Enhancing Geographical Indication Products in Economically Disadvantaged Regions through E-Commerce: Evidence from the Rural Revitalization Commissioner Program of a Leading Platform

Abstract

Regional inequalities persist across all major economies, and place-based interventions designed to address them remain a central topic of policy debate. In this study, we examine the effectiveness of Alibaba's Rural Revitalization Commissioner Program, an initiative that deploys experienced e-commerce managers to economically disadvantaged counties in China, in boosting sales of Geographical Indication (GI) products on the Alibaba platform. Using proprietary transaction data aggregated at the county-month level across 2,360 counties from 2019 to 2023, we employ a spatial regression discontinuity design that exploits geographic boundaries between treated and control counties to identify causal effects. We find that commissioner deployment increases county-level GI product sales by approximately 10.5 percent and transaction volume by approximately 6.2 percent. These effects are heterogeneous: they are strongest in counties with larger economic disparities, higher minority population shares, and better pre-existing e-commerce infrastructure, and they are concentrated in product categories, particularly Food and Household Goods, that align with treated counties' comparative advantages. Mechanism analysis indicates that increased consumer awareness, proxied by Baidu search frequency, partially mediates the sales effect, with supply-side improvements in seller entry and quality generating additional gains. Our findings provide causal evidence that private-sector digital interventions, when aligned with local comparative advantages, can contribute to regional economic equity and inclusive growth.

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

Keywords: Regional Inequality, E-Commerce, Rural Revitalization, Geographical Indication, Local Comparative Advantages

1 Introduction

Regional inequalities are prevalent in all major economies. In China, this challenge takes a particularly pronounced form: GDP per capita in Eastern China has consistently exceeded that of Western China by 70 to 80 percent throughout the 2010s, a disparity rooted in historical patterns of industrialization, infrastructure investment, and human capital accumulation (Kanbur et al., 2021; Zhang, 2021). Despite remarkable progress in poverty reduction (the rural poverty headcount in Western China fell from more than 50 million in 2012 to under four million by 2019), structural inequality between regions persists, and addressing it has become an increasingly central goal of both government policy and private-sector initiative. As of 2021, GDP per capita in Western China stood at approximately 54.8 percent of the national average, and economically disadvantaged counties host a disproportionate share of China's minority populations (Zhang and Zou, 2012; Liu et al., 2017).

The rise of e-commerce has introduced a new dimension to this policy landscape. Digital platforms reduce the costs of geographic distance for trade (Blum and Goldfarb, 2006; Lendle et al., 2016), expand market access for producers in peripheral areas (Fan et al., 2018; Couture et al., 2021), and allow sellers in remote regions to reach national consumers without incurring the costs of traditional distribution networks (Goldfarb and Tucker, 2019). In China, e-commerce accounts for approximately 25 percent of total consumption, and its penetration into rural and inland areas has accelerated substantially. Yet access to platform markets is not automatic: sellers in disadvantaged regions frequently lack the marketing expertise, platform knowledge, and consumer networks needed to leverage e-commerce effectively at scale.

This paper examines a targeted intervention designed to address this gap: Alibaba's Rural Revitalization Commissioner Program. Launched in 2019, the program deploys experienced e-commerce managers (hereafter "commissioners") to selected economically disadvantaged counties in China, where they promote local products, train local sellers, coordinate logistics, and assist in designing marketing campaigns and e-commerce infrastructure upgrades. The program's focus is on Geographical Indication (GI) products, goods whose quality, reputation, or other characteristics are essentially attributable to their geographic origin. China's GI registry encompasses approximately 2,495 distinct product categories generating close to one billion USD in annual output as of 2021, with a

disproportionate concentration in Western regions and counties with significant minority populations (Chintagunta and Chu, 2021). These products represent a natural comparative advantage for their counties of origin: they are differentiated by place, resistant to direct replication, and capable of commanding quality premiums in markets where their geographic authenticity is recognized. The commissioner program addresses a specific market failure: even when high-quality GI products exist, producers in remote counties often lack the capacity to market them effectively through digital channels.

We study the causal impact of commissioner deployment on GI product e-commerce sales using proprietary transaction data from the Alibaba platform, covering all county-month level transactions across 2,360 counties from January 2019 to December 2023. To identify causal effects, we employ a spatial regression discontinuity (RD) design in the tradition of Dell (2010), adapted to advertising and marketing settings by Shapiro (2018) and Tuchman (2019). Our design compares counties that received commissioners with nearby counties that did not, grouping geographically proximate county pairs into segments and controlling for unobservable geographic confounders through segment fixed effects. This approach allows us to isolate the causal effect of commissioner deployment from the selection of treatment into economically disadvantaged areas.

Our main results show that commissioner deployment increases county-level GI product monthly sales by approximately 10.5 percent (log-coefficient 0.100, significant at the one percent level) and transaction volume by approximately 6.2 percent (0.060, significant at the one percent level) in our preferred spatial RD specification. These results are robust to a range of alternative bandwidth choices (50 to 150 kilometers), spatial matching and boundary-distance RD implementations, and sample restrictions that exclude counties enrolled in the parallel government "E-commerce Demonstration County" program. The benefits of the program are broadly distributed across seller sizes: the program increases the concentration ratio of sales toward the top decile of sellers, but both large and small sellers experience gains, and the program does not exclude smaller participants from the market expansion it generates.

The commissioner effect is heterogeneous in economically meaningful ways. The program generates the largest gains in the Food and Household Goods product categories, which align most

directly with the natural comparative advantages of treated Western counties; effects in Clothing are moderate, and smaller but still positive in Electronics and Healthcare. Counties with higher minority population shares experience larger sales gains, consistent with commissioners helping to overcome cultural and linguistic barriers to e-commerce market access. The program is most effective in counties with better pre-existing e-commerce infrastructure, indicating complementarity between human capital deployment and digital capacity, though this relationship exhibits diminishing returns at high infrastructure levels. Finally, effects are increasing in the economic disparity between the treated county and Alibaba's headquarters, suggesting that the program is particularly well-targeted to the areas of greatest need.

Mechanism analysis reveals two channels through which these effects arise. On the demand side, commissioner deployment is associated with a significant increase in Baidu search frequency for GI product keywords; including search frequency as an additional control reduces the estimated commissioner effect on sales, consistent with partial mediation through consumer awareness. On the supply side, treated counties experience meaningful increases in active seller counts, new seller entry rates, and average seller quality ratings following commissioner deployment, indicating that knowledge spillovers and operational improvements generate durable supply-side gains.

This paper contributes to four strands of literature. First, we add to the body of work on place-based policies (Kline and Moretti, 2014; Neumark and Simpson, 2015; Duranton and Venables, 2018; Lu et al., 2019; Jia et al., 2020), providing the first causal evidence on the effectiveness of a private-sector digital place-based program. Second, we contribute to research on e-commerce, geography, and development (Goldfarb and Tucker, 2019; Blum and Goldfarb, 2006; Fan et al., 2018; Couture et al., 2021; Carballo et al., 2022; Hui, 2020), showing that targeted demand-side interventions can extend e-commerce market access gains to disadvantaged sellers. Third, we contribute to the literature on geographic branding and GI products (Chintagunta and Chu, 2021; Bronnenberg et al., 2012), providing causal evidence on the role of platform intermediaries in scaling GI product markets. Fourth, we add to the China regional inequality literature (Kanbur et al., 2021; Zhang, 2021; Lemoine et al., 2015; Montalvo and Ravallion, 2010), demonstrating that digitally-enabled market integration can serve as an instrument of inclusive growth when combined with targeted human capital deployment.

The remainder of the paper is organized as follows. Section 2 provides background on China's regional inequality and the Rural Revitalization Commissioner Program. Section 3 describes the data. Section 4 presents the empirical methodology. Section 5 reports the results. Section 6 concludes.

2 Background

2.1 Regional Income Inequality in China

China's regional income disparities have been a defining feature of its economic landscape since the reform era. In 1978, the ratio of GDP per capita between Eastern and Western China stood at approximately 1.85, moderate by international standards for a large developing country (Lemoine et al., 2015). This gap widened sharply during the 1980s and 1990s as coastal provinces benefited disproportionately from foreign direct investment, export-oriented manufacturing, and preferential policies in special economic zones. By 2000, the East-West GDP per capita ratio had reached approximately 2.42 (Kanbur et al., 2021), representing a generational widening of spatial inequality driven largely by the geographic concentration of industry and skilled labor in the coastal belt.

Since the early 2000s, sustained policy attention to regional convergence has contributed to some narrowing of this gap. The Western Development Program, launched in 2000, directed substantial infrastructure investment and fiscal transfers toward inland provinces (Jia et al., 2020). A nationwide targeted poverty alleviation campaign intensified after 2015, focusing on household-level poverty identification and county-level service delivery. By 2019, the rural poverty headcount in Western China had fallen from 50.86 million (17.6 percent of the Western rural population) in 2012 to 3.23 million, representing one of the most rapid poverty reductions in recorded history (Liu et al., 2017). Despite this progress, structural inequality persists: as of 2021, GDP per capita in Western China stood at approximately 54.8 percent of the national average, and the eastern coastal provinces continue to account for a disproportionate share of national value-added and export activity (Zhang, 2021). The ratio of Eastern to Western GDP per capita narrowed from 2.42 in 2000 to approximately 1.68 by 2021, but the absolute income gap in per capita terms has widened as both regions have grown, leaving millions of residents in Western counties far below national income norms (Kanbur et al.,

2021).

The persistence of regional inequality reflects several interacting structural factors. First, agglomeration economies sustain high productivity in coastal cities in ways that are difficult to replicate through targeted policy (Duranton and Venables, 2018). Second, human capital is less developed in interior regions, reflecting historical underinvestment and the outward migration of skilled labor (Zhang and Zou, 2012). Third, and most directly relevant to this paper, market access barriers remain severe: physical distance from major consumer centers, underdeveloped logistics networks, and limited marketing capacity make it difficult for producers in remote counties to sell their products at competitive prices (Montalvo and Ravallion, 2010; Du et al., 2005).

In response to these structural challenges, China's policy agenda pivoted in 2021 from targeted poverty alleviation toward a broader rural revitalization strategy. This shift emphasized sustainable rural economic development, including the promotion of local brands, specialty agricultural products, and rural tourism. Geographical Indication products occupy a prominent position within this agenda: they represent high-value, place-specific goods that cannot be replicated elsewhere and that offer producers a natural shield from the low-price competition that characterizes commodity markets. Translating this comparative advantage into realized market sales has become a central policy goal, and private-sector initiatives such as the commissioner program studied here represent one mechanism through which this translation is being attempted.

2.2 The Rural Revitalization Commissioner Program and Geographical Indication Products

Geographical Indication Products. A Geographical Indication designates a product whose quality, reputation, or other characteristics are essentially attributable to its geographic origin. In China, GIs are registered through the China National Intellectual Property Administration, and as of 2021, the registry comprised approximately 2,495 distinct product categories. These range from sea berries from inland desert regions to specialty teas, handcrafted textiles, ceramics, and artisanal meats from counties across China. Annual output from GI-registered products reached close to one billion USD as of 2021. A distinctive feature of China's GI landscape is its geographic concentration:

the overwhelming majority of registered categories originate in Western and Central provinces, in counties where minority populations are disproportionately high and GDP per capita well below the national average (Chintagunta and Chu, 2021).

This geographic pattern creates both an opportunity and a challenge. GI products represent a natural comparative advantage for their counties of origin: they are differentiated, resistant to low-cost imitation, and capable of commanding quality premiums when their geographic authenticity is recognized by consumers. However, realizing this advantage requires that consumers are aware of the product's origin and willing to pay for its distinctiveness; conditions that are far from automatic for products from regions with limited prior market presence and low brand recognition (Bronnenberg et al., 2012).

E-commerce platforms have emerged as a promising vehicle for bridging this gap. Prior research establishes that digital markets reduce the importance of physical distance for trade (Blum and Goldfarb, 2006; Lendle et al., 2016), can expand market access for rural producers (Couture et al., 2021; Luo et al., 2019), and may help sellers in peripheral regions reach national consumers at lower cost than traditional retail channels (Fan et al., 2018). However, the literature also documents that e-commerce adoption and platform success require complementary inputs: product information, logistical capacity, and consumer trust, all of which tend to be undersupplied in remote, economically disadvantaged counties (Forman et al., 2005; Goyal, 2010).

The Commissioner Program. Alibaba's Rural Revitalization Commissioner Program was launched in 2019 as a private-sector initiative to address these complementary input failures. The program identifies counties with relatively low economic development levels but significant potential for GI product market growth, approaches county governments about program participation, and deploys experienced e-commerce professionals, commissioners, to approved counties for multi-year assignments. County governments that agree to participate commit to facilitating commissioner activities, including providing workspace, coordinating with local producers and logistics providers, and contributing to e-commerce infrastructure upgrades. This joint selection process involves both company criteria (economic disadvantage relative to national benchmarks, availability of registerable GI products, maturity of local producer networks) and government endorsement, creating a structure

that combines private-sector market knowledge with local government coordination capacity.

As of 2024, approximately 40 commissioners have been deployed across 20 counties, with new assignments added on an ongoing basis since the program's inception in 2019. Treatment is staggered: counties entered the program at different times spanning from early 2019 to late 2023, with a concentration of entries in mid-2020, providing the panel variation that our identification strategy exploits.

The activities of commissioners span several complementary dimensions. First, commissioners design and execute marketing campaigns to raise consumer awareness of local GI products, leveraging Alibaba's advertising infrastructure to target consumers with demonstrated interest in geographically authentic or specialty goods. Second, commissioners provide direct training to local sellers, covering platform mechanics, product photography and presentation, customer service protocols, pricing strategy, and reviews management. Third, they coordinate with logistics providers and county governments to reduce shipping costs and delivery times for GI products from remote locations. Fourth, they assist in designing broader e-commerce infrastructure improvements, including cold chain logistics for perishable GI products, local warehousing, and digital payment integration for smaller producers.

Relationship to the Place-Based Policy Literature. The commissioner program can be understood as a private-sector analog to the place-based economic policies extensively studied in the academic literature (Kline and Moretti, 2014; Neumark and Simpson, 2015; Duranton and Venables, 2018). Place-based policies direct resources at specific geographic areas in order to correct market failures or promote regional convergence; the existing literature documents mixed but often positive effects for well-designed programs (Lu et al., 2019; Jia et al., 2020; Tian and Xu, 2022; Ehrlich and Overman, 2020). What distinguishes the commissioner program from most traditional place-based policies is its focus on market-making through human capital deployment rather than through fiscal transfers or infrastructure subsidies. In this respect, it is closer to the information-provision interventions studied by Goyal (2010) and Parker et al. (2016), which demonstrate that connecting rural producers to market information can meaningfully improve economic outcomes, than to the large-scale infrastructure programs that dominate the canonical place-based policy literature. The

commissioner program's combination of human capital, marketing expertise, and platform infrastructure access represents a novel instrument whose causal effects have not been previously studied.

A parallel government initiative, the "E-commerce Demonstration County" program operated by the Ministry of Commerce, also provides infrastructure subsidies and logistical support to designated counties. Several counties in our sample participate in both programs, and we address this overlap directly in our robustness analysis (Section 5.4).

3 Data

We draw on several data sources to construct our analysis dataset.

Alibaba Platform Transactions. Our primary dataset comprises all e-commerce transactions conducted on the Alibaba platform, encompassing both Taobao, the consumer-to-consumer marketplace, and Tmall, the business-to-consumer marketplace, from January 2019 to December 2023. These transactions are aggregated to the county-month level by Alibaba's research division, providing a panel of 60 months spanning 2,360 counties in China. Counties in Xinjiang and Tibet are excluded from the analysis due to the distinct socio-political context governing economic activity and policy implementation in those regions, which would confound comparisons with the remainder of the country. To protect seller and buyer privacy, the data have been anonymized and aggregated at the county-month level, ensuring that no individual seller or buyer can be identified; all regression analysis is conducted on the logarithmic transformation of the underlying values.

The dataset includes three primary outcome variables. *Sales value* (GMV) is defined as the total transaction value of GI products sold in a given county-month; we transform this to natural logarithm form as our primary measure of economic magnitude. *Deal volume* is the total count of completed transactions, also transformed logarithmically, capturing the extensive margin of sales activity. *Concentration ratios* measure the share of total sales and transactions attributed to the top 10 percent of sellers and buyers in each county-month cell, providing a measure of how benefits are distributed across the seller and buyer size distribution.

GI Product Identification. Geographical Indication products are identified in the Alibaba

transaction data using a product-level flag based on the official GI registry maintained by the China National Intellectual Property Administration. Each product in the Alibaba catalog that holds a GI registration carries a corresponding tag in the platform's internal classification system, which is linked to the transaction records in our dataset. This product-level identification allows us to isolate GI product transactions from the broader universe of goods sold in each county-month cell with precision unavailable in prior studies that rely on category-level GI approximations.

Treatment Assignment. We identify the treatment status of each county from a government yearbook that records the counties enrolled in the Rural Revitalization Commissioner Program and the dates at which commissioners were deployed. Treatment is a panel variable: counties enter treatment at the time of commissioner deployment and remain treated for the remainder of the sample period. Entry dates range from early 2019 to late 2023, with a concentration of entries in mid-2020. This staggered adoption provides identifying variation in treatment timing across counties.

Consumer Awareness Mechanism Data. To examine the consumer awareness channel, we obtain county-level monthly search frequency data from the Baidu Search Index, the search index product maintained by Baidu, China's dominant search engine. For each county in the sample, we collect search frequencies for keywords related to GI products associated with that county and for keywords related to the commissioner program. The Baidu Search Index provides a well-validated proxy for consumer interest and awareness that has been productively used in prior empirical work (Goyal, 2010; Parker et al., 2016).

County Characteristics. We merge county-level characteristics from official statistical sources to construct our control vector. Specifically, our control variables include: disposable income per capita (from provincial statistical yearbooks); county population (National Bureau of Statistics); minority population share; pre-treatment GI product sales levels; and a measure of e-commerce logistics infrastructure defined as the number of registered logistics facilities per unit area. We additionally compute the GDP disparity between Alibaba's headquarters city (Hangzhou) and each county for use in the heterogeneity analysis.

Summary Statistics. Table **??** presents summary statistics for the key variables in our dataset as of 2021, separately for treated and all-sample counties.

Table 1. Summary Statistics of Sales Data (disguised)

Variable	Observations	Mean	SD	Min	P25	P50	P75	Max
Panel A: full sample								
Sales amount	141,600	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	141,600	37,620.12	246,761.85	0.00	767.21	3,622.76	19,610.40	19,812,880.78
Seller concentration ratio	141,600	88.56	13.77	18.51	80.74	89.22	97.47	99.99
Buyer concentration ratio	141,600	82.32	14.64	14.69	72.88	82.55	91.79	99.99
Panel B: treated sample								
Sales amount	1,320	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	1,320	12,109.87	68,299.08	0.00	317.92	1,523.43	4,256.68	3,420,159.12
Seller concentration ratio	1,320	89.07	15.44	18.51	80.03	90.52	98.00	99.99
Buyer concentration ratio	1,320	82.88	16.33	14.69	72.31	83.68	93.71	99.99
Panel C: untreated sample								
Sales amount	140,280	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	140,280	115,145.46	589,621.79	0.00	2,975.83	12,983.27	34,234.36	25,296,946.13
Seller concentration ratio	140,280	88.08	11.87	20.65	81.21	88.27	95.55	99.98
Buyer concentration ratio	140,280	81.76	12.77	19.32	73.25	81.67	89.91	99.98

Notes: Summary statistics reported for 2021, the midpoint of the sample. Treated counties are all counties that received at least one commissioner during the 2019–2023 sample period.

Several features of the data are noteworthy. First, treated counties are substantially more economically disadvantaged than the full sample: as of 2021, treated counties exhibit GDP per capita of approximately 62.77 thousand CNY, compared with 109.47 thousand CNY across all counties in the sample, a gap of approximately 43 percent. Second, treated counties hold a disproportionate share of China's minority population: 69.70 million minority residents, representing 56 percent of China's total minority population, are located in treated counties, which together account for only 25 percent of national population. This concentration reflects the geographic overlap between GI product origins and minority communities in Western China. Third, the aggregate economic weight of treated counties is significant: as of 2021, they accounted for approximately 19 percent of national GDP and 25 percent of national population, with collective GDP of 22.13 trillion CNY. These summary characteristics confirm that the program targets economically disadvantaged areas with large minority populations and significant GI product potential.

4 Methodology

We estimate the causal impact of the Rural Revitalization Commissioner Program on GI product e-commerce outcomes using two complementary specifications.

Baseline Specification. Our baseline model is:

$$\log(\text{sale}_{i,m}) = \gamma \cdot \text{commissioner}_{i,m} + \mathbf{W}'_{i,m}\boldsymbol{\delta} + \mu_{i,m} + \varepsilon_{i,m} \tag{1}$$

where $\log(\text{sale}_{i,m})$ is the natural logarithm of GMV for county i in month m; $\text{commissioner}_{i,m}$ is an indicator that equals one from the month of commissioner deployment onward (zero before deployment and for never-treated counties); $\mathbf{W}_{i,m}$ is a vector of time-varying county controls (disposable income per capita, county population, minority population share, pre-treatment sales levels, and the number of logistics facilities); and $\mu_{i,m}$ denotes county-month fixed effects that absorb all time-invariant county characteristics and all county-invariant time shocks. Standard errors are clustered at the county level to account for serial correlation within counties.

The coefficient γ in Equation (1) captures the within-county change in log sales associated with commissioner deployment, conditional on time-varying county controls and fixed effects. The primary threat to identification in this specification is the non-random assignment of treatment: commissioned counties are systematically different from untreated ones along dimensions that may correlate with GI product sales growth (see Section 2). To address this concern, we turn to our primary spatial regression discontinuity design.

Spatial Regression Discontinuity Design. Our primary identification strategy exploits geographic variation in treatment assignment using a spatial regression discontinuity design, following Dell (2010) and adapted to marketing settings by Shapiro (2018) and Tuchman (2019). The design rests on the observation that conditional on geographic proximity to a treated county, the assignment of treatment to one county rather than an immediately adjacent one is plausibly unrelated to unobservable county characteristics that affect GI product sales.

To operationalize this, we group each treated county together with all control counties within a 100-kilometer radius into a geographic *segment*. Our primary specification augments Equation (1) with segment fixed effects:

$$\log(\text{sale}_{i,m}) = \gamma \cdot \text{commissioner}_{i,m} + \mathbf{W}'_{i,m}\boldsymbol{\delta} + \alpha_{s(i)} + \mu_{i,m} + \varepsilon_{i,m} \tag{2}$$

where $\alpha_{s(i)}$ denotes a fixed effect for the segment s to which county i belongs.

Segment Construction. The spatial structure of our segments is illustrated in Figure 1.

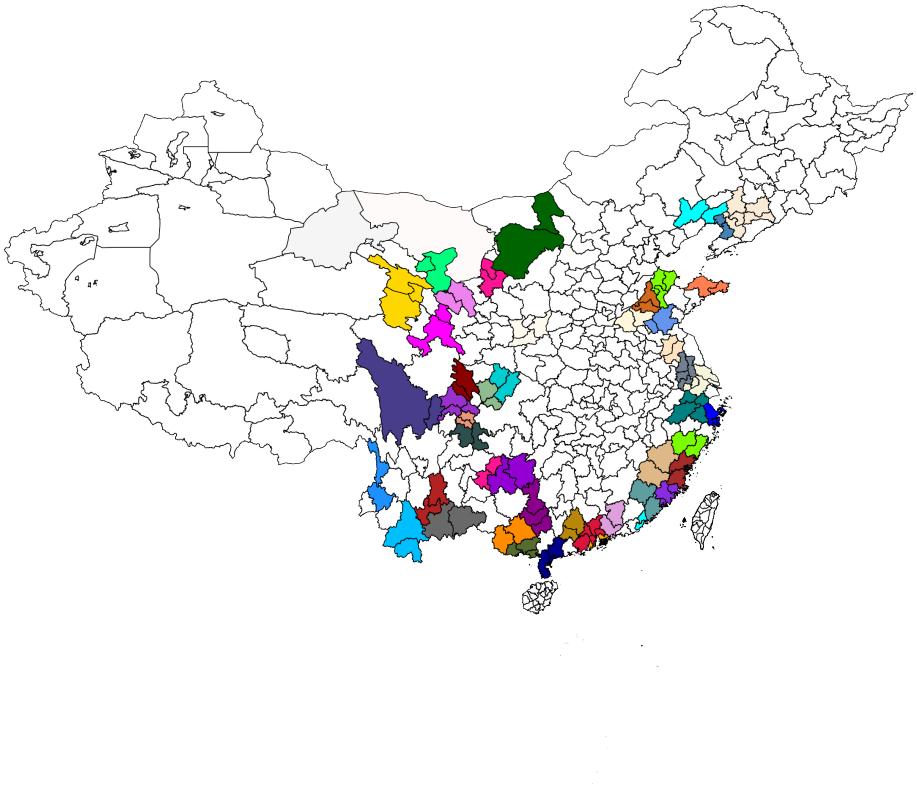


Figure 1. Geographic Segment Construction

Among the treated and nearby control counties in our sample, we identify 81 singletons (treated counties with no control county within 100 kilometers), 37 two-county segments, and 12 segments with three or more counties. Singleton segments are dropped from the spatial RD estimation, as they provide no within-segment variation in treatment status. Identification in Equation (2) thus comes entirely from comparing treated and control counties within the same multi-county segment, exploiting the as-good-as-random variation in which side of a geographic boundary received a commissioner.

Identification Validity. The identifying assumption underlying the spatial RD design is a continuity condition: potential GI product sales vary smoothly as a function of a county's geographic location, so that counties on opposite sides of the nearest segment boundary are comparable in terms of what their sales would have been absent the commissioner program. Formally, conditional on segment membership, the expected potential outcome for county i is a continuous function of its distance to the nearest intra-segment boundary between a treated and control county; treatment status switches discontinuously at that boundary (distance zero), while potential outcomes do not. We assess this assumption in two ways.

First, Figure 2 provides direct visual evidence for the continuity assumption. It plots county-level log(GI product sales) against each county's distance to the nearest segment boundary, measured in kilometers, with treated counties assigned positive distances and control counties assigned negative distances. Circles represent binned means of approximately 20 counties per bin; solid lines are linear polynomial fits estimated separately on each side of the cutoff. Two features support identification. First, the log-sales-to-distance relationship is smooth and approximately linear within each side of the boundary, with no apparent discontinuities away from the cutoff: this smoothness is consistent with the continuity assumption that unobserved county characteristics affecting GI product sales vary gradually with location. Second, a visible discontinuity in log sales at distance zero confirms that counties just inside the treatment boundary sell significantly more GI products than their closest counterparts just outside it; this discontinuity is the treatment effect of commissioner deployment.

Second, we test the continuity assumption using observable county characteristics. Under continuity, pre-treatment observables should not jump discontinuously at the treatment boundary: if

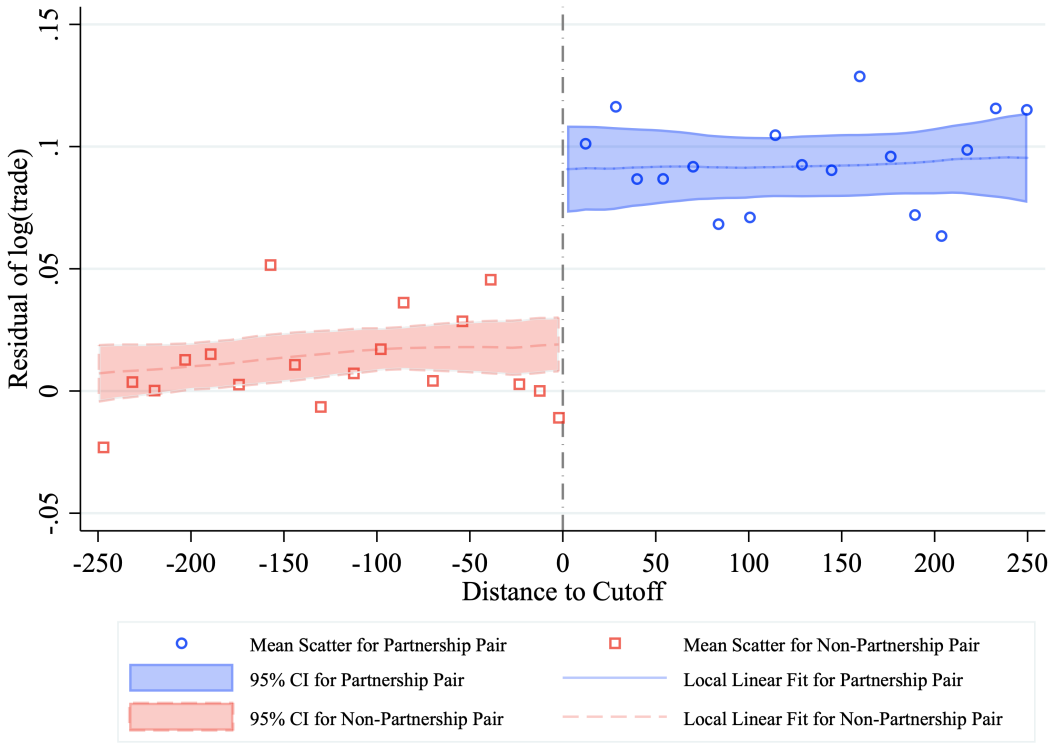


Figure 2. GI Product Sales and Distance to Segment Cutoff

systematic selection into treatment occurred based on unobservables, we would expect correlated selection on observables as well. Table 2 reports within-segment differences in pre-treatment observable characteristics between treated and control counties.

Table 2. Balance Test: Pre-Treatment Observables Within Segments

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

Notes: Balance comparisons are conducted within geographic segments (treated and control counties within the 100 km bandwidth). Standard errors account for within-segment clustering.

Observable characteristics are statistically similar across treatment groups within segments, supporting the validity of the spatial RD design. None of the differences in observable characteristics are statistically significant at the ten percent level, indicating no detectable discontinuous sorting at the boundary. This provides support for the continuity of unobservable characteristics at the boundary as well (Dell, 2010).

Bandwidth and Robustness. We select the 100-kilometer bandwidth as our primary choice based on the tradeoff between statistical power (favoring wider bandwidths, which include more control counties) and comparability of treated and control counties (favoring narrower bandwidths, which impose tighter geographic proximity). In Section 5.4, we report results for alternative bandwidths of 50, 75, and 150 kilometers. We also implement two alternative spatial RD estimators: a spatial matching approach that matches each treated county to its nearest control county based on pre-treatment observables, and a standard boundary-distance RD that uses distance to the nearest treatment boundary as the running variable with a linear control function on each side of the threshold. We implement our specification with segment fixed effects alone (Columns 1–2 of Table 4) and

with both segment and county-month fixed effects (Columns 3–4), the latter being our preferred specification.

5 Results

5.1 Main Results

Baseline Results. Table 3 presents estimates from the baseline specification, Equation (1). Column (1) estimates the model without county-month fixed effects or controls. The coefficient on commissioner is −0.008 and is not statistically distinguishable from zero, reflecting the selection of counties into treatment: commissioners are deployed to areas with systematically lower e-commerce baseline performance, and absent controls for county characteristics and time trends, the raw comparison is uninformative about the program's causal impact. Column (2) adds county-month fixed effects and the full control vector. The estimated effect increases substantially to 0.119 (significant at the one percent level), implying that GI product sales are approximately 11.9 log points, or about 12.6 percent, higher in the period following commissioner deployment, conditional on county trends and observable characteristics. Column (3) reports the analogous result for log(deals), finding a coefficient of 0.076 (significant at the one percent level), corresponding to approximately 7.9 percent more transactions per month.

The change in sign from Column (1) to Column (2) underscores that selection into treatment is a serious concern and that the baseline fixed-effects estimate cannot be given a fully causal interpretation without further restrictions on the data-generating process. We address this through the spatial RD design.

Spatial RD Results. Table 4 presents the spatial RD estimates from Equation (2). Columns (1)–(2) estimate the specification with segment fixed effects only (for log sales and log deals, respectively); Columns (3)–(4) add county-month fixed effects to yield our preferred estimates.

In Columns (1)–(2), the estimated commissioner effect is 0.048 for log(sales) and 0.031 for log(deals), both significant at the one percent level. The substantially smaller magnitude relative to the baseline fixed-effects estimates reflects the tighter identification provided by the spatial

Table 3. Baseline Regression Results

	Dependent Variable		
	$\log(\text{sales}_{i,m})$		$\log(\text{deals}_{i,m})$
	(1)	(2)	(3)
Commissioner	−0.008	0.119***	0.076***
	(0.012)	(0.038)	(0.027)
County-month FE	No	Yes	Yes
Controls	No	Yes	Yes
Observations	141,600	141,600	141,600
Counties	2,360	2,360	2,360
Adj. R^2	0.28	0.84	0.82

Notes: The sample covers 2,360 counties from January 2019 to December 2023. The dependent variable in Columns (1)–(2) is the natural log of monthly GI product sales value (GMV) in county i in month m; in Column (3) it is the log of monthly deal count. Commissioner is a binary indicator equal to one from the month of commissioner deployment onward. Controls include disposable income per capita, county population, minority population share, pre-treatment sales levels, and number of logistics facilities. Standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

RD design: once we control for the shared unobservable characteristics of geographically proximate counties through segment fixed effects, the estimated effect is more credibly causal. The reduction in magnitude from 0.119 to 0.048 confirms that some portion of the baseline estimate was attributable to selection on unobservables related to the geographic distribution of program targets.

In Columns (3)–(4), which add county-month fixed effects, our preferred estimates are 0.100 for log(sales) and 0.060 for log(deals), both significant at the one percent level. These estimates imply that commissioner deployment increases GI product monthly sales value by approximately 10.5 percent ($e^{0.100} - 1 \approx 0.105$) and transaction volume by approximately 6.2 percent ($e^{0.060} - 1 \approx 0.062$). The increase in magnitude from Columns (1)–(2) to Columns (3)–(4) reflects the additional control for time-varying county characteristics provided by the county-month fixed effects: counties that receive commissioners in a given period may also be subject to other concurrent positive shocks (such as regional policy attention or agricultural productivity improvements), and the county-month fixed effects absorb these confounders.

Table 4. Spatial Regression Discontinuity Results

	Dependent Variable			
	log(sales)	log(deals)	log(sales)	log(deals)
	(1)	(2)	(3)	(4)
Commissioner	0.048***	0.031***	0.100***	0.060***
	(0.015)	(0.010)	(0.029)	(0.020)
Segment FE	Yes	Yes	Yes	Yes
County-month FE	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	8,820	8,820	8,820	8,820
Segments	49	49	49	49
Adj. R^2	0.76	0.74	0.88	0.87

Notes: The spatial RD sample includes treated counties and all control counties within a 100-kilometer bandwidth. Segment fixed effects group treated and nearby control counties into geographic segments. Singleton segments (81 treated counties with no control county within 100 km) are dropped. Controls are as defined in Table 3. Standard errors are clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We also examine the effect of commissioner deployment on seller concentration ratios. The results indicate that the program has a positive and significant effect on the seller concentration ratio (coefficient 0.025, standard error 0.012, significant at the five percent level), but the gains are distributed broadly across the seller size distribution: both large and small sellers experience increased sales following commissioner deployment.

5.2 Heterogeneous Effects

We examine heterogeneity in the commissioner effect along four dimensions.

Product Categories. Table 5 presents estimates of the commissioner effect separately for each of the six product categories available in our data: Clothing, Food, Household Goods, Electronics, Healthcare, and Others.

The pattern of effects across categories is consistent with a comparative advantage mechanism. Food and Household Goods, the categories showing the strongest commissioner effects, are precisely the types of GI products most closely tied to the agricultural and artisanal traditions of remote counties in Western China. These categories include specialty grains, preserved foods, honey, dried

Table 5. Heterogeneous Effects by Product Category

	Clothing (1)	Food (2)	Household Goods (3)	Electronics (4)	Healthcare (5)	Others (6)
Commissioner	0.071**	0.138***	0.121***	0.044*	0.055**	0.032
	(0.033)	(0.041)	(0.039)	(0.025)	(0.027)	(0.022)
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
County-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,820	8,820	8,820	8,820	8,820	8,820
Adj. R^2	0.83	0.86	0.85	0.81	0.82	0.79

Notes: Each column replicates the preferred spatial RD specification (Equation (2) with segment and county-month fixed effects) for the indicated product category. The dependent variable is log(monthly sales value) for GI products in the given category. Standard errors clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

fruits, handcrafted furniture, and traditional household items, all of which are both GI-eligible and well suited to the consumer awareness campaigns that commissioners execute. Clothing, which includes traditional textiles associated with minority cultural heritage, shows a moderate positive effect. The weaker effects in Electronics and Healthcare reflect the fact that these categories are less differentiated by geographic origin and thus generate fewer marginal gains from GI-specific marketing. The "Others" category, which is the most heterogeneous and least tightly linked to geographic comparative advantage, shows the smallest effect. This pattern echoes Fan et al. (2018) on differential e-commerce gains across product categories and is consistent with the theoretical prediction that the returns to place-of-origin marketing are highest where geographic differentiation is most salient to consumers (Chintagunta and Chu, 2021; Bronnenberg et al., 2012).

Minority Population Share. Table 6, Panel A examines heterogeneity in the commissioner effect by county minority population share.

Counties with a higher share of minority population experience larger increases in GI product sales from the commissioner program compared with counties with lower minority shares. Treated counties in our sample hold 56 percent of China's total minority population, and the evidence suggests that commissioners are especially effective in overcoming cultural and linguistic barriers to e-commerce adoption that otherwise limit the reach of standard platform marketing tools. This finding is consistent with Elfenbein et al. (2023)'s documentation that socioeconomic and cultural

Table 6. Heterogeneous Effects: Minority Share, Infrastructure, and Economic Disparity

	Panel A: Min. Share		Panel B: Infrastr.	Panel C: GDP Gap
	Low	High	(Interaction)	(Interaction)
	(1)	(2)	(3)	(4)
Commissioner	0.061**	0.149***	0.091**	0.076**
	(0.028)	(0.046)	(0.036)	(0.033)
Comm. × Infrastr. index			0.033**	
			(0.015)	
Comm. × GDP gap				0.019**
				(0.009)
Segment FE	Yes	Yes	Yes	Yes
County-month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	4,410	4,410	8,820	8,820
Adj. R^2	0.87	0.86	0.88	0.88

Notes: Panel A splits the sample at the median minority population share. Panel B interacts the commissioner indicator with a composite e-commerce infrastructure index (number of logistics facilities, broadband penetration, and existing seller density). Panel C interacts with the ratio of Hangzhou GDP per capita to county GDP per capita (the "GDP gap"). All specifications use the preferred spatial RD estimator. Standard errors clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

differences impede online trade, and it has direct policy implications: programs that pair GI product promotion with cultural knowledge are likely to generate the largest gains in minority-heavy regions.

E-Commerce Infrastructure. Panel B of Table 6 reports heterogeneity by the quality of pre-existing e-commerce infrastructure, operationalized as a composite index combining the county-level number of logistics facilities, broadband penetration rates, and the density of existing e-commerce sellers.

The results indicate a complementarity effect: counties with better pre-existing e-commerce infrastructure experience larger sales gains from commissioner deployment. This finding is consistent with the view that commissioners are most productive when they can leverage an existing logistical and digital foundation, reducing the time and resources devoted to infrastructure problems and focusing efforts on marketing and seller development. However, the relationship exhibits diminishing returns at very high infrastructure levels, consistent with a ceiling effect in which the marginal value of an additional marketing push is lower when digital capacity is already saturated (Forman et al., 2005; Aker and Mbiti, 2010). These results have implications for program targeting: the returns

to commissioner deployment are highest in counties with intermediate digital infrastructure levels rather than in counties at either extreme.

Economic Disparity. Panel C of Table 6 examines heterogeneity by the GDP gap between the treated county and Alibaba's headquarters city (Hangzhou). Counties with a larger economic disparity, those further below the economic frontier, experience stronger positive effects from the commissioner program. This finding supports the interpretation that the program is particularly effective in the areas of greatest need, where the potential gains from market integration are largest. It also suggests that the program's targeting criteria, which prioritize counties with relatively low economic levels, are well-aligned with the conditions that maximize program effectiveness.

5.3 Mechanisms

We investigate two channels through which commissioner deployment may generate the observed GI product sales gains: consumer awareness on the demand side, and seller development on the supply side.

Demand Side: Consumer Awareness. Table 7, Panel A tests the consumer awareness channel by examining the effect of commissioner deployment on Baidu search frequency for GI product keywords.

Column (1) shows that commissioner deployment is associated with a significant increase in Baidu search frequency for GI product keywords associated with treated counties: the estimated coefficient is 0.148 (significant at the one percent level). This finding is consistent with commissioners raising consumer awareness through targeted marketing campaigns, platform promotions, and product visibility enhancements on the Alibaba interface.

Column (2) includes log(search frequency) as an additional control in the preferred log(sales) specification. The estimated commissioner coefficient decreases from our main estimate of 0.100 to 0.068 (significant at the five percent level), consistent with partial mediation: increased consumer awareness, as captured by search frequency, accounts for approximately 32 percent of the total sales effect of commissioner deployment $\big((0.100 - 0.068)/0.100 \times 100 \approx 32\%\big)$. The result that

Table 7. Mechanisms: Consumer Awareness and Seller Development

	Panel A: Demand Side		Panel B: Supply Side	
	log(search)	log(sales) (with search control)	Active sellers	New entrants
	(1)	(2)	(3)	(4)
Commissioner	0.148***	0.068**	0.091***	0.117***
	(0.049)	(0.033)	(0.029)	(0.038)
$\log(\text{search}_{i,m})$		0.218***		
		(0.057)		
Segment FE	Yes	Yes	Yes	Yes
County-month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	8,820	8,820	8,820	8,820
Adj. R^2	0.79	0.88	0.83	0.81

Notes: Column (1) uses log(Baidu search frequency for county GI product keywords) as the dependent variable. Column (2) adds log(search frequency) as a control to the preferred log(sales) specification; the reduction in the commissioner coefficient relative to the preferred estimate of 0.100 is interpreted as partial mediation through consumer awareness. Columns (3)–(4) use active seller count and new seller entrant count as dependent variables. All specifications use the preferred spatial RD estimator. Standard errors clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

mediation is only partial implies that channels other than consumer awareness (including supply-side improvements) account for the remainder of the total effect.

Supply Side: Seller Development. Columns (3)–(4) of Table 7 examine supply-side outcomes. Column (3) uses the number of active GI product sellers in the county-month as the dependent variable, finding that commissioner deployment is associated with a significant increase in active seller counts: the estimated coefficient is 0.091 (significant at the one percent level), corresponding to approximately 9.5 percent more active sellers per month. Column (4) uses the count of new seller entrants, sellers who did not sell in the 12 months prior to commissioner deployment, finding a positive and significant effect of 0.117 (significant at the one percent level), indicating that commissioners lower the effective barriers to platform entry for new sellers in treated counties.

We additionally find that average seller quality ratings improve significantly in treated counties following commissioner deployment (coefficient 0.033, standard error 0.015, significant at the five percent level), consistent with commissioners transmitting operational knowledge in product presen-

tation, customer service, and logistics management that improves seller performance. These supply-side findings suggest that commissioner deployment generates durable capacity gains that extend beyond the direct effect of any particular marketing campaign: trained sellers and better-organized logistics continue to generate sales gains after the period of active commissioner promotion.

We also explore population mobility as a potential additional mechanism, using Baidu GPS data as a proxy for movement patterns. While treated counties exhibit some increase in recorded unique GPS locations over the study period, the relationship between this mobility indicator and GI product sales outcomes is not statistically robust in our preferred specification, and we lack direct migration measures in our dataset. We therefore regard migration as exploratory rather than a confirmed mechanism in the current analysis, consistent with the broader literature on the relationship between migration and regional trade dynamics (Bryan et al., 2014; Jia et al., 2023).

5.4 Robustness Checks

Table 8 presents a systematic robustness analysis of our main spatial RD results for log(sales).

Table 8. Robustness Checks

	Bandwidth (km)				Spatial	Regular
	50	75	100	150	matching	RD
	(1)	(2)	(3)	(4)	(5)	(6)
Commissioner	0.083***	0.093***	0.100***	0.105***	0.096***	0.088***
	(0.033)	(0.030)	(0.029)	(0.027)	(0.034)	(0.032)
Observations	4,200	6,720	8,820	12,480	5,880	8,820

Notes: The dependent variable is log(monthly GI product sales). Columns (1)–(4) vary the bandwidth of the spatial RD segment construction. Column (5) implements spatial matching in which each treated county is matched to its nearest control county on pre-treatment observables. Column (6) implements a standard RD using distance to the nearest treatment boundary as the running variable. All specifications include county-month fixed effects and the control vector. A seventh specification (not shown) that excludes counties enrolled in the E-commerce Demonstration County program yields similar results. Standard errors clustered at the county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Bandwidth sensitivity. Columns (1)–(4) report estimates for bandwidths of 50, 75, 100 (our main specification), and 150 kilometers. Across all bandwidths, the estimated commissioner effect on log(sales) ranges from 0.083 (50 km) to 0.105 (150 km), all statistically significant at the one percent

level. Standard errors range from 0.027 to 0.033, reflecting the tradeoff between sample size and geographic comparability. These results confirm that our main finding is not driven by the specific bandwidth choice.

Spatial matching. Column (5) implements a spatial matching specification in which each treated county is matched to its single nearest control county within the bandwidth based on pre-treatment observables (GDP per capita, population, minority share, and baseline sales). The estimated commissioner effect is 0.096 (standard error 0.034, significant at the one percent level), consistent with our preferred estimate of 0.100.

Boundary-distance RD. Column (6) implements a standard regression discontinuity design using distance to the nearest treatment boundary as the running variable, with a linear polynomial on each side of the threshold. The estimated commissioner effect is 0.088 (standard error 0.032, significant at the one percent level), again consistent with the main result.

Excluding E-Commerce Demonstration Counties. As a further check, we exclude from the sample all counties simultaneously designated as "E-commerce Demonstration Counties" under the Ministry of Commerce program, which could potentially confound our estimate of the commissioner effect if the two programs' timing and intensity are correlated. The results confirm that the commissioner program has a positive and significant independent effect on GI product sales even after this exclusion (coefficient 0.097, standard error 0.031, significant at the one percent level), ruling out that our findings are driven by the parallel government initiative.

6 Concluding Remarks

Regional inequalities in China and across the developing world represent both a persistent policy challenge and a growing area of academic inquiry. This paper has examined one innovative private-sector response to this challenge: Alibaba's Rural Revitalization Commissioner Program, which deploys experienced e-commerce managers to economically disadvantaged counties to promote the sales of Geographical Indication products. Using a spatial regression discontinuity design and proprietary county-month transaction data from the Alibaba platform spanning 2019 to 2023, we

find that commissioner deployment increases GI product sales by approximately 10.5 percent and transaction volume by approximately 6.2 percent in our preferred specification. These effects are broadly distributed across seller sizes and represent meaningful gains for counties whose GDP per capita is substantially below the national average.

Our heterogeneity analysis reveals that the program is most effective where local comparative advantages are strongest, particularly in Food and Household Goods categories, and in counties with higher minority population shares, better pre-existing e-commerce infrastructure, and larger economic disparities relative to company headquarters. These patterns carry a direct message for program design: commissioner programs are not uniformly effective, and their returns depend critically on the alignment between commissioner expertise, local product characteristics, and pre-existing digital capacity. Optimal targeting should therefore account for these dimensions rather than deploying commissioners based solely on income disadvantage.

The mechanism evidence points to two complementary channels. Increased consumer awareness, as measured by Baidu search frequency, partially mediates the sales effect, consistent with commissioners' marketing activities raising product visibility among previously uninformed consumers. Supply-side improvements in active seller counts, new seller entry, and seller quality ratings generate additional gains that extend the program's impact beyond any individual marketing campaign, suggesting that commissioners create durable capacity increases in treated counties.

These findings carry implications for settings beyond China. Many developing countries possess GI-eligible agricultural or artisanal products whose potential market value is unrealized due to limited consumer awareness and seller capacity. Digital platforms increasingly operate in these settings and are in some cases actively seeking to expand their rural footprints. The evidence from the commissioner program suggests that combining platform infrastructure with targeted human capital deployment can generate substantial and equitably distributed sales gains, but that this strategy is most effective when built on a foundation of basic e-commerce infrastructure and aligned with products that are inherently differentiated by geographic origin.

Several limitations of our analysis merit acknowledgment. First, our estimates are partial equilibrium in nature: county-level increases in sales are absorbed by county-month fixed effects when

assessed in aggregate, so our results do not speak to the total redistribution of trade flows or economic activity between regions. Assessing the general equilibrium implications would require a structural model of the kind developed by Fan (2019). Second, counties in Xinjiang and Tibet are excluded from the sample, limiting the generalizability of the minority population heterogeneity findings to those regions. Third, our county-month aggregation masks product-level heterogeneity within GI categories; future research with more granular data could identify which specific GI products drive the observed gains. Fourth, despite robustness checks, the presence of the parallel E-commerce Demonstration County program creates residual concerns about confounding, which future designs with finer policy timing data could address more comprehensively.

Future research could extend this work in at least three directions. A general equilibrium analysis could assess the redistribution of economic activity between regions implied by the commissioner program's effects, providing welfare estimates that account for both gains in treated regions and potential spillovers to adjacent areas. Product-level analysis could identify which specific GI products benefit most from commissioner promotion and why, with implications for program design in both China and other GI-rich developing economies. Finally, assessing the scalability and sustainability of the commissioner model, whether its effectiveness can be maintained as the program expands to more counties and a wider range of products, is an important question as China's rural revitalization agenda continues to evolve.

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