiang	Shaoxing	Qinghai	Haixi
25	Zhejiang	Taizhou	Qinghai	Haixi
26	Shandong	Weihai	Qinghai	Haibei
27	Shandong	Binzhou	Qinghai	Haibei

28	Shandong	Linyi	Qinghai	Haibei
29	Shandong	Liaocheng	Qinghai	Haibei
30	Tianjin	Tianjin	Gansu	Gannan
31	Tianjin	Tianjin	Gansu	Tianshui
32	Tianjin	Tianjin	Gansu	Qingyang
33	Tianjin	Tianjin	Gansu	Baiyin
34	Tianjin	Tianjin	Gansu	Pingliang
35	Tianjin	Tianjin	Gansu	Wuwei
36	Tianjin	Tianjin	Gansu	Lanzhou
37	Fujian	Xiamen	Gansu	Linxia
38	Fujian	Fuzhou	Gansu	Dingxi
39	Shandong	Qingdao	Gansu	Longnan
40	Liaoning	Dalian	Guizhou	Liupanshui
41	Shanghai	Shanghai	Guizhou	Zunyi
42	Jiangsu	Suzhou	Guizhou	Tongren
43	Zhejiang	Ningbo	Guizhou	Qianxinan
44	Zhejiang	Hangzhou	Guizhou	Qiandongnan
45	Shandong	Qingdao	Guizhou	Anshun
46	Guangdong	Guangzhou	Guizhou	Qiannan
47	Guangdong	Guangzhou	Guizhou	Bijie
48	Shanghai	Shanghai	Yunnan	Honghe
49	Shanghai	Shanghai	Yunnan	Wenshan
50	Shanghai	Shanghai	Yunnan	Puerh
51	Shanghai	Shanghai	Yunnan	Dali
52	Shanghai	Shanghai	Yunnan	Lincang
53	Shanghai	Shanghai	Yunnan	Chuxiong
54	Shanghai	Shanghai	Yunnan	Xishuangbanna
55	Shanghai	Shanghai	Yunnan	Dehong
56	Shanghai	Shanghai	Yunnan	Baoshan
57	Shanghai	Shanghai	Yunnan	Kunming
58	Shanghai	Shanghai	Yunnan	Qujing
59	Shanghai	Shanghai	Yunnan	Lijiang
60	Shanghai	Shanghai	Yunnan	Diqing
61	Guangdong	Zhuhai	Yunnan	Nujiang
62	Guangdong	Dongguan	Yunnan	Zhaotong
63	Guangdong	Zhongshan	Yunnan	Zhaotong

64	Jiangsu	Wuxi	Shaanxi	Yan'an
65	Jiangsu	Zhenjiang	Shaanxi	Weinan
66	Jiangsu	Nanjing	Shaanxi	Shangluo
67	Jiangsu	Yangzhou	Shaanxi	Yulin
68	Jiangsu	Xuzhou	Shaanxi	Baoji
69	Jiangsu	Changzhou	Shaanxi	Ankang
70	Jiangsu	Nantong	Shaanxi	Hanzhong
71	Jiangsu	Taizhou	Shaanxi	Xianyang
72	Jiangsu	Yancheng	Shaanxi	Tongchuan
73	Jiangsu	Suzhou	Shaanxi	Xi'an
74	Zhejiang	Huzhou	Sichuan	Liangshan
75	Zhejiang	Wenzhou	Sichuan	Aba
76	Zhejiang	Jiaxing	Sichuan	Aba
77	Zhejiang	Jinhua	Sichuan	Aba
78	Zhejiang	Taizhou	Sichuan	Aba
79	Zhejiang	Shaoxing	Sichuan	Aba
80	Zhejiang	Jiaxing	Sichuan	Yibin
81	Zhejiang	Quzhou	Sichuan	Leshan
82	Zhejiang	Shaoxing	Sichuan	Leshan
83	Zhejiang	Wenzhou	Sichuan	Nanchong
84	Zhejiang	Jinhua	Sichuan	Nanchong
85	Zhejiang	Taizhou	Sichuan	Nanchong
86	Zhejiang	Taizhou	Sichuan	Guangyuan
87	Zhejiang	Lishui	Sichuan	Guangyuan
88	Zhejiang	Huzhou	Sichuan	Guangyuan
89	Zhejiang	Quzhou	Sichuan	Mianyang
90	Zhejiang	Quzhou	Sichuan	Luzhou
91	Zhejiang	Zhoushan	Sichuan	Dazhou
92	Zhejiang	Lishui	Sichuan	Bazhong
93	Guangdong	Shenzhen	Sichuan	Ganzi
94	Guangdong	Guangzhou	Sichuan	Ganzi
95	Guangdong	Zhuhai	Sichuan	Ganzi
96	Guangdong	Zhongshan	Sichuan	Ganzi
97	Guangdong	Dongguan	Sichuan	Ganzi
98	Guangdong	Jiangmen	Sichuan	Ganzi
99	Guangdong	Huizhou	Sichuan	Ganzi

100	Guangdong	Foshan	Sichuan	Ganzi
101	Guangdong	Foshan	Sichuan	Liangshan
102	Guangdong	Shenzhen	Guangxi	Baise
103	Guangdong	Shenzhen	Guangxi	Hechi
104	Guangdong	Jiangmen	Guangxi	Chongzuo
105	Guangdong	Zhaoqing	Guangxi	Guilin
106	Guangdong	Zhaoqing	Guangxi	Hezhou
107	Guangdong	Zhanjiang	Guangxi	Liuzhou
108	Guangdong	Maoming	Guangxi	Nanning
109	Guangdong	Maoming	Guangxi	Laibin
110	Shandong	Linyi	Chongqing	Chongqing
111	Shandong	Weihai	Chongqing	Chongqing
112	Shandong	Binzhou	Chongqing	Chongqing
113	Shandong	Yantai	Chongqing	Chongqing
114	Shandong	Taian	Chongqing	Chongqing
115	Shandong	Zaozhuang	Chongqing	Chongqing
116	Shandong	Jinan	Chongqing	Chongqing
117	Shandong	Rizhao	Chongqing	Chongqing
118	Shandong	Zibo	Chongqing	Chongqing
119	Shandong	Dezhou	Chongqing	Chongqing
120	Shandong	Dongying	Chongqing	Chongqing
121	Shandong	Liaocheng	Chongqing	Chongqing
122	Shandong	Jining	Chongqing	Chongqing
123	Shandong	Weifang	Chongqing	Chongqing
124	Fujian	Quanzhou	Ningxia	Wuzhong
125	Fujian	Fuzhou	Ningxia	Guyuan
126	Fujian	Putian	Ningxia	Guyuan
127	Fujian	Xiamen	Ningxia	Guyuan
128	Fujian	Zhangzhou	Ningxia	Zhongwei

Note: This table presents the city pairs in China's East-West Poverty Alleviation Partnership. The data is collected from the 2018 Yearbook of China's Poverty Alleviation and Development (see page 768-777).

Table A.2. Summary Statistics of E-commerce Trade Flow Ratios between the Paired Cities Relative to the Full Sample

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: all cities								
Trade amount	137	4.78	5.19	0.03	0.74	2.05	9.91	30.20
Trade amount (Export)	137	4.55	4.41	0.15	0.94	2.24	8.50	20.38
Trade amount (Import)	137	4.76	5.50	0.02	0.30	1.96	10.29	30.66
Deal volume	137	4.46	5.32	0.04	0.71	1.54	8.91	30.12
Deal volume (Export)	137	4.57	4.41	0.12	0.95	2.62	8.85	20.10
Deal volume (Import)	137	4.41	5.60	0.02	0.28	1.41	8.92	30.66
Panel B: west cities								
Trade amount	81	5.36	5.61	0.03	0.91	2.84	10.27	30.20
Trade amount (Export)	81	5.00	4.49	0.22	1.29	3.14	8.46	20.38
Trade amount (Import)	81	5.36	5.68	0.02	0.90	2.84	10.29	30.66
Deal volume	81	4.73	5.76	0.04	0.71	2.33	8.82	30.12
Deal volume (Export)	81	4.92	4.34	0.25	1.39	3.25	8.39	20.10
Deal volume (Import)	81	4.71	5.85	0.03	0.65	2.35	8.80	30.66
Panel C: east cities								
Trade amount	56	3.94	4.42	0.13	0.68	1.41	9.88	12.07
Trade amount (Export)	56	3.90	4.23	0.15	0.76	1.51	9.41	12.09
Trade amount (Import)	56	3.89	5.15	0.03	0.19	0.56	10.39	15.76
Deal volume	56	4.07	4.65	0.13	0.66	1.40	10.87	12.29
Deal volume (Export)	56	4.06	4.49	0.12	0.77	1.44	10.62	12.23
Deal volume (Import)	56	3.99	5.24	0.02	0.23	0.60	11.64	12.55

Note: This table reports the summary statistics, including the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max), for the trade flow ratios between the cities in the partnership relative to the full sample. Panel A, B, and C correspond to the summary statistics of all cities, west cities, and east cities in the partnership, respectively. E-commerce trade amount and deal volume are defined in Section 3.2. The sample covers the period from January 2017 through December 2021.

Table A.3. Correlation Coefficients Between West-to-East Migration Flows

	Post-CNY (2019)	Post-CNY (2020)	Post-CNY (2021)	Post-CNY (Mean)	Pre-CNY (2019)	Pre-CNY (2020)	Pre-CNY (2021)	Pre-CNY (Mean)
Post-CNY (2019)	1							
Post-CNY (2020)	0.90	1						
Post-CNY (2021)	0.90	0.98	1					
Post-CNY (Mean)	0.96	0.99	0.99	1				
Pre-CNY (2019)	0.81	0.75	0.79	0.80	1			
Pre-CNY (2020)	0.88	0.96	0.95	0.95	0.71	1		
Pre-CNY (2021)	0.87	0.97	0.97	0.96	0.70	0.95	1	
Pre-CNY (Mean)	0.92	0.97	0.98	0.98	0.86	0.96	0.96	1

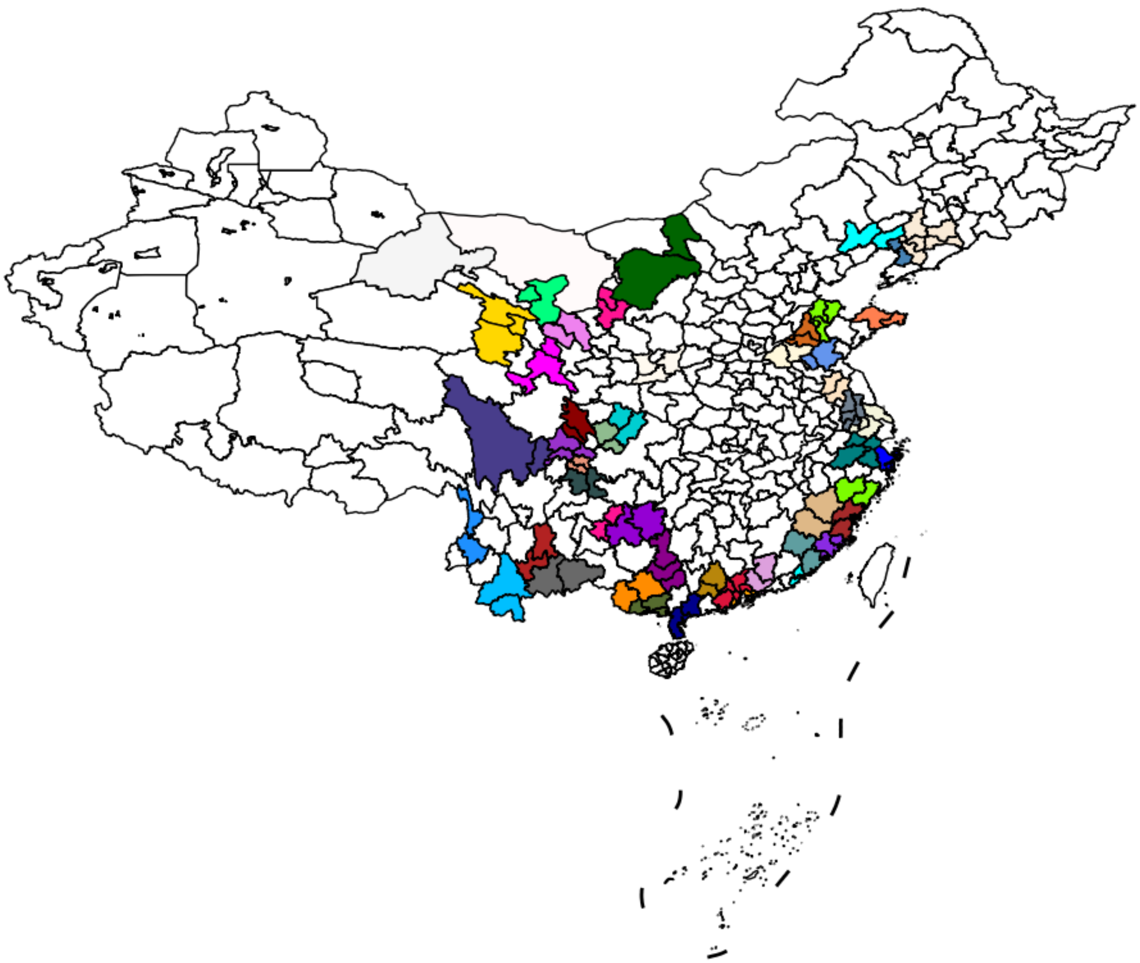
Note: This table reports the correlation coefficients between eight West-to-East migration flow measures constructed using Baidu Map migration records, as detailed in Section 3.4 of the main text.

Table A.4. Distribution of Segment Size

	Segment Size								
	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	Total
$d=50$km	150	16	5	0	0	0	0	0	171
	N.A.	(31.17)	(29.41)	N.A.	N.A.	N.A.	N.A.	N.A.	
$d=75$km	131	22	3	2	1	0	0	0	159
	N.A.	(42.22)	(32.67)	(41.80)	(38.88)	N.A.	N.A.	N.A.	
$d=100$km	81	37	8	2	2	0	0	0	130
	N.A.	(70.96)	(62.45)	(50.30)	(49.08)	N.A.	N.A.	N.A.	
$d=125$km	59	29	16	4	2	1	0	0	111
	N.A.	(85.50)	(85.11)	(72.87)	(55.30)	(63.12)	N.A.	N.A.	
$d=150$km	53	22	10	11	0	3	0	1	100
	N.A.	(93.16)	(95.82)	(94.53)	N.A.	(83.27)	N.A.	(80.05)	

Note: This table presents the distribution of segment size and the average within-cluster distance for various threshold distances. The average within-cluster distance is measured in kilometers (km) and is provided in parentheses.

Figure A.1. Graphical Illustration for the City Segments ($d = 100$km)



Note: This figure displays the city segments as determined by the algorithm detailed in Section 4. Cities marked with the same color are part of the same segment. The distance threshold is set at 100km.

B Additional Results

Table A.5. Gravity Regression: Results with Province-Province Fixed Effects

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership Pair	0.028**	-0.010	0.066***	0.030***	-0.001	0.062***
	(0.012)	(0.013)	(0.020)	(0.009)	(0.008)	(0.016)
log(distance)	-0.246***	-0.251***	-0.241***	-0.204***	-0.168***	-0.239***
	(0.011)	(0.013)	(0.018)	(0.009)	(0.013)	(0.013)
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Prov.-Imp. Prov. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.976	0.987	0.957	0.992	0.995	0.985
F-statistic	242.54	174.30	95.93	246.87	84.75	201.91
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	-0.019	0.118	-0.158	-0.045	0.093	-0.184
	(0.202)	(0.190)	(0.357)	(0.172)	(0.173)	(0.298)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Prov.-Imp. Prov. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.508	0.649	0.421	0.518	0.664	0.426
F-statistic	13.29	10.84	4.69	11.08	14.28	1.46
Observations	1,136,426	574,134	562,292	1,137,650	574,135	563,515

Note: This table reports the regression results of the baseline gravity model with export province-import province fixed effects. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount, deal volume, seller concentration ratio, and buyer concentration ratio. The independent variable of interest is the partnership pair. All columns control the export city-month and import city-month fixed effects, as well as the export province-import province fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.6. Spatial RD: Partnership Pair Prediction

Dependent Variable	Partnership Pair					
	50km	75km	100km	125km	150km	Full Sample
log(distance)	0.059	0.027	0.071	0.022	0.006	0.001***
	(0.182)	(0.116)	(0.055)	(0.036)	(0.030)	(0.000)
GDP Difference	0.337	0.457	0.531	0.737**	0.609**	0.699**
	(0.356)	(0.425)	(0.356)	(0.311)	(0.308)	(0.274)
Population Difference	-0.000	-0.002	0.001	-0.000	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	No
Adj. R^2	0.248	0.289	0.249	0.295	0.317	0.014
F-statistic	0.213	0.397	1.730	2.323	2.022	43.064
Observations	4,386	5,660	8,140	8,940	8,978	9,570

Note: This table reports the regression results for the prediction of partnership pairs. The dependent variable is the dummy variable indicating a partnership between city pairs. The independent variables include the logarithms of the distance between city centers, GDP difference, and population difference. The data of GDP difference and population difference in 2017 are from the China City Statistical Yearbook. All columns control for the export segment-import segment fixed effects. We consider five distance thresholds used in the construction of the segments, including 50km, 75km, 100km, 125km, and 150km. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.7. Additional Heterogeneity Analyses for West-to-East E-commerce Trade

Dependent Variable	log(trade)				
	(1)	(2)	(3)	(4)	(5)
Partnership pair	0.089*	0.085**	0.086***	-0.013	-0.020
	(0.047)	(0.035)	(0.025)	(0.028)	(0.029)
Partnership pair × $\mathbb{I}$(High GDP growth rate)	0.055**				
	(0.026)				
Partnership pair × $\mathbb{I}$(High export growth rate)		0.055**			
		(0.024)			
Partnership pair × $\mathbb{I}$(Larger distance between city pairs)			0.014		
			(0.055)		
Partnership pair × $\mathbb{I}$(Better e-commerce infrastructure, 1-year lagged)				0.203***	
				(0.049)	
Partnership pair × $\mathbb{I}$(Better e-commerce infrastructure in 2016)					0.208***
					(0.049)
log(distance)	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.935	0.935	0.935	0.935	0.934
F-statistic	13.84	13.79	12.84	16.82	16.94
Observations	574,200	574,200	574,200	574,200	574,200

Note: This table reports the additional regression results of the spatial RD model, testing the heterogeneity in the main effect. The distance threshold is set to be 100km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the West-to-East e-commerce trade amount. The independent variables of interest are the interaction terms of the partnership pair and the corresponding subgroup indicators. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.8. Correlation Between Characteristics in Western Cities

Panel A		log(Number of GI products)		log(Number of e-commerce firms)	
Minority share		0.037***		0.093***	
		(0.003)		(0.005)	
Adj. R^2		0.398		0.503	
F-statistic		155.94		395.01	
Observations		110		110	
Panel B	**log(High-speed rail commencement)**	**log(Freeway density)**	**log(Road density)**	**log(Internet penetration rate)**	**log(Mobile phone penetration rate)**
log(GDP per capita)	3.840***	0.024***	0.529***	0.237***	0.734***
	(0.057)	(0.002)	(0.026)	(0.009)	(0.011)
Adj. R^2	0.976	0.674	0.792	0.866	0.976
F-statistic	4,568.73	228.76	420.44	712.21	4,391.32
Observations	110	110	110	110	110

Note: This table reports regression results examining the correlation between various characteristics in Western cities. Panel A reports the relationship between the logarithm of the number of GI (Geographical Indication) products and the logarithm of the number of e-commerce firms, each in relation to the minority share. Panel B explores the relationship between a set of economic development measures and the logarithm of GDP per capita. Specifically, high-speed rail commencement refers to the number of months from the high-speed rail's start date until December 2023. Robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

C Robustness Checks of Spatial RD Regression

Table A.9. Spatial RD: Segment-Segment-Month Fixed Effects

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.046**	-0.004	0.096***	0.030**	0.002	0.059***
	(0.019)	(0.019)	(0.032)	(0.012)	(0.013)	(0.020)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg.-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.967	0.988	0.936	0.994	0.996	0.988
F-statistic	3.37	7.00	13.64	3.88	2.16	9.41
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.055	0.101	0.007	0.104	0.191	0.016
	(0.257)	(0.285)	(0.427)	(0.227)	(0.294)	(0.346)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg.-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.524	0.657	0.447	0.538	0.679	0.452
F-statistic	0.79	3.18	6.47	0.32	2.69	3.91
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200

Note: This table reports the regression results of the robustness checks for the spatial RD model. The distance threshold is set to be 100km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount, deal volume, seller concentration ratio, and buyer concentration ratio. The independent variable of interest is the partnership pair. All columns control the export city-month, import city-month, and export segment-import segment-month fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.10. Spatial RD: City and Month Fixed Effects

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.047**	-0.004	0.098***	0.031***	0.002	0.060***
	(0.019)	(0.018)	(0.032)	(0.012)	(0.012)	(0.020)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.962	0.984	0.928	0.988	0.992	0.977
F-statistic	3.49	7.14	13.94	4.01	2.20	9.66
Observations	1,148,400	574,200	574,200	1,148,100	574,200	574,200
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.069	0.101	0.035	0.106	0.191	0.020
	(0.251)	(0.282)	(0.416)	(0.224)	(0.291)	(0.340)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.484	0.618	0.403	0.489	0.638	0.396
F-statistic	0.83	3.25	6.64	0.34	2.74	4.04
Observations	1,148,100	574,200	574,200	1,148,100	574,200	574,200

Note: This table reports the regression results of the robustness checks for the spatial RD model. The distance threshold is set to be 100km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount, deal volume, seller concentration ratio, and buyer concentration ratio. The independent variable of interest is the partnership pair. All columns control the export city, import city, month, and export segment-import segment-month fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.11. Spatial RD: Alternative Distance Thresholds

Distance Threshold	50km			75km		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.039*	-0.021	0.099***	0.038**	-0.026	0.083**
	(0.021)	(0.017)	(0.038)	(0.019)	(0.018)	(0.032)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.968	0.989	0.937	0.967	0.989	0.936
F-statistic	1.69	0.76	3.41	6.52	5.13	5.42
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200
Distance Threshold	125km			150km		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.057***	0.002	0.112***	0.051***	0.011	0.091***
	(0.015)	(0.013)	(0.028)	(0.015)	(0.014)	(0.026)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.966	0.988	0.934	0.966	0.988	0.933
F-statistic	7.77	2.83	14.67	45.70	21.90	26.14
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200

Note: This table presents the regression results for the spatial RD model when an alternative distance threshold is used in the construction of city segments. We consider four alternative distance thresholds: 50km, 75km, 125km, and 150km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.12. Spatial RD: The Same Dialect Region

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.044***	-0.011	0.099***	0.031***	-0.003	0.064***
	(0.014)	(0.014)	(0.024)	(0.008)	(0.007)	(0.015)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.967	0.989	0.936	0.993	0.996	0.987
F-statistic	5.03	10.62	19.98	6.71	5.41	11.41
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.120	0.149	0.090	0.067	0.010	0.124
	(0.198)	(0.227)	(0.325)	(0.191)	(0.260)	(0.284)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.536	0.677	0.450	0.542	0.689	0.449
F-statistic	0.21	8.48	5.53	0.42	6.55	9.93
Observations	1,148,400	574,200	574,200	1,148,400	574,200	574,200

Note: This table presents the regression results of the robustness checks for the spatial RD model, addressing the potential cultural differences between treatment and control pairs. The treated and control cities are required to be in the same dialect district, in addition to satisfying the distance requirement. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount and deal volume, seller concentration ratio, and buyer concentration ratio. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.13. Spatial RD: Excluding Segments with Multiple Treated Pairs

Distance Threshold: 100km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.039**	-0.006	0.085***	0.023*	0.003	0.042**
	(0.019)	(0.017)	(0.026)	(0.012)	(0.012)	(0.019)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.965	0.988	0.934	0.992	0.996	0.987
F-statistic	4.56	10.23	12.09	2.39	3.12	9.81
Observations	1,139,400	569,700	569,700	1,139,400	569,700	569,700
Distance Threshold: 75km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.040**	-0.026	0.074***	0.025*	-0.009	0.058***
	(0.019)	(0.018)	(0.023)	(0.014)	(0.011)	(0.021)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.966	0.989	0.936	0.992	0.996	0.987
F-statistic	4.00	5.28	3.33	7.47	13.40	5.84
Observations	1,145,640	572,820	572,820	1,145,640	572,820	572,820
Distance Threshold: 125km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.049**	-0.004	0.091***	0.033***	0.003	0.063***
	(0.022)	(0.014)	(0.027)	(0.012)	(0.010)	(0.018)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.965	0.988	0.934	0.992	0.996	0.986
F-statistic	2.23	2.47	8.30	4.17	4.39	7.18
Observations	1,134,600	567,300	567,300	1,134,600	567,300	567,300

Note: This table reports the regression results of the robustness checks for the spatial RD model, excluding observations from segments with multiple treated pairs. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the e-commerce trade amount and deal volume. The primary independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.14. Migration Ratio and Partnership Pair

Dependent Variable	Daily pre-CNY traffic ratio				
	50km	75km	100km	125km	150km
Partnership pair	3.562***	4.074**	3.232***	3.023***	2.103**
	(1.175)	(1.708)	(1.156)	(1.040)	(1.070)
Exp. City-Day FEs	Yes	Yes	Yes	Yes	Yes
Imp. City-Day FEs	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.671	0.561	0.549	0.501	0.481
F-statistic	9.184	5.689	7.822	8.443	3.862
Observations	870,870	870,870	870,870	870,870	870,870
Dependent Variable	Daily post-CNY traffic ratio				
	50km	75km	100km	125km	150km
Partnership pair	4.046***	3.851**	3.615**	3.789***	2.077
	(1.505)	(1.841)	(1.486)	(1.351)	(1.462)
Exp. City-Day FEs	Yes	Yes	Yes	Yes	Yes
Imp. City-Day FEs	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.690	0.595	0.581	0.535	0.508
F-statistic	7.231	4.375	5.917	7.861	2.017
Observations	870,870	870,870	870,870	870,870	870,870

Note: This table presents the estimation results of the regression analysis in which the daily pre-CNY and post-CNY traffic ratios are respectively regressed on the partnership pair. All columns account for the export city-day, import city-day, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.15. Mechanisms: Intercity Migration

Panel A	log(trade)			
	Year 2019		Year 2020	
	(1)	(2)	(3)	(4)
Partnership pair	0.053^{***}	0.058^{***}	0.058^{***}	0.058^{***}
	(0.019)	(0.018)	(0.019)	(0.019)
Pre-CNY traffic ratio	0.006^{***}		0.008^{***}	
	(0.001)		(0.001)	
Post-CNY traffic ratio		0.010^{***}		0.007^{***}
		(0.002)		(0.001)
log(distance)	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes
Adj. R^2	0.949	0.949	0.949	0.949
F-statistic	18.34	20.75	19.52	23.94
Observations	574,200	574,200	574,200	574,200

Panel B	log(trade)			
	Year 2021		Three-year Average	
	(5)	(6)	(7)	(8)
Partnership pair	0.059^{***}	0.057^{***}	0.055^{***}	0.057^{***}
	(0.019)	(0.018)	(0.019)	(0.018)
Pre-CNY traffic ratio	0.005^{***}		0.009^{***}	
	(0.001)		(0.001)	
Post-CNY traffic ratio		0.005^{***}		0.008^{***}
		(0.001)		(0.001)
log(distance)	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes
Adj. R^2	0.951	0.949	0.949	0.949
F-statistic	20.97	26.17	24.71	25.36
Observations	574,200	574,200	574,200	574,200

Note: This table reports the regression results of the spatial RD model, testing the mechanisms of intercity migration. The distance threshold is set at 100km. The unit of observation is by city-pair-month. The dependent variable is the logarithm of the West-to-East e-commerce trade amount. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.16. Mechanism: Reverse Intercity Migration

Panel A	Pre-CNY traffic ratio (reverse)
Partnership pair	0.088**
	(0.043)
log(distance)	Yes
Exp. City FEs	Yes
Imp. City FEs	Yes
Exp. Seg.-Imp. Seg. FEs	Yes
Adj. R^2	0.736
F-statistic	10.33
Observations	19,140

Panel B	log(trade)		
	Both Directions	East-to-West	West-to-East
Partnership pair	0.027**	-0.004	0.059***
	(0.012)	(0.015)	(0.019)
Pre-CNY traffic ratio (reverse)	0.001	-0.001	0.002
	(0.001)	(0.001)	(0.002)
log(distance)	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes
Adj. R^2	0.975	0.988	0.949
F-statistic	2.42	7.73	14.01
Observations	1,148,400	574,200	574,200

Note: This table reports the regression results of the spatial RD model, testing the mechanism of intercity migration. The distance threshold is set at 100km. The unit of observation is by city-pair-month. In Panel A, the dependent variable is the mean of reverse pre-CNY traffic ratios during 2019-2021, while the independent variable of interest is the partnership pair. In Panel B, the dependent variable is the logarithm of the e-commerce trade amount, and the independent variable of interest is the mean of reverse pre-CNY traffic ratios during 2019-2021. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.17. Mechanisms: Intercity Migration and Awareness of Partnered Cities (East-to-West E-commerce Trade)

Dependent Variable	log(trade)		
	(1)	(2)	(3)
Partnership pair	-0.007	-0.006	-0.008
	(0.015)	(0.015)	(0.016)
Pre-CNY traffic ratio	0.006^{***}		0.006^{***}
	(0.001)		(0.002)
log(Baidu search index)		0.014^{***}	0.014^{***}
		(0.002)	(0.002)
log(distance)	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes
Adj. R^2	0.988	0.988	0.988
F-statistic	8.06	17.78	14.17
Observations	574,200	574,200	574,200

Note: This table reports the regression results of the spatial RD model, testing the mechanisms of intercity migration and awareness of partnered cities. The distance threshold is set at 100km. The unit of observation is by city-pair-month. The dependent variable is the logarithm of the East-to-West e-commerce trade amount. All columns control for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.18. Number of Intercity Flights and Partnership Pair

Dependent Variable	Flight of Both Directions						
	50km	75km	100km	125km	150km	175km	200km
Partnership pair	-3.703*	-2.479*	-0.477	-0.532	-1.233	-0.963	-0.347
	(2.011)	(1.468)	(1.160)	(0.885)	(0.790)	(0.875)	(0.812)
Exp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.197	0.184	0.218	0.239	0.256	0.259	0.268
F-statistic	3.390	2.850	0.168	0.361	2.435	1.211	0.183
Observations	8,772	11,320	16,280	17,880	17,956	18,344	18,412
Dependent Variable	East-to-West Flight						
	50km	75km	100km	125km	150km	175km	200km
Partnership pair	-3.691	-2.461	-0.306	-0.503	-1.218	-1.037	-0.210
	(2.819)	(2.057)	(1.696)	(1.317)	(1.194)	(1.321)	(1.176)
Exp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.199	0.183	0.478	0.242	0.259	0.261	0.268
F-statistic	1.714	1.431	0.222	0.146	1.041	0.617	0.032
Observations	4,386	5,660	8,140	8,940	8,978	9,167	9,206
Dependent Variable	West-to-East Flight						
	50km	75km	100km	125km	150km	175km	200km
Partnership pair	-3.716	-2.496	-0.647	-0.561	-1.248	-0.889	-0.484
	(2.850)	(2.085)	(1.578)	(1.181)	(1.034)	(1.146)	(1.120)
Exp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.205	0.192	0.218	0.240	0.256	0.260	0.271
F-statistic	1.699	1.433	0.168	0.225	1.459	0.601	0.187
Observations	4,386	5,660	8,140	8,940	8,978	9,167	9,206

Note: This table presents the estimation results of the regression analysis in which the number of intercity flights is regressed on the partnership pair. All columns control the export city, import city, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.19. Spatial RD: Number of Intercity Flights

Dependent Variable	log(trade)		
	Both Directions	East-to-West	West-to-East
Partnership pair	0.048***	-0.005	0.101***
	(0.019)	(0.018)	(0.032)
log(1 + Number of flights)	-0.006***	0.007***	-0.020***
	(0.002)	(0.002)	(0.003)
log(distance)	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes
Adj. R^2	0.967	0.989	0.937
F-statistic	7.60	11.32	27.87
Observations	1,148,400	574,200	574,200

Note: This table presents the regression results of the spatial RD model, testing the potential effects of intercity flights. The distance threshold is set at 100km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount. All columns account for the export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.20. Summary Statistics of the Import Shares

	N	Mean	SD	Min	P25	P50	P75	Max
Panel A: city-level import shares								
Clothing	197	28.53	6.23	18.41	21.74	31.48	34.40	37.89
Food and Beverage	197	11.04	8.74	1.91	3.22	3.80	20.70	24.38
Household Goods	197	29.48	1.46	26.68	28.36	29.16	30.39	34.01
Electronics	197	15.48	4.77	8.16	10.73	16.94	19.14	27.00
Healthcare	197	1.48	0.21	1.12	1.31	1.46	1.56	2.26
Others	197	14.00	1.64	10.06	12.87	13.72	14.99	18.45
Panel B: within-segment absolute import share difference ($d = 100$km)								
Clothing	93	1.15	1.35	0.00	0.36	0.80	1.50	8.48
Food and Beverage	93	0.84	0.79	0.01	0.30	0.59	1.16	3.80
Household Goods	93	0.98	0.93	0.00	0.29	0.76	1.36	5.63
Electronics	93	0.84	0.92	0.02	0.28	0.48	0.91	4.60
Healthcare	93	0.14	0.14	0.00	0.05	0.11	0.17	0.62
Others	93	1.13	0.97	0.02	0.35	0.85	1.66	4.05

Note: This table presents the summary statistics for the city-level import share and the within-segment absolute import share difference for each category. The reported summary statistics include the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max). The sample spans the period from January 2017 through December 2021. Panel A provides the city-level summary statistics. Panel B presents the summary statistics for the absolute difference in import share between each city pair within the segments of d = 100km. All values, except the number of observations, are expressed as percentages.

Table A.21. Spatial RD: Excluding Type-I City Pairs

Distance Threshold: 100km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.036**	-0.004	0.095***	0.027**	0.002	0.053***
	(0.017)	(0.015)	(0.024)	(0.011)	(0.011)	(0.016)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.965	0.989	0.935	0.993	0.996	0.987
F-statistic	2.61	6.75	14.42	3.62	2.10	9.19
Observations	1,040,520	520,260	520,260	1,040,520	520,260	520,260
Distance Threshold: 75km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.008	-0.025	0.041**	0.027*	-0.007	0.060***
	(0.019)	(0.017)	(0.020)	(0.014)	(0.010)	(0.021)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.966	0.989	0.936	0.993	0.997	0.988
F-statistic	1.98	1.81	3.71	5.96	10.10	5.42
Observations	1,040,520	520,260	520,260	1,040,520	520,260	520,260
Distance Threshold: 125km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.046***	0.002	0.091***	0.035***	0.004	0.065***
	(0.017)	(0.013)	(0.025)	(0.010)	(0.009)	(0.015)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.965	0.988	0.934	0.993	0.996	0.987
F-statistic	5.27	0.48	11.70	6.69	1.27	11.26
Observations	1,040,520	520,260	520,260	1,040,520	520,260	520,260

Note: This table reports the regression results of the robustness checks for the spatial RD model, excluding type-I city pairs in the control group. Specifically, the city pairs in the control group are classified into four types: (1) neither the Eastern city nor the Western city is in the program; (2) only the Eastern city is in the program; (3) only the Western city is in the program; and (4) both cities are in the program but are not paired with each other. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the e-commerce trade amount and deal volume. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.22. Spatial RD: Excluding Type-II City Pairs

Distance Threshold: 100km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.029	0.000	0.057**	0.022*	0.004	0.041**
	(0.019)	(0.016)	(0.027)	(0.011)	(0.011)	(0.018)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.962	0.988	0.929	0.992	0.996	0.986
F-statistic	2.68	3.39	14.00	2.93	0.39	7.48
Observations	953,520	476,760	476,760	953,520	476,760	476,760
Distance Threshold: 75km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.010	-0.021	0.051**	0.033**	-0.001	0.068***
	(0.019)	(0.017)	(0.025)	(0.014)	(0.009)	(0.021)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.962	0.988	0.931	0.992	0.996	0.987
F-statistic	1.51	2.69	1.87	6.14	8.11	5.91
Observations	953,520	476,760	476,760	953,520	476,760	476,760
Distance Threshold: 125km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.045**	0.011	0.079***	0.032***	0.007	0.057***
	(0.018)	(0.013)	(0.028)	(0.010)	(0.009)	(0.015)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.962	0.987	0.928	0.992	0.996	0.986
F-statistic	3.31	2.34	7.42	5.64	3.17	7.47
Observations	953,520	476,760	476,760	953,520	476,760	476,760

Note: This table reports the regression results of the robustness checks for the spatial RD model, excluding type-II city pairs in the control group. Specifically, the city pairs in the control group are classified into four types: (1) neither the Eastern city nor the Western city is in the program; (2) only the Eastern city is in the program; (3) only the Western city is in the program; and (4) both cities are in the program but are not paired with each other. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the e-commerce trade amount and deal volume. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.23. Spatial RD: Excluding Type-III City Pairs

Distance Threshold: 100km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.037**	0.005	0.070***	0.030***	0.005	0.056***
	(0.016)	(0.016)	(0.022)	(0.011)	(0.011)	(0.017)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.970	0.990	0.940	0.993	0.997	0.988
F-statistic	2.74	11.37	12.34	3.78	5.18	11.52
Observations	847,080	423,540	423,540	847,080	423,540	423,540
Distance Threshold: 75km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.021	-0.013	0.054**	0.024	-0.007	0.055**
	(0.030)	(0.040)	(0.033)	(0.015)	(0.011)	(0.022)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.971	0.991	0.942	0.994	0.997	0.989
F-statistic	7.36	9.03	4.67	11.84	25.49	4.70
Observations	847,080	423,540	423,540	847,080	423,540	423,540
Distance Threshold: 125km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.049***	0.010	0.089***	0.037***	0.006	0.068***
	(0.016)	(0.013)	(0.023)	(0.010)	(0.009)	(0.015)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.970	0.990	0.940	0.993	0.997	0.988
F-statistic	5.57	1.10	11.49	7.10	1.23	11.44
Observations	847,080	423,540	423,540	847,080	423,540	423,540

Note: This table reports the regression results of the robustness checks for the spatial RD model, excluding type-III city pairs in the control group. Specifically, the city pairs in the control group are classified into four types: (1) neither the Eastern city nor the Western city is in the program; (2) only the Eastern city is in the program; (3) only the Western city is in the program; and (4) both cities are in the program but are not paired with each other. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the e-commerce trade amount and deal volume. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.24. Spatial RD: Excluding Type-IV City Pairs

Distance Threshold: 100km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.046*	-0.057*	0.149***	0.034*	-0.024	0.091***
	(0.027)	(0.034)	(0.037)	(0.019)	(0.017)	(0.031)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.963	0.985	0.937	0.991	0.995	0.987
F-statistic	2.39	9.91	18.72	4.13	1.31	12.16
Observations	619,440	309,720	309,720	619,440	309,720	309,720
Distance Threshold: 75km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.009	-0.077*	0.094***	0.049**	0.006	0.091**
	(0.030)	(0.040)	(0.033)	(0.024)	(0.025)	(0.036)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.963	0.986	0.938	0.991	0.995	0.987
F-statistic	2.64	5.33	5.67	6.20	2.07	11.35
Observations	619,440	309,720	309,720	619,440	309,720	309,720
Distance Threshold: 125km	log(trade)			log(deal)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.045*	-0.053*	0.144***	0.057***	-0.017	0.130***
	(0.024)	(0.029)	(0.034)	(0.020)	(0.015)	(0.034)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.963	0.985	0.937	0.991	0.995	0.986
F-statistic	1.75	10.68	11.53	3.93	4.92	8.62
Observations	619,440	309,720	309,720	619,440	309,720	309,720

Note: This table reports the regression results of the robustness checks for the spatial RD model, excluding type-IV city pairs in the control group. Specifically, the city pairs in the control group are classified into four types: (1) neither the Eastern city nor the Western city is in the program; (2) only the Eastern city is in the program; (3) only the Western city is in the program; and (4) both cities are in the program but are not paired with each other. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the e-commerce trade amount and deal volume. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.25. Spatial RD: Offline Trade

Dependent Variable: log(trade)	Year 2012			Year 2017		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	-0.015	-0.020	-0.011	-0.013	-0.048*	0.022
	(0.018)	(0.034)	(0.013)	(0.019)	(0.026)	(0.025)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Seg.-Imp. Seg. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.987	0.984	0.990	0.990	0.990	0.989
F-statistic	13.22	2.99	20.63	0.23	3.33	0.77
Observations	12,780	6,390	6,390	12,780	6,390	6,390

Note: This table reports the regression results of the spatial RD model for offline trade. The distance threshold is set at 100km. The unit of observation is by city-pair-month. The dependent variables are the logarithms of the offline trade flows. The independent variable of interest is the partnership pair. All columns control for export city-month, import city-month, and export segment-import segment fixed effects. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

D Alternative Identification Strategies

In this section, we describe the methods and results from two alternative implementations of spatial RD: spatial matching and regular RD. Both yield similar results to the main findings using the segment-segment fixed-effect model.

D.1 Spatial Matching

In spatial matching, we construct the sample as follows: for every treated city pair ij, we search for all cities $k \in K$ such that i and k are within a certain distance. Similarly, we find control pairs in the other direction $l \in L$ such that the distance between j and l falls within a threshold. We then include $kj, k \in K$, $il, l \in L$, as well as $kl, k \in K, l \in L$ as control pairs. In doing so, the same city pair may appear multiple times - for example, a city pair kj may serve as the control for both treated pair ij and treated pair $i'j'$. In that case, we conduct the analysis using both frequency-weighted and unweighted samples (in the latter, all repeated city pairs count only once). Table A.26 and Table A.27 show the summary statistics for the weighted and unweighted samples. Table A.28 displays the results of balance checks for spatially matched sample. Table A.29 presents the estimation results.

Table A.26. Summary Statistics for the Weighted Spatially Matched Sample

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: city partnership								
Partnership pair	1,688	0.500	0.599	0.00	0.00	0.50	1.00	1.00
Panel B: e-commerce trade flows (full sample)								
Trade amount	99,960	11,100,657.32	36,552,629.90	0.00	178,951.35	525,486.40	4,813,547.33	1,253,110,135.84
Deal volume	99,960	77,278.98	222,990.01	0.00	1,629.22	4,664.63	33,279.50	7,541,393.53
Seller concentration ratio	99,223	89.12	13.43	23.89	82.36	90.22	97.17	99.99
Buyer concentration ratio	99,343	81.11	14.49	19.16	71.87	81.34	90.75	99.99
Panel C: e-commerce trade flows (east-to-west sample)								
Trade amount	49,980	19,955,190.77	44,437,226.22	3,211.56	532,903.16	2,576,767.81	12,030,840.83	1,418,879,671.77
Deal volume	49,980	140,382.95	272,651.32	23.05	6,036.51	29,582.99	113,248.96	7,329,889.55
Seller concentration ratio	49,980	89.19	10.89	37.76	83.01	89.70	95.53	99.98
Buyer concentration ratio	49,980	81.48	12.05	40.16	72.88	80.76	89.53	99.98
Panel D: e-commerce trade flows (west-to-east sample)								
Trade amount	49,980	1,802,048.87	4,641,737.36	0.00	38,699.29	234,441.78	633,354.95	146,639,811.98
Deal volume	49,980	14,189.00	67,439.09	0.00	367.03	2,157.55	5,350.47	1,508,708.23
Seller concentration ratio	49,243	89.03	15.59	23.89	81.29	90.90	98.00	99.99
Buyer concentration ratio	49,363	80.74	16.60	19.16	70.17	82.03	91.88	99.99
Panel E: city-pair characteristics								
Distance	1,688	1,332.99	427.47	170.05	1,075.66	1,383.43	1,685.28	2,417.84
GDP Difference	1,672	2.63	5.07	-9.93	0.88	1.87	3.54	14.23
Panel F: intercity migration flow								
Pre-CNY traffic ratio	1,672	5.33	11.63	0.000	0.370	1.070	4.230	116.78
Post-CNY traffic ratio	1,672	6.32	13.11	0.000	0.340	1.230	5.470	128.26

Note: This table reports the summary statistics, including the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), medium (P50), 75th percentile (P75), and maximum (Max), for the weighted spatially matched sample. The sample covers the period from January 2017 through December 2021. To satisfy the data privacy requirements of Alibaba Group, the summary statistics for the e-commerce trade flows shown in Panels B, C, and D are obtained by transforming the original values using a linear model with randomly generated coefficients, which preserves the rank of the data. Partnership pair is a dummy that equals one if two cities form a partnership pair. Trade amount, deal volume, seller concentration ratio, and buyer concentration ratio are monthly variables of e-commerce trade flows as detailed in Section 3.2. Distance and GDP difference are city-pair characteristics defined in 3.3. Pre-CNY and post-CNY traffic ratios are detailed in Section 3.4.

Table A.27. Summary Statistics for the Unweighted Spatially Matched Sample

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: city partnership								
Partnership pair	760	0.213	0.410	0.00	0.00	0.00	1.00	1.00
Panel B: e-commerce trade flows (full sample)								
Trade amount	45,600	7,904,892.64	22,849,077.21	0.00	109,801.22	844,041.73	4,776,089.32	1,582,932,479.96
Deal volume	45,600	83,005.03	307,528.68	0.00	1,829.15	5,395.27	34,235.65	6,476,141.87
Seller concentration ratio	45,303	89.71	13.27	23.89	82.72	90.57	97.83	99.99
Buyer concentration ratio	45,352	81.85	14.24	19.16	72.71	81.87	91.03	99.99
Panel C: e-commerce trade flows (east-to-west sample)								
Trade amount	22,800	17,047,077.95	54,526,972.20	3,331.70	721,393.15	3,547,087.31	8,495,172.33	898,492,102.19
Deal volume	22,800	103,141.91	349,885.49	33.62	7,040.83	18,895.17	94,872.77	8,745,392.13
Seller concentration ratio	22,800	89.49	11.18	37.76	83.11	89.80	96.06	99.98
Buyer concentration ratio	22,800	81.52	12.28	40.16	72.88	80.80	89.28	99.98
Panel D: e-commerce trade flows (west-to-east sample)								
Trade amount	22,800	1,366,612.55	3,901,226.06	0.00	66,307.75	145,261.81	472,884.25	208,075,069.77
Deal volume	22,800	12,431.93	53,268.44	0.00	596.11	2,767.01	7,832.12	1,398,965.96
Seller concentration ratio	22,503	89.94	15.09	23.89	82.02	91.62	98.00	99.99
Buyer concentration ratio	22,552	82.20	15.98	19.16	72.48	83.11	92.63	99.99
Panel E: city-pair characteristics								
Distance	760	1,319.15	455.30	170.05	1,056.12	1,371.57	1,687.75	2,417.84
GDP Difference	757	2.13	5.12	-9.93	0.75	1.69	3.26	14.23
Panel F: intercity migration flow								
Pre-CNY traffic ratio	757	5.72	12.74	0.000	0.350	1.070	4.110	116.78
Post-CNY traffic ratio	757	6.66	13.98	0.000	0.280	1.430	5.870	128.26

Note: This table reports the summary statistics, including the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), medium (P50), 75th percentile (P75), and maximum (Max), for the unweighted spatially matched sample. The sample covers the period from January 2017 through December 2021. To satisfy the data privacy requirements of Alibaba Group, the summary statistics for the e-commerce trade flows shown in Panels B, C, and D are obtained by transforming the original values using a linear model with randomly generated coefficients, which preserves the rank of the data. Partnership pair is a dummy that equals one if two cities form a partnership pair. Trade amount, deal volume, seller concentration ratio, and buyer concentration ratio are monthly variables of e-commerce trade flows as detailed in Section 3.2. Distance and GDP difference are city-pair characteristics defined in 3.3. Pre-CNY and post-CNY traffic ratios are detailed in Section 3.4.

Table A.28. Balance Checks for the Spatially Matched Sample

Panel A: Weighted Spatially Matched Sample	Treatment group		Control group		t-test	
	Mean	SD	Mean	SD	Difference	t-statistic
Distance	1,341.90	429.19	1324.09	426.32	-17.81	-0.60
log(distance)	7.13	0.45	7.11	0.45	-0.01	-0.39
Fiscal Expenditure Difference	0.93	0.80	0.94	0.94	0.01	0.06
Population Difference	0.75	1.12	0.63	1.04	-0.12	-1.64
Observations	422		422			
Panel B: Unweighted Spatially Matched Sample	Treatment group		Control group		t-test	
	Mean	SD	Mean	SD	Difference	t-statistic
Distance	1,387.63	466.76	1,300.60	451.54	-87.02	-1.50
log(distance)	7.15	0.50	7.08	0.47	-0.06	-1.02
Fiscal Expenditure Difference	1.02	0.97	0.82	0.90	-0.20	-1.63
Population Difference	0.88	1.17	0.56	1.06	-0.31**	-2.18
Observations	81		299			

Note: This table reports the results of balance checks for the weighted and unweighted spatially matched sample. The data of city-level fiscal expenditure difference and population are in 2018 and are collected from the China City Statistical Yearbook. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.29. Spatial Matching Regression: Main Results

Dependent Variable	log(trade)			log(deals)		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.029***	0.020	0.039***	0.028***	0.004	0.051***
	(0.010)	(0.015)	(0.015)	(0.007)	(0.008)	(0.011)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Prov.-Imp. Prov. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.988	0.994	0.975	0.997	0.999	0.994
F-statistic	5.14	1.17	6.13	9.70	0.78	12.80
Observations	99,960	49,980	49,980	99,960	49,980	49,980
Dependent Variable	Seller Concentration Ratio			Buyer Concentration Ratio		
	Both Directions	East-to-West	West-to-East	Both Directions	East-to-West	West-to-East
Partnership pair	0.055	0.408*	-0.310	0.260	0.521**	-0.008
	(0.189)	(0.214)	(0.309)	(0.160)	(0.217)	(0.226)
log(distance)	Yes	Yes	Yes	Yes	Yes	Yes
Exp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Imp. City-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exp. Prov.-Imp. Prov. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.681	0.823	0.612	0.722	0.847	0.655
F-statistic	0.21	1.97	0.83	1.75	2.881	1.18
Observations	99,223	49,980	49,243	99,343	49,980	49,363

Note: This table presents the regression results of the weighted spatial matching model. The distance threshold is defined as 100km. Each unit of observation is identified by city-pair-month. The dependent variables include the logarithms of e-commerce trade amount, deal volume, buyer concentration ratio, and seller concentration ratios. The independent variable of interest is the partnership pair. All columns include controls for the export city-month, import city-month, and export province-import province fixed effects. Standard errors are clustered at the city pair level and are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

D.2 Regular RD

In the regular RD method, we also search for control pairs following the spatial matching approach described in D.1 in the Appendix. The difference is that we now introduce a running variable that measures the distance from the treated city i to its corresponding control city k. This running variable takes a negative value for the control pair kj and a positive value for the treated pair ij. We then apply a standard local linear regression to evaluate the treatment effects. Essentially, this method assigns more weight to treated and control pairs that are closer to each other, while spatial matching assigns equal weight to all pairs provided they are within the sample. Table A.30 and Table A.31 present the estimation results of the spatial RD design. Figure A.2 depicts the RD plot demonstrating the local treatment effect.

Table A.30. Regular RD Design: E-commerce Trade Amount and Deal Volume

	Distance to City Boundary							
	60km	70km	80km	90km	100km	110km	120km	130km
Panel A: the logarithm of trade volume								
Both Directions	0.041*	0.040**	0.036*	0.041**	0.043***	0.041**	0.037**	0.034**
	(0.023)	(0.020)	(0.018)	(0.017)	(0.027)	(0.017)	(0.017)	(0.015)
Observations	91,258	116,207	139,219	169,889	199,284	229,014	262,333	294,192
East-to-West	0.019	0.011	0.015	0.020	0.019	0.020	0.016	0.017
	(0.028)	(0.025)	(0.022)	(0.020)	(0.019)	(0.017)	(0.017)	(0.016)
Observations	45,720	58,200	69,720	85,080	99,840	114,720	131,400	147,360
West-to-East	0.070**	0.075**	0.061**	0.066**	0.071***	0.064**	0.060**	0.054**
	(0.035)	(0.031)	(0.028)	(0.027)	(0.027)	(0.026)	(0.028)	(0.026)
Observations	45,538	58,007	69,499	84,809	99,444	114,294	130,933	146,832
Panel B: the logarithm of deal volume								
Both Directions	0.037*	0.035**	0.031**	0.035**	0.036***	0.035***	0.033**	0.029**
	(0.019)	(0.017)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
Observations	91,258	116,207	139,219	169,889	199,284	229,014	262,333	294,192
East-to-West	0.024	0.014	0.015	0.015	0.013	0.010	0.007	0.005
	(0.018)	(0.017)	(0.016)	(0.014)	(0.013)	(0.012)	(0.012)	(0.011)
Observations	45,720	58,200	69,720	85,080	99,840	114,720	131,400	147,360
West-to-East	0.055*	0.059**	0.051**	0.059**	0.062***	0.062**	0.060**	0.054***
	(0.031)	(0.027)	(0.025)	(0.024)	(0.023)	(0.022)	(0.022)	(0.021)
Observations	45,538	58,007	69,499	84,809	99,444	114,294	130,933	146,832

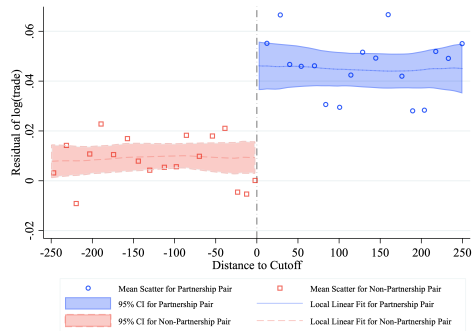
Note: This table reports the estimation results of the spatial RD design. The unit of observation is by city-pair-month. The dependent variables are the logarithms of e-commerce trade amount and deal volume. The independent variable of interest is the partnership pair. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table A.31. Regular RD Design: Seller and Buyer Concentration Ratios

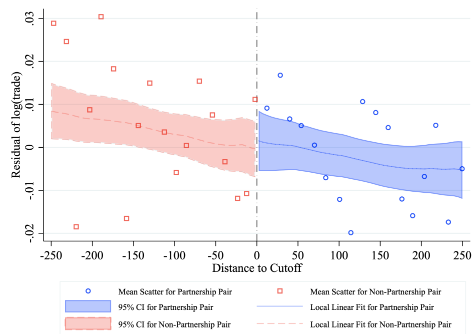
	Distance to City Boundary							
	60km	70km	80km	90km	100km	110km	120km	130km
Panel A: seller concentration ratio								
Both Directions	0.109	-0.097	-0.202	-0.277	-0.271	-0.201	-0.230	-0.247
	(0.374)	(0.333)	(0.300)	(0.271)	(0.254)	(0.238)	(0.234)	(0.221)
Observations	91,258	115,697	138,658	169,199	198,412	228,090	261,352	293,096
East-to-West	0.230	0.107	0.082	0.028	0.094	0.168	0.146	0.149
	(0.490)	(0.429)	(0.380)	(0.338)	(0.309)	(0.282)	(0.268)	(0.252)
Observations	45,720	58,200	69,720	85,080	99,839	114,719	131,399	147,359
West-to-East	0.009	-0.291	-0.480	-0.574	-0.632	-0.567	-0.608	-0.642*
	(0.568)	(0.512)	(0.466)	(0.424)	(0.404)	(0.383)	(0.382)	(0.362)
Observations	45,063	57,497	68,938	84,119	98,573	113,371	129,953	145,737
Panel B: buyer concentration ratio								
Both Directions	0.025	0.052	0.045	0.005	0.003	0.023	-0.003	-0.009
	(0.306)	(0.274)	(0.254)	(0.235)	(0.221)	(0.210)	(0.203)	(0.196)
Observations	90,881	115,802	138,778	169,349	198,596	228,287	261,566	293,333
East-to-West	-0.071	0.198	0.271	0.278	0.285	0.363	0.347	0.333
	(0.383)	(0.337)	(0.314)	(0.293)	(0.273)	(0.251)	(0.237)	(0.230)
Observations	45,720	58,200	69,720	85,080	99,839	114,719	131,399	147,359
West-to-East	0.144	-0.082	-0.173	-0.259	-0.272	-0.311	-0.352	-0.349
	(0.480)	(0.433)	(0.401)	(0.369)	(0.350)	(0.336)	(0.329)	(0.318)
Observations	45,161	57,602	69,058	84,269	98,757	113,568	130,167	145,974

Note: This table reports the estimation results of the spatial RD design. The unit of observation is by city-pair-month. The dependent variables are the seller concentration ratio and buyer concentration ratio. The independent variable of interest is the partnership pair. Standard errors are clustered at the city pair level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

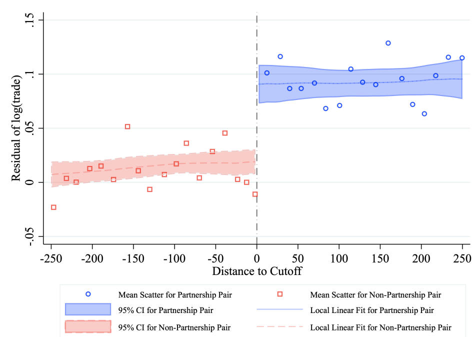
Figure A.2. Regular RD Design for E-commerce Trade Amount



(a) Full Sample



(b) East-to-West Trade



(c) West-to-East Trade

Note: This figure illustrates the discontinuity in the residuals of the logarithm of e-commerce trade in relation to the distance to the treated city's boundary. For each treated pair ij, we identify neighboring cities of i, such as city k, and use $distance_{ik}$ as the running variable. This variable takes a negative value for the control pair kj and a positive value for the treated pair ij. Pink squares denote the residuals of log(distance) averaged over twenty evenly spaced distance bins for non-partnership pairs, while blue circles represent the same for partnership pairs. These observations are fitted using a local linear regression model with a fixed bandwidth of 60km, denoted by the dashed pink line for non-partnership pairs and the solid blue line for partnership pairs. The pink and blue shaded areas represent the corresponding 95% confidence intervals of the local linear fits.

E Unit-level Results

E.1 Summary Statistics

Table A.32. Summary Statistics of the Ratios of E-commerce Trade Flows between the Partnered Cities Pairs

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: all cities								
Trade amount	8,220	4.77	5.25	0.02	0.73	1.90	9.93	33.41
Trade amount (Export)	8,220	4.64	4.96	0.09	0.91	2.26	8.62	85.67
Trade amount (Import)	8,220	4.77	5.62	0.00	0.28	1.61	10.13	55.42
Deal volume	8,220	4.48	5.35	0.02	0.67	1.61	8.60	32.28
Deal volume (Export)	8,220	4.67	4.61	0.07	0.92	2.61	8.71	35.44
Deal volume (Import)	8,220	4.45	5.67	0.00	0.30	1.34	8.72	32.82
Panel B: Western cities								
Trade amount	4,860	5.35	5.68	0.02	0.80	2.88	10.11	33.41
Trade amount (Export)	4,860	5.16	5.36	0.10	1.17	3.00	8.53	85.67
Trade amount (Import)	4,860	5.35	5.75	0.01	0.76	2.84	10.16	33.53
Deal volume	4,860	4.76	5.79	0.02	0.67	2.23	8.43	32.28
Deal volume (Export)	4,860	5.10	4.66	0.07	1.31	3.35	8.50	35.44
Deal volume (Import)	4,860	4.73	5.87	0.02	0.63	2.21	8.43	32.82
Panel C: Eastern cities								
Trade amount	3,360	3.94	4.42	0.07	0.68	1.36	9.55	23.75
Trade amount (Export)	3,360	3.89	4.21	0.09	0.78	1.45	8.98	14.13
Trade amount (Import)	3,360	3.92	5.31	0.00	0.17	0.54	10.05	55.42
Deal volume	3,360	4.08	4.63	0.08	0.68	1.37	10.55	13.75
Deal volume (Export)	3,360	4.05	4.46	0.08	0.78	1.41	10.01	14.06
Deal volume (Import)	3,360	4.05	5.34	0.00	0.21	0.57	10.90	15.95

Note: This table reports the summary statistics for the ratios of trade flows between city pairs in the partnership relative to total trade flows. The summary statistics encompass the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max). The sample spans from January 2017 to December 2021. Trade flows are aggregated at the city-month level, yielding a sample size of 8,220 ($137 \times 5 \times 12$) for the full sample of city pairs in the partnership and 4,860 and 3,360 for the samples of Western cities in the partnership and Eastern cities in the partnership, respectively.

Table A.33. Summary Statistics for E-commerce Trade Flows by City

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: all cities								
Trade amount	11,820	871,612,803	3,050,654,881	5,521,911	205,275,991	355,320,490	662,326,169	23,907,738,509
Trade amount (Export)	11,820	414,099,156	1,574,864,292	3,706	11,312,092	42,559,449	257,110,160	20,642,215,478
Trade amount (Import)	11,820	395,796,789	1,119,366,002	4,988,659	72,624,681	229,566,350	702,308,143	26,135,818,800
Deal volume	11,820	9,913,687	21,349,098	22,295	1,694,110	4,557,497	7,129,014	243,753,325
Deal volume (Export)	11,820	3,424,704	17,825,916	34	96,114	493,610	1,846,584	189,383,616
Deal volume (Import)	11,820	3,542,646	8,900,032	32,047	545,194	2,570,110	6,720,577	200,520,447
Panel B: Western cities								
Trade amount	6,600	838,391,850	1,990,457,053	5,948,442	216,659,872	540,403,105	856,525,425	28,946,105,911
Trade amount (Export)	6,600	85,936,101	549,047,550	3,181	6,672,364	16,706,002	73,934,429	6,621,870,382
Trade amount (Import)	6,600	881,479,442	2,071,448,212	4,098,909	244,095,900	434,492,409	870,391,656	17,140,246,728
Deal volume	6,600	7,288,703	20,322,123	31,556	3,208,445	3,950,013	8,329,571	245,742,313
Deal volume (Export)	6,600	1,153,834	4,086,603	30	75,341	214,698	566,961	43,877,899
Deal volume (Import)	6,600	9,407,842	10,669,524	27,630	1,999,496	5,547,138	5,706,405	206,310,830
Panel C: Eastern cities								
Trade amount	5,220	1,518,383,477	3,136,459,337	10,177,741	135,107,067	309,479,810	1,052,819,248	31,579,719,380
Trade amount (Export)	5,220	1,202,134,361	2,450,707,139	2,640,721	51,508,769	185,100,599	792,859,431	30,341,882,749
Trade amount (Import)	5,220	134,204,497	181,665,622	9,700,533	40,653,322	61,513,855	166,062,561	1,777,890,073
Deal volume	5,220	9,499,685	16,819,917	74,107	995,053	2,406,413	11,819,593	250,050,213
Deal volume (Export)	5,220	6,779,486	26,230,505	24,431	634,323	1,753,389	7,097,919	142,907,686
Deal volume (Import)	5,220	1,450,370	1,347,577	80,218	330,665	789,686	1,278,491	16,705,806

Note: This table reports summary statistics for e-commerce trade flows aggregated at the city-month level. The statistics include the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max). The sample period ranges from January 2017 to December 2021. To satisfy the data privacy requirements of Alibaba Group, the summary statistics for the e-commerce trade flows shown in Panels A, B, and C are obtained by transforming the original values using a linear model with randomly generated coefficients, which preserves the rank of the data. With trade flows aggregated at the city-month level, the total sample size amounts to 11,820 ($197 \times 5 \times 12$). Of this, 6,600 pertain to Western cities and 5,220 to Eastern cities. Definitions for trade amount and deal volume can be found in Section 3 of the main text.

Table A.34. Summary Statistics of E-commerce Trade Flows Between Paired Cities

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: all cities								
Trade amount	11820	34,118,760	162,534,064	0	0	3,890,759	17,718,357	2,634,843,291
Trade amount (Export)	11820	17,375,613	76,077,201	0	0	356,129	3,967,563	2,959,379,533
Trade amount (Import)	11820	18,513,294	47,252,613	0	0	889,825	8,189,484	1,207,038,795
Deal volume	11820	246,241	939,320	0	0	24,996	137,078	14,611,185
Deal volume (Export)	11820	157,555	765,335	0	0	4,241	37,015	17,326,478
Deal volume (Import)	11820	140,763	406,520	0	0	5,872	54,895	7,556,893
Panel B: west cities								
Trade amount	6600	28,923,421	86,138,187	0	0	4,449,801	39,044,411	1,373,587,620
Trade amount (Export)	6600	3,930,873	16,611,641	0	0	234,491	891,248	190,972,161
Trade amount (Import)	6600	23,826,082	78,893,362	0	0	3,238,708	31,082,804	1,042,738,740
Deal volume	6600	284,904	793,782	0	0	33,010	173,049	10,131,948
Deal volume (Export)	6600	38,263	123,315	0	0	1,573	9,927	2,629,025
Deal volume (Import)	6600	237,831	666,216	0	0	23,471	216,270	5,842,397
Panel C: east cities								
Trade amount	5220	50,193,174	118,869,468	0	0	39,021,22	18,733,186	3,635,869,467
Trade amount (Export)	5220	25,461,762	113,496,859	0	0	3,016,136	13,630,955	2,465,994,370
Trade amount (Import)	5220	4,371,050	22,138,916	0	0	238,951	2,221,464	280,823,594
Deal volume	5220	299,339	1,604,799	0	0	32,469	132,303	16,369,656
Deal volume (Export)	5220	283,363	1,000,615	0	0	18,829	128,083	13,562,182
Deal volume (Import)	5220	30,189	118,377	0	0	1,665	22,200	1,729,942

Note: This table reports summary statistics for e-commerce trade flows between the partnered city pairs aggregated at the city-month level. The statistics include the mean, standard deviation (SD), minimum (Min), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max). The sample period ranges from January 2017 to December 2021. To satisfy the data privacy requirements of Alibaba Group, the summary statistics for the e-commerce trade flows shown in Panels A, B, and C are obtained by transforming the original values using a linear model with randomly generated coefficients, which preserves the rank of the data. With trade flows aggregated at the city-month level, the total sample size amounts to 11,820 ($197 \times 5 \times 12$). Of this, 6,600 pertain to Western cities and 5,220 to Eastern cities. Definitions for trade amount and deal volume can be found in Section 3 of the main text.

E.2 Evidence for E-commerce Development and Economic Growth

Table A.35. Relationship between Economic Development and E-commerce Trade

Panel A: the logarithm of per capita values	Dependent variable			
	GDP	First Sector	Secondary Sector	Tertiary Sector
log(e-commerce export amount)	0.072***	0.085***	0.033	0.064**
	(0.022)	(0.031)	(0.034)	(0.029)
Constant	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Adj. R^2	0.903	0.847	0.963	0.876
F-statistic	10.43	7.51	0.95	4.75
Observations	985	985	985	985
Panel B: the logarithm of overall values	Dependent variable			
	GDP	First Sector	Secondary Sector	Tertiary Sector
log(e-commerce export amount)	0.031	0.044*	0.025	0.045**
	(0.021)	(0.025)	(0.034)	(0.022)
Constant	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Adj. R^2	0.979	0.918	0.944	0.971
F-statistic	2.24	2.37	1.15	0.66
Observations	985	985	985	985

Note: This table reports the regression results examining the relationship between economic development and e-commerce trade. The unit of observation is city-year. Panel A corresponds to the dependent variables of the logarithm of GDP per capita, first-sector product per capita, second-sector product per capita, and tertiary-sector product per capita. Panel B corresponds to the dependent variables of the logarithm of GDP, first-sector product, second-sector product, and tertiary-sector product. The independent variable of interest is the logarithm of the city-specific e-commerce export amount. All columns control for the city and year fixed effects. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.