Digital Revitalization or Useless Effort? Public E-commerce Support and Local Specialty Sales*

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Abstract

We examine how a government-initiated e-commerce platform (GEP) affects sales of a local specialty in China's Pu'er tea market. Using a unique dataset from field experiments and surveys of 983 farmers, we examine changes in online and offline sales over time. We employ two-way fixed effects (TWFE) models to identify the causal impact of GEP access. The results reveal significant substitution effects: access to the GEP increases online sales by 16.649% and decreases offline sales by 15.549%, indicating an overall shift from offline to online sales. On the extensive margin, households that previously sold only offline become more likely to sell online. On the intensive margin, adopters expand their online channels and offer a wider range of tea qualities. The mediation analysis suggests that the increase in online sales channels and product variety accounts for the impact of GEP access on the shift to online transactions.

Keywords: government-initiated e-commerce platform, public services, online channels, specialty sales
JEL: L13; L81; O33; Q13

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1 Introduction

The distinct advantages of e-commerce over traditional channels have led to an unprecedented surge in its adoption across many regions. Specifically, the shift to online transactions would remove fixed entry costs and eliminate geographic barriers to trade. According to a recent report (Intelligence, 2024), e-commerce sales are expected to exceed 6 trillion dollars in 2024, with digital retail accounting for 20.1% of total sales. As e-commerce platforms become increasingly popular and widely used, policymakers are recognizing their transformative potential as a driver of agricultural productivity and rural economic growth, particularly in low- and middle-income countries (LMIC). In India, the government launched its own Open Network for Digital Commerce (ONDC) in 2022 and has been promoting it nationwide. Designed to compete with Amazon, this platform offers a variety of products, including groceries, beverages, and other consumer goods (Mandavia, 2022). Similarly, China's e-commerce policy has been a major focus in recent decades, guided by directives from the central government. Despite government initiatives aimed at facilitating rural e-commerce, small farmers continue to face significant barriers. These include logistical challenges, a lack of expertise, and difficulty building trust and brand recognition. In response, the Chinese government launched public e-commerce support programs to help farmers overcome these obstacles (World Bank, 2019; Vidal and Faz, 2020).

Starting in 2014, the Government of China launched the National Rural E-commerce Comprehensive Demonstration Program to support rural counties in developing e-commerce centers (Ma et al., 2023; Li et al., 2025). Beginning in 2017, many local governments across China established government-initiated e-commerce platforms (GEPs) in their regions.[1] Despite the proliferation of GEP programs, empirical evidence on their effects remains scarce, particularly on farmer online versus offline sales choices and the ensuing economic impacts. Furthermore, it is unclear whether rural GEPs and their bundled public services make a

1. In Online Appendix A, we provide a table that lists several GEPs established by local governments in China from 2017 to 2023.

meaningful contribution to local economic growth. Progress has been limited by two obstacles: (i) exogenous policy variation suitable for causal identification is rare, and (ii) the collection of microlevel data on farmer output, channel use, and sales volumes requires extensive fieldwork.[2]

Drawing on detailed micro-level data, we analyze the impact of local GEP access on local farmers' sales channel decisions in Pu'er City, Yunnan Province. Our region of study serves as the main hub for the cultivation of Pu'er tea in China, where farmers produce approximately 90% of all Pu'er tea. Historically, these farmers sold their tea in bulk to tourists or large tea processing factories. Local authorities responded to the central government's e-commerce initiative by launching a GEP in 2018, allowing farmers to sell directly to consumers. When an order is placed on the platform, farmers process their tea leaves into cakes at a very low cost in government-established cooperatives. The cooperatives label the cakes and ship them to customers.

One of the main empirical challenges of this study is to distinguish the effects on online versus offline sales (Johnson et al., 2017). Before gaining access to the GEP, farmers sold only a small amount of tea online. Even after the platform became available, most tea transactions were still conducted offline. Over a two-year period, we conducted a household survey in six regions of the two main tea-producing areas in Pu'er City. Importantly, these regions adopted the local GEP in a staggered fashion between 2018 and 2020. With the help of the local government, we organized six survey teams, each led by a village leader or a local tea expert, to carry out the data collection.[3] Our data set covers more than 95% of local tea farmers, capturing information on production such as the number of trees and the yearly output of different quality teas. Most importantly, for each year, it records the quantities

2. Couture et al. (2021) is an exception. They use household-level data from a randomized controlled trial (RCT) to analyze the impact of rolling out a commercial e-commerce program nationwide, and find substantial benefits for rural households (e.g., lower living costs). However, their study mainly examines the entry of the largest Chinese e-commerce platform into rural areas, where most farmers were buyers rather than sellers on those platforms.

3. Each team included college and university students on vacation, as well as young, educated local residents. The general manager was responsible for coordinating the survey work and cleaning the data.

each household sold through offline and online channels. Therefore, our data set offers a unique opportunity to causally examine the effect of GEP access on farmers' specialty sales and the underlying economic mechanisms.

We employ a two-way fixed effects (TWFE) regression model to evaluate the causal impact of the GEP on online sales. Our model includes fixed effects for both household and year to control for unobservable household factors and common time trends. To address potential within-village correlations over time, we cluster standard errors at the village level. Our model accounts for variation in the number of nearby tea-processing factories and shipping companies as proxies for changes in the local market infrastructure and access to processing services. This enables us to analyze how these factors affect farmers' online channel choices over time. The results indicate a significant substitution effect: for tea of a given quality, offline sales decrease by 15.549% on average, while online sales increase by 16.649%. Given recent critiques of TWFE regressions (De Chaisemartin and d'Haultfoeuille, 2020; Jakiela, 2021; Roth et al., 2023), we employ the interaction-weighted estimator proposed by Sun and Abraham (2021) to address the potential biases that may arise from staggered platform access. We also conduct several robustness checks, including placebo tests and additional diagnostics, to confirm the reliability of our results. These tests confirm that the observed substitution effects originate from the introduction of GEP and are not driven by unobserved factors.

To investigate the mechanisms behind the substitution effect, we stratify households by characteristics measured before GEP access, including annual output, cultivated area, and quality of tea. Total sales remain roughly unchanged across groups, but there is a clear and statistically significant shift from offline to online, with the strongest impact for larger farmers who sell premium-quality tea. We also find both extensive and intensive margin responses: previously offline producers start selling online, and producers who were already selling online expand their use of online channels and increase their product offerings. Most farmers use social media as their initial online channel rather than the GEP, especially first-time adopters.

This pattern suggests spillovers from complementary public services surrounding the GEP, including training, cooperative packaging, and regional branding, which lower capability and credibility barriers, allowing farmers to benefit even without utilizing the GEP storefront. For sellers already online with premium tea, the program provides a low-cost route to list lower-quality tea, thereby increasing the variety available online. Additional evidence shows that once channel breadth and product variety are included as mediators, the substitution effect attenuates to near zero.

2 Relevant Literature and Contributions

Our analysis of a government-initiated e-commerce support program leverages household panel data and its staggered rollout. This approach enables us to distinguish between extensive-margin effects (i.e., who starts selling online) and intensive-margin effects across sales channels and tea quality levels.

2.1 Market Access and Transaction Volumes

In LMICs, reducing barriers to information and transportation can expand market access and transaction volumes. For example, studies on the adoption of mobile phones have shown that improved communication technology reduces price variation and waste in remote markets, thus improving efficiency in fishing and agriculture (Jensen, 2007; Aker, 2010). Similarly, investments in transportation infrastructure have expanded market access. For example, the expansion of railroads in colonial India significantly increased interregional trade and real income (Donaldson, 2018). Likewise, investments in rural road connectivity have been shown to reduce poverty by connecting remote producers with markets (Aggarwal, 2018). Increased Internet access has further improved market integration. Even before the rise of dominant e-commerce platforms, the spread of the Internet in China led to notable increases in export growth for local firms, as it improved communication (Fernandes et al., 2019).

Consistent with this, recent evidence from Africa suggests that expanding mobile broadband coverage in rural areas increases household consumption and reduces poverty rates, primarily by enhancing market opportunities and labor outcomes for previously isolated communities (Bahia et al., 2024). Regarding rural e-commerce, direct-to-farmer procurement has raised farmer sales prices and output in India (Goyal, 2010), while the randomized expansion of e-commerce in rural China has resulted in significant gains in consumer welfare but only modest changes in producer income (Couture et al., 2021). In terms of platform design, studies show that ensuring seller reputations (through ratings or certification) and providing buyer protections can mitigate adverse selection in online markets (Jin and Kato, 2006; Saeedi, 2019). Consistent with these findings, commercial platform rules (fees, deposits, etc.) differ sharply from those of the commission-free GEP (see Online Appendix B). Thus the lowering of fixed and operational barriers by the GEP should shift transactions toward the new platform.

Public e-commerce support programs differ from purely private e-commerce entry. By bundling services such as training, cooperative processing, and regional branding, the GEP in our study serves as an enabling infrastructure for small producers, rather than simply competing directly with other online platforms. Our study contributes to the literature by examining a government-initiated e-commerce marketplace in a rural setting. We explore how improved market access through this platform affects the distribution of transactions across both quality levels and sales channels. Using the staggered rollout of the platform, we isolate extensive margin effects (which producers begin selling online) from intensive margin effects (the range of products listed online). In doing so, we uncover reallocation patterns that would be concealed in more aggregated data. Our producer-focused findings complement evidence on consumer benefits from commercial platforms (Couture et al., 2021) and on how digital connectivity opens market opportunities (Bahia et al., 2024; Fernandes et al., 2019). This study provides new micro-level evidence from the producers' perspective: public digital support services can reallocate sales from offline to online and expand the range of products sold online, despite short-run supply constraints.

2.2 Supply-Side Reallocation and Market Dynamics

The entry of new sales channels can shift market shares and change the product mixes of firms. Empirical research shows evidence of both cannibalization (new channels taking share from existing ones) and expansion (market growth) effects when a new sales channel enters. For example, the introduction of bike rental services increased total ridership, even as existing bike rental companies lost some customers (Cao et al., 2021). Competition between online food delivery platforms boosted overall usage and revenue, mostly benefiting higher-quality incumbents, rather than simply splitting the existing market (Reshef, 2023). On the supply side, online markets enable a wide range of niche or unique products to find buyers. Increasing variety can attract new consumption rather than simply replacing existing ones (Brynjolfsson et al., 2003). In LMICs, gaining access to larger markets often encourages producers to diversify their offerings or improve the quality of the product rather than simply increasing the quantity. For example, when small rug manufacturers in Egypt were randomly given access to high-income foreign buyers, they responded by significantly improving product quality while reducing the output per hour, rather than increasing total production (Atkin et al., 2017).

In our context, we document a supply-side reallocation mechanism in which the GEP encourages farmers to sell online and diversify their product range. Farmers who get access to the platform early increase the variety of tea products they sell online, including lower-end teas with limited local demand. We observe heterogeneous effects: larger farmers with higher output shift a greater share of their sales online and introduce more product varieties after the GEP, consistent with evidence that better-endowed producers tend to adopt more profitable innovations earlier and more extensively (Foster and Rosenzweig, 1995). From a general equilibrium perspective, our findings help explain why total sales do not increase despite the introduction of the new channel. With fixed short-term production capacity, gains in online sales are offset by decreases in offline sales (Foster and Rosenzweig, 2004). This substitution effect aligns with the view that supply constraints can limit the impact of market expansion efforts. This finding aligns with other evidence from developing markets: in Kenya, an experimental increase in grain traders had a minimal impact on prices or quantities, largely due to high entry costs and persistent market power among intermediaries (Bergquist and Dinerstein, 2020). Therefore, without complementary investments to ease production constraints, digital integration can alter who is reached and what is sold rather than increasing overall production. Consistent with this literature, we find evidence that the public e-commerce platform and its associated public services increased online participation and assortment, rather than total sales.

2.3 Institutional Role and Design of GEPs

Digital platform markets often feature strong network effects and distinct competitive behaviors. A long-standing question is whether market forces result in a single dominant platform or allow multiple platforms to coexist. Classic theory suggests that network externalities can push markets towards a single dominant platform as the optimal outcome from both social and private perspectives (Katz and Shapiro, 1994; Shapiro and Varian, 1999). However, subsequent research has challenged this view, showing that smaller platforms can survive by differentiating themselves and targeting niche markets rather than competing in a winner-take-all scenario (Cennamo and Santalo, 2013). Empirical evidence from studies of new platform entries in established markets reveals a variety of outcomes. For example, the emergence of a peer-to-peer rental platform such as Airbnb greatly cannibalized the business of existing hotels in affected areas (Zervas et al., 2017). Similarly, the launch of ride-sharing services such as Uber caused significant declines in earnings for traditional taxi drivers (Berger et al., 2018). These cases demonstrate that privately operated digital platforms often act as new competitors for incumbents, eroding existing market shares.

We consider the public-service aspect as an essential part of the impact of the GEP:

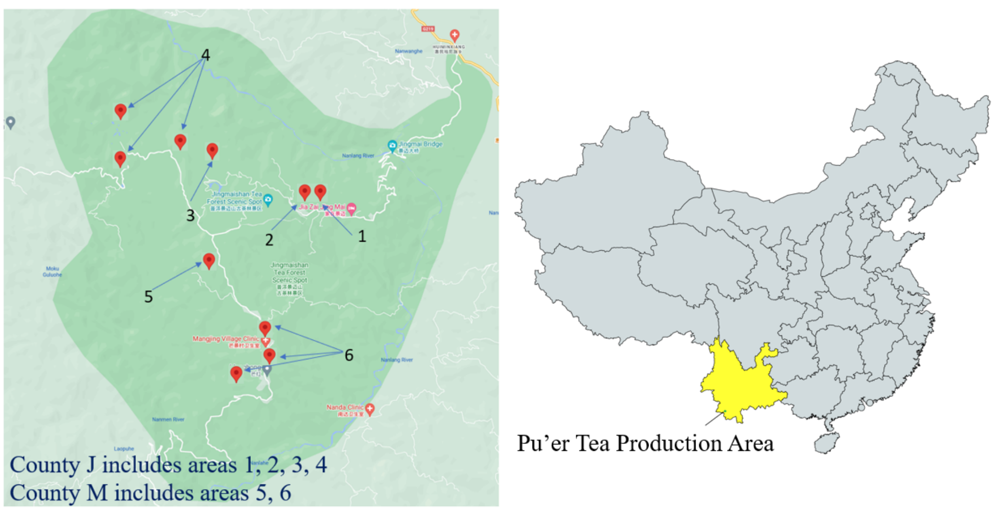
The range of government-provided services (including training, cooperative processing, and branding support) is integrated into the platform's operations and helps producers who were previously excluded from participating in e-commerce. Therefore, the objective of our study is to estimate the effect of a public-service ecosystem, rather than that of a government-initiated marketplace competing with giant commercial platforms (e.g., Taobao or JD). Our micro-level findings contribute to the broader development literature on the role of government in market integration, suggesting that for small-scale producers in LMICs, public digital services complement private platforms by reducing both financial and operational costs. For example, policy reforms that improved local governance and reduced bureaucratic steps in China have been shown to boost economic performance by enhancing market efficiency (Li et al., 2016). Similarly, special economic zones created by the government have significantly increased output and exports in Chinese cities by easing business restrictions (Wang, 2013). Likewise, the GEP functions as an infrastructural intervention that reduces barriers to entry for rural sellers. Our study demonstrates that public digital service provision boosts households' multichannel presence. This trend aligns with cross-channel spillovers from GEP access, as farmers broaden their online engagement beyond the public storefront to social media and other online marketplaces. A supplemental voluntary survey confirms these patterns, showing an expanded channel reach and more diverse online offerings after gaining access. Overall, these findings suggest that GEP access has lasting effects, supporting sustained online sales across multiple platforms over time.

3 Institutional Background

This section provides an overview of Pu'er tea production and sales. It explains the central government's guidelines for promoting online Pu'er tea sales and analyzes how local governments adapt these policies to suit local needs.

3.1 A Brief Description of the Local Specialty

This study focuses on Pu'er tea—a unique variety grown predominantly in six mountainous areas around Pu'er City, Yunnan Province. In 2008, Pu'er tea received protected Geographical Indication status from the Chinese government, which legally restricts the use of the name "Pu'er" to tea produced in that region. The study focuses on two major tea farming counties in Pu'er City (Counties J and M), home to the world's largest ancient tea forest. Figure 1 shows the location of Yunnan within China and highlights the main Pu'er tea zones. It also marks the exact locations of two counties, along with the six areas surveyed. Data for this study were obtained mainly from surveys conducted with residents of these areas.



Notes: The map on the left shows the six surveyed areas in Pu'er City, Yunnan Province, which are grouped into two administrative counties: County J (Areas 1–4) and County M (Areas 5–6). These areas are located within the world's largest ancient tea forest, recognized as a UNESCO World Heritage Site in 2023. The map on the right highlights Yunnan Province (in yellow) within mainland China. Pu'er tea is a protected geographical indication associated with specific areas in Yunnan. The depiction of map boundaries is for research illustration only and does not imply any position by the authors or the publisher on jurisdictional claims.

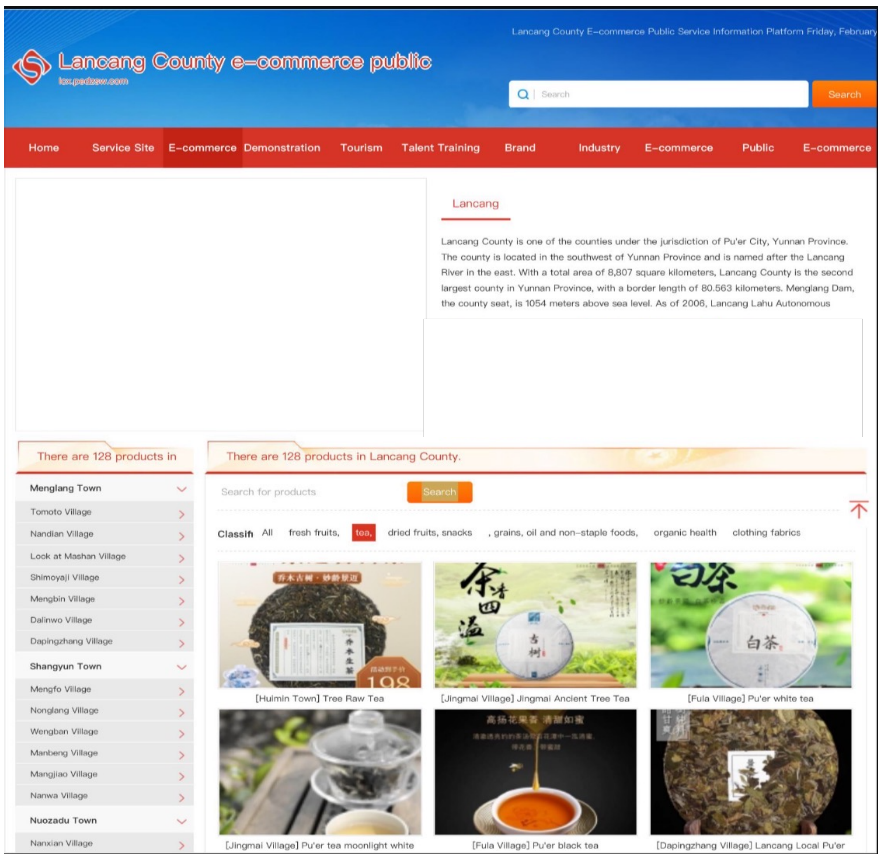
Figure 1: Geographical Location of Pu'er Tea Farming Areas

The dataset includes farming output and sales data for three primary tea varieties in the region: premium-quality, high-quality, and regular tea, which together account for over 98% of the local tea farming output during the study period. Premium-quality tea is characterized by its origin from the central buds of single, ancient trees over 50 years old, representing the highest grade. High-quality tea is a mixture of leaves from several ancient trees, each over 20 years old. Regular tea, the most commonly produced type, is harvested in spring from younger trees in plantation tea gardens.

3.2 Policy Treatment: Launch of the Platform

The Chinese government has initiated a series of efforts to promote e-commerce for specialty products in rural areas. In 2017, the Ministry of Commerce and the Ministry of Agriculture and Rural Affairs jointly issued a directive (Commerce Construction Letter [2017] No.597) calling for "deepening agro-commercial cooperation and vigorously developing agricultural e-commerce." This and related policies encouraged local governments to build an infrastructure of public services in e-commerce in rural regions, for example, by establishing government-supported e-commerce public service centers and training programs that help farmers sell their agricultural products online (Ma et al., 2023; Li et al., 2025). Starting in 2014 (and expanded in 2017), the Central Government's National Rural E-Commerce Comprehensive Demonstration Program allocated 20 million RMB per pilot county to develop e-commerce support systems (Ma et al., 2023; Li et al., 2025). The aim was not to build entirely new online marketplaces, but to improve the local e-commerce environment, offer training services, and develop regional brands as public goods.

In response to the central government initiative, the local government launched the Lancang County E-commerce Public Platform in late 2017 (with full implementation in early 2018) as a support system for online tea sales from farmers. This platform (essentially a regional e-commerce service center) was created to guide farmers in marketing their tea through digital channels. In practice, the Lancang platform is government-initiated and commission-free, operating as a public service rather than a profit-driven platform. Through the platform arrangements, farmers receive online orders from external customers and process raw tea leaves into compressed tea cakes at local cooperatives to fulfill orders. The cooperatives, established by the local government, provide packaging and branding services to farmers at a minimal cost (5 RMB per kilogram of processed tea). The finished tea cakes are labeled with the cooperatives' regional brand, lending credibility and a shared regional identity to the product (Yunnan Provincial Department of Natural Resources, 2024). This branding support through cooperatives and regional labels helps small farmers overcome trust and recognition barriers in online markets. The minimal processing fees and zero commissions enable farmers to engage in online sales without incurring the high costs typically imposed by commercial e-commerce platforms.



Notes: Screenshot of the Lancang county portal (translated). The interface allows filtering by region (lower left) and lists cooperative-branded tea products (bottom).

Figure 2: Snapshot of Lancang County E-commerce Public Platform

The platform was introduced at the end of 2017, with implementation starting in early

2018 across various regions, creating a valuable quasi-experimental setting for our analysis.[4] Figure 2 shows a snapshot of the platform's website interface. Importantly, the Lancang local government also invested in training and outreach programs to ensure farmers could effectively use this new channel. During the initial rollout, government personnel were dispatched to villages throughout the county to introduce the platform to tea farmers and demonstrate how to participate, including registering and listing products, adhering to online quality standards, and managing online orders. All tea producers in the area were informed about the platform and encouraged to sell their tea through it. Additionally, the government organized interactive training sessions and established WeChat groups that included local farmers and platform administrators. These groups served as continuous support and compliance training forums where farmers could ask questions, share experiences, and receive timely guidance on online sales.

Lancang's government was not alone in this effort - in fact, many local governments throughout China established similar public e-commerce service programs in the late 2010s in line with the national demonstration policy. In Online Appendix A, we list public service centers for e-commerce, established by various counties, alongside similar platforms, from 2017 to 2023, as part of this rural digitization initiative. Online Appendix B further provides more details and a comparative discussion of Lancang's public e-commerce service versus other online sales channels available to farmers. Despite the nationwide rollout of such public e-commerce centers, their effectiveness in boosting rural incomes remains largely understudied. Our study addresses this gap by carefully evaluating Lancang's program at the household level, analyzing how access to the GEP affected sales patterns for tea farmers in the region.

4. In Online Appendix C, we document the timeline of adoption of the platform in various townships and villages, highlighting the staggered rollout and its timing in each location.

4 Data Collection and Descriptive Statistics

This section describes the two administrative counties in the sample, describes the survey methodology, and explains the steps taken to ensure data quality. The second half of this section presents the descriptive statistics.

4.1 Data Collection

To gather data on the farming output, sales volumes, and sales channels, we selected two administrative counties (pseudonymously County J and County M) in the Pu'er tea production region for our household survey. The locations of both counties and their subareas are shown in Figure 1. County J comprises four distinct areas covering a total of 66.9 square kilometers. Its population is 3,339 people living in 801 households. A large portion of the population has lived in this mountainous region for many generations. To the south of County J is County M, which comprises two areas and has a population of 2,645 people, spread across 639 households.

A household survey was conducted in Counties M and J to collect the data needed for the study. A comprehensive survey was carried out in each area. The survey team was organized in collaboration with the local government. In County J, 785 of 801 households (98%) provided complete questionnaire responses. In County M, 198 households were surveyed and responded to the questionnaire. It is important to note that this does not imply that County M had a lower response rate. Unlike County J, where tea farming is nearly universal among households, County M has only 202 households involved in tea farming. Together, our survey covers more than 98% of tea-farming households in these areas, producing an almost complete household panel for the years 2016–2020. For each household, data were collected on variables such as annual tea production, the yearly area of accessible agricultural land, the yearly output of different quality tea leaves, and the quantities sold online and through offline channels. In Online Appendix D, we provide a detailed description of the data collection method and show a photo of the interview process.

4.2 Summary Statistics

Table 1 summarizes the key variables in our dataset. Tea sales occur through two primary channels: offline and online. Offline, tea farmers typically sell raw leaves to nearby processing factories right after harvest. By contrast, the online sales avenues consist of two types: social media (e.g., TikTok or Douyin) and e-commerce platforms (e.g., Taobao and Tmall). Before 2018, most farmers who sold online did so through social networks because they had lower entry and operating costs compared to e-commerce platforms, which often required brand registration and relevant certifications. When we consider 2018 as the year of policy change and overlook the specific adoption times for farmers in different areas accessing the GEP, it becomes clear that online sales of the three grades of tea (i.e., premium-quality, high-quality, and regular tea) have increased significantly after 2018. In contrast, the average offline sales figures for all grades of tea decreased compared to the pretreatment period. Despite these notable substitution effects, online sales still account for less than half of total household sales, as of 2018.

Table 1: Summary Statistics for Sales Volume

		Before 2018			**After 2018**		
		Premium	High	Regular	Premium	High	Regular
Sales Volume (Kg)	Online	113.50	104.33	176.67	199.54	188.91	375.01
		(79.34)	(75.53)	(181.23)	(129.51)	(120.29)	(409.94)
	Offline	459.84	391.49	873.37	394.04	346.62	832.72
		(279.23)	(257.69)	(725.81)	(264.01)	(235.28)	(691.25)

Notes: We report the standard deviation in parentheses.

In addition to the variables listed in Table 1, our sample also includes variables on time-varying environmental changes in these six areas. Additional data have been collected on the number of tea processing factories and freight companies located near each area during the five-year period covered by the dataset. In Online Appendix E, we provide a further statistical summary of the data, broken down by household and area. We find that the sizes of agricultural land for each farmer, as well as the number of factories and shipping companies, remain relatively stable during our sample period. This suggests that the local environment did not undergo significant changes other than the introduction of the GEP and that the shift toward online sales is not primarily driven by these factors.

5 Econometric Model and Estimation Results

In this section, we introduce the econometric model used to evaluate the impact of the GEP access on tea sales and discuss our key identification assumptions. We then present the baseline results and conclude with a series of robustness checks employing alternative estimators and specifications.

5.1 Econometric Model

To quantify the effect of gaining access to the GEP, we employ an econometric model with the following specifications:

$$q_{i,j,t} = \alpha + \gamma D_{i,t} + \delta mode_{i,j,t} + \theta D_{i,t} \times mode_{i,j,t} + \zeta \times Z_{i,j,t} + \mu_i + \eta_j + \psi_t + \epsilon_{i,j,t}, \qquad (1)$$

where $q_{i,j,t}$ denotes the logarithm of the total amount (in kg) of quality j leaves sold by household i in period t. $D_{i,t}$ represents the treatment variable. It equals 1 if the amount of quality tea leaves j has been sold by household i in period t through an online channel. $mode_{i,j,t}$ is a binary indicator that captures online and offline sales channels. This variable is equal to 1 if the sale of j quality tea leaves by household i in period t was made through an online channel.

The use of panel data enables the incorporation of two-way fixed effects, specifically household- and year-fixed effects. The potential impact of time-invariant unobserved household characteristics and time trends on estimates is captured by variables μ_i and ψ_t, respectively. Additionally, a binary variable, $Z_{i,j,t}$, is included, taking a value of 1 when the farming output of type j tea leaves by household i in period t is 0. This approach helps avoid biased estimates that could result from some households producing only a single type of tea. The variable ζ captures this effect. The variable η_j indicates fixed effects at the quality level. The household level time-varying unobserved quality-specific error term is represented by the variable $\epsilon_{i,j,t}$.

Equation 1 closely resembles a traditional difference-in-differences econometric model. The model captures the first difference by comparing tea sales at the household level before and after access to the GEP, designated as the treatment variable $D_{i,t}$. The second difference is obtained by the mode of sale. That is, the change in online sales before and after treatment is compared to the change in offline sales before and after the treatment. By calculating these differences, we can estimate the effect of treatment on offline and online sales through the parameters γ and θ as long as $D_{i,t}$ is assigned randomly.

5.2 Baseline Results

Table 2 presents the baseline results. Column (1) shows estimates with no fixed effects, Column (2) adds household fixed effects, and Column (3) includes both household and year fixed effects. The estimated coefficients are statistically significant at the 1% level, indicating that the policy has a significant impact on how households choose between online and offline sales channels. The following is a description of the interpretation of our coefficients. Following the acquisition of access to the platform, the volume of offline sales is observed to increase or decrease by an average of $100\times(\exp(\gamma)-1)\%$. Similarly, online sales experience an average increase or decrease of $100\times(\exp(\gamma+\theta)-1)\%$ after obtaining access to the platform. Based on Column (3) of Table 2, after an area gains access to the GEP, online sales increase by 16.649% on average for tea of a given quality. In contrast, offline sales drop by an average of 15.549% after the area has access to the GEP. Our findings indicate a statistically and economically significant shift by households from selling their tea through offline channels, such as factories and local markets, to online channels, including the GEP and various social media and commercial e-commerce platforms.

Table 2: Effect of GEP Access on Sales

Dependent Variable:	Log(sales): $q_{i,j,t}$					
	Without Clustering			**With Clustering**		
	(1)	(2)	(3)	(4)	(5)	(6)
Platform Access (γ)	-0.148^{***}	-0.179^{***}	-0.169^{***}	-0.148^{**}	-0.179^{**}	-0.169^{***}
	(0.011)	(0.013)	(0.014)	(0.049)	(0.065)	(0.035)
Platform Access × Online Sales (θ)	0.316^{***}	0.316^{***}	0.323^{***}	0.316^{***}	0.316^{***}	0.323^{***}
	(0.015)	(0.015)	(0.014)	(0.076)	(0.076)	(0.078)
Online Sales (δ)	-0.474^{***}	-0.474^{***}	-0.482^{***}	-0.474^{***}	-0.474^{***}	-0.482^{***}
	(0.008)	(0.008)	(0.007)	(0.036)	(0.036)	(0.038)
Zero Output (ζ)	-5.484^{***}	-5.483^{***}	-5.429^{***}	-5.484^{***}	-5.483^{***}	-5.429^{***}
	(0.007)	(0.007)	(0.007)	(0.073)	(0.072)	(0.065)
Constant (α)	5.739^{***}	5.748^{***}	5.715^{***}	5.739^{***}	5.748^{***}	5.715^{***}
	(0.007)	(0.007)	(0.007)	(0.094)	(0.096)	(0.055)
Observations	29,490	29,490	29,490	29,490	29,490	29,490
Quality FE	NO	NO	YES	NO	NO	YES
Household FE	NO	NO	YES	NO	NO	YES
Year FE	NO	YES	YES	NO	YES	YES
R^2	0.956	0.956	0.965	0.956	0.956	0.965

Notes: Standard errors are indicated in parentheses. In Columns (4), (5), and (6), error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Although panel data helps us better isolate the treatment effect by controlling for various fixed effects, we remain cautious about potential correlations in the error term caused by unobserved area-specific factors that change over time. According to our baseline specifications, the unit of analysis is household-quality-year sales (both online and offline). However, our treatment, which is gaining access to the GEP, occurs at the area level rather than the individual level. As a result, we cluster standard errors at the area level for our baseline model and all subsequent models where this discrepancy exists. Estimates for the baseline specification, with standard errors clustered at the area level, are shown in Columns (4), (5), and (6) of Table 2. After clustering standard errors at the area level, our estimated treatment effect remains statistically significant at the 1% level.

5.3 Robustness Check 1: Unobserved Trends and Environmental Changes

One of the key assumptions underlying the identification of our model is that no factors changing over time at the area level are correlated with both treatment (access to the GEP) and result (tea sales). For example, imagine a scenario where farmers become more productive over time. In that case, an incorrect conclusion might be drawn, attributing the increase in online sales to the introduction of the GEP. However, the increase in online sales could actually be due to a boost in farming output. Therefore, it is crucial to address these issues to accurately measure the impact of the GEP on online and offline sales. To achieve this, we incorporate additional control variables into our model, including the volume of tea produced by each household and the number of factories and shipping companies in each area. These controls help us distinguish the effects of the policy from other area-specific factors that change over time and could affect our outcome variables. We estimate the following equation:

$$q_{i,j,t} = \alpha + \gamma D_{i,t} + \delta mode_{i,j,t} + \theta D_{i,t} \times mode_{i,j,t} + \zeta \times Z_{i,j,t} + \beta^{'} X_{i,t} + \mu_i + \eta_j + \psi_t + \epsilon_{i,j,t}, \quad (2)$$

where $X_{i,t}$ is a vector of controls that includes the log of the amount of tea produced by household i in year t and the number of factories and shipping companies in the area of household i in year t.

Furthermore, even after including area-level controls, we acknowledge the possibility of unobserved area-specific, time-varying factors that could be linked to both the treatment and outcome variables. For example, if certain areas adopt smartphone technology more quickly than others, those with higher smartphone adoption rates may show higher online sales. Failing to account for these unobserved time-varying differences across areas could lead to biased estimates of the treatment effect. To address this, we incorporate area-specific trends into Equation 2. Specifically, we estimate the following equation:

$$\begin{aligned} q_{i,j,t} = \alpha + \gamma D_{i,t} + \delta mode_{i,j,t} + \theta D_{i,t} \times mode_{i,j,t} + \zeta \times Z_{i,j,t} + \\ \beta' X_{i,t} + \mu_i + \eta_j + \psi_t + area_i \times TT_t + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

where $area_i$ represents the area where household i resides. TT_t denotes a polynomial time trend, and $area_i \times TT_t$ constitutes the interaction term.

Detailed results are shown in Online Appendix F. The first two columns of Table F.1 indicate that online sales increase by an average of 18.412%, while offline sales decrease by an average of 16.222% when controls for area-specific factors varying over time are included in Equation 2. The last two columns incorporate additional controls for household-level farming output and area characteristics in Equation 3, respectively. Our results are consistent with different specifications, suggesting that there are no significant trend differences across counties.

5.4 Robustness Check 2: Treatment Endogeneity

The presence of unobserved variables that influence both treatment and outcome simultaneously can also cause endogeneity bias in our estimates. This bias may mistakenly assign the effects of these hidden factors to the treatment itself (Angrist and Pischke, 2009). To improve the causal interpretation of our estimates, it is crucial to confirm that the timing of GEP access is not associated with unobserved time-varying factors at the area level that could also affect tea sales. While the local government confirmed that no specific criteria or special considerations were used to determine which area gained access to the platform first, we conducted additional tests to verify the assumption of randomization.

The first step is to determine whether the probability of gaining access to the GEP depends on area-level characteristics, such as the level of farming output, the number of tea processing factories, and the number of shipping companies. Following the methodology proposed by Zervas et al. (2017), we analyze whether GEP access was systematically related to these area characteristics. The detailed results are provided in Online Appendix G. Our results indicate that area-specific time-varying factors, such as total tea production, the number of factories, and the number of shipping companies, are not correlated with the timing of GEP adoption.

To further strengthen the robustness of our findings, we propose a series of placebo tests. These tests aim to verify whether the estimated effect of treatment truly reflects the impact of the government's policy intervention, rather than being influenced by other confounders related to treatment and the farmer's choice of online or offline sales channels.

In our first placebo test, we randomly assigned the years during which a household or area has access to the platform, while keeping the total number of years of access fixed. The results of this test are shown in Columns (1) and (2) of Table G.2 in Online Appendix G. In Column (1), we reshuffle treatment at the area level. For example, if an area had access to the GEP in 2019 and 2020 (a two-year period), we randomly select two years between 2016 and 2020 and assign a value of one to a new variable called 'placebo treatment' for those selected years. The placebo treatment is applied consistently to all households within a given area. In Column (2), the treatment status is reshuffled for each household, rather than each area. After creating the placebo treatment, we then estimate its effect on offline and online sales. The results of both columns indicate that the placebo treatment has no statistically significant effect on online or offline sales of a household at the specified significance level. In the second placebo test, we estimate Equation 1 using a subset of households that have never participated in online sales during the entire sample period. Our data indicate that roughly 9% of the total sample falls into this category. If the impact of the GEP on tea sales across different channels is solely due to GEP access, these non-online sellers should remain unaffected by the policy change. The results, presented in Column (3) of Table G.2 in Online Appendix G, support this idea. We find that the GEP had no effect on sales volumes for non-adopters.

5.5 Robustness Check 3: Bias Correction Related to TWFE Estimators

As highlighted by recent econometric studies (De Chaisemartin and d'Haultfoeuille, 2020; Jakiela, 2021), the estimation of TWFE is unbiased when the effects are homogeneous across units and periods. In other words, when there are no dynamic changes in the effects of the treatment. The bias in TWFE estimation persists even when treatment is randomly assigned, as interactions between treatment effects and time still occur with random assignment. This section includes additional robustness checks to prevent bias that arises when previously treated observations are implicitly used as controls for newly treated observations.

5.5.1 Negative Treatment Weights

Following Jakiela (2021), $\hat{\theta}^{TWFE}$ in Equation 1 can be derived using the Frisch-Waugh-Lovell Theorem:

$$\hat{\theta}^{TWFE} = \sum_{ijt} q_{ijt} \left(\frac{\hat{\epsilon}_{i,j,t}}{\sum_{i,j,t} \hat{\epsilon}^2_{i,j,t}} \right), \tag{4}$$

with $\hat{\epsilon}_{i,j,t}$ representing the residual of regressing the treatment indicator in the effects fixed in the household, year, and quality. The effect of treatment is therefore a weighted sum of the outcome variable, where the weights are the residualized treatment weights. Jakiela (2021) indicates that bias arises when treated units have negative treatment weights and when treatment effects are heterogeneous. To identify such biases, we examine whether treated units have negative weights and then test for homogeneity of treatment effects.

In Online Appendix I.1, we provide a detailed analysis of the robustness of our findings, following the procedures outlined by Jakiela (2021) to show the weights for treated and untreated units. It is noted that only 15% of the treated units have negative weights. For comparison, Jakiela (2021) found that about 25% of the treated units had negative weights, yet the treatment effect remained robust after removing those observations. Since our estimate of the Average Treatment Effect (ATE) is a weighted sum of outcomes, these small negative weights are unlikely to cause bias. As an additional robustness check, we reestimated the model, this time excluding treated units with negative weights. Results in Online Appendix I.1 show that the effect of GEP access on substitution remains significant.

5.5.2 Interaction Weighted Estimator

To avoid the potential for bias inherent in TWFE estimators, we have also implemented the interaction weighted (IW) fixed effects estimator, as proposed by Sun and Abraham (2021) and Callaway and Sant'Anna (2021). The IW estimator is robust to heterogeneous treatment effects in models with staggered treatment and can be used even without a never-treated group. According to the methodology proposed by Sun and Abraham (2021), our sample was divided into different cohorts based on the year that each household gained access to the platform. In our study, these results were obtained in three distinct cohorts (2018, 2019, and 2020), as well as a cohort that had not received treatment.

In Online Appendix I.2, we provide a detailed analysis and results from the implementation of the IW estimator. As shown in Table I.2, our IW estimates confirm our initial findings on the impact of the GEP on tea sales. Converting our estimates to the effects on online and offline sales, we find that the GEP resulted in an average 14.444% decrease in offline sales and a 12.524% increase in online sales. Figure 3 shows the estimated effects across cohorts. We observe a consistent effect, indicating a significant positive impact on online sales and a negative impact on offline sales after the platform's implementation.

6 Heterogeneous Treatment Effects

Our heterogeneity analysis focuses on two dimensions: (1) differences between households with low vs. high production levels, and (2) differences across product quality tiers.

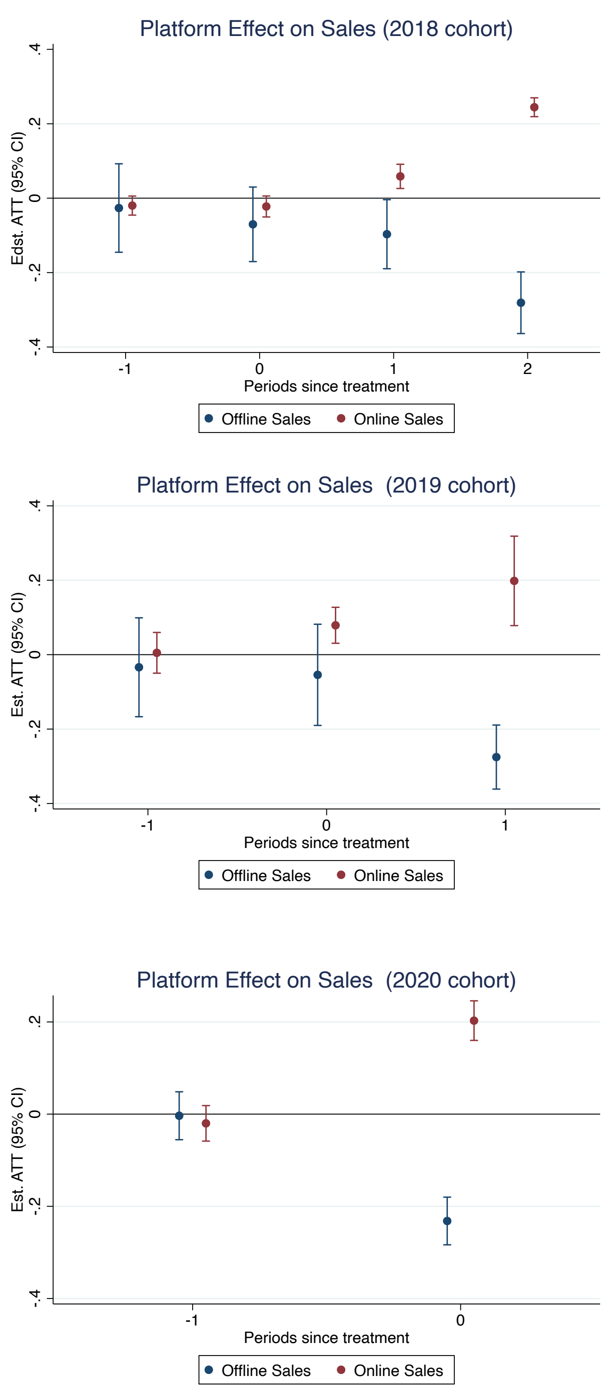


Figure 3: Average Treatment Effects by Cohort

Notes: The above figure illustrates the impact of the GEP on online and offline tea sales for different cohorts. The blue dots represent the impact on offline sales, while the red dots indicate the effect on online sales. The horizontal axis represents the periods since the treatment, and the vertical axis represents the estimated ATT with 95% confidence intervals. Although the figure clearly demonstrates that the trends of the groups were parallel before the intervention (parallel pre-trends), we also provide additional checks in Online Appendix H to further validate the assumption of parallel trends.

6.1 Effects Across Different Output Levels

We hypothesized that the impact of GEP access could differ by farm size (output level). Specifically, the impact of the platform could differ for farmers with high and low output levels. To address this, we divided the households into three production-level groups: low output (0–405 kg/year), medium output (406–870 kg), and high output (>870 kg). We perform subsample regressions for each category to assess two outcomes: the overall change in sales volume and the shift in sales from offline to online after gaining access to the GEP.

The findings are presented in Table 3. It is indicated that the largest producers moved a greater share of their sales online than medium or small farmers. Additionally, we find that the introduction of the GEP did not significantly change the total volume of tea sales. However, it led to a notable shift in sales from offline to online, particularly for the largest tea farmers. Structural factors (e.g., limited garden acreage and a finite number of ancient tea trees) limit how much tea output can grow. Such restrictions, particularly the lengthy maturation time required for high-quality tea leaves, hinder any rapid expansion in production. Changes in ownership among households were minimal, further indicating that total output remained stable before and after the intervention. Because total sales remain unchanged, the shift from offline to online appears to be a profit-maximizing reallocation by farmers to sales channels with higher margins or lower transaction costs.

6.2 Effects Across Different Product Qualities

We also examine whether the impact of the GEP varies by grade of tea quality. We classify tea into three quality tiers (premium, high, and regular) and run separate regressions for each in Table 4. Consistent with our previous results, we find that gaining access to the GEP had no significant impact on total sales volume across quality grades. Further analysis reveals that online sales of regular tea increased by 11.963%, high-quality tea by 15.604%, and premium-quality tea by 21.653%. Although the premium-quality tea segment shows the

Table 3: Heterogeneous Effects of GEP Access on Sales by Quantity

Dependent Variable:	Log(sales): $q_{i,j,t}$							
	All Households		**0-405 Kg**		**406-870 Kg**		**871+ Kg**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Platform Access	-0.008	-0.169***	-0.006	-0.093***	-0.022	-0.182***	0.006	-0.230***
	(0.008)	(0.035)	(0.007)	(0.010)	(0.017)	(0.029)	(0.013)	(0.060)
Platform Access × Online Sales		0.323***		0.173***		0.319***		0.447***
		(0.078)		(0.019)		(0.056)		(0.140)
Online Sales	-0.392***	-0.482***	-0.125***	-0.175***	-0.393***	-0.477***	-0.689***	-0.816***
	(0.027)	(0.038)	(0.020)	(0.012)	(0.024)	(0.020)	(0.012)	(0.027)
Zero Output	-5.438***	-5.429***	-4.887***	-4.883***	-5.412***	-5.404***	-5.757***	-5.737***
	(0.069)	(0.065)	(0.058)	(0.056)	(0.031)	(0.029)	(0.041)	(0.032)
Observations	29,490	29,490	9,900	9,900	9,780	9,780	9,810	9,810
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Quality FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.965	0.965	0.970	0.970	0.971	0.972	0.964	0.965

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

largest percentage increase in online sales, this is primarily due to its significantly smaller online sales volume compared to regular tea. In contrast, although online sales of regular tea increased by just under 12%, they experienced the largest volume increase (in kilograms per year) among online sales.

Table 4: Heterogeneous Effects of GEP Access on Sales by Quality

Dependent Variable:	Log(sales): $q_{i,j,t}$							
	All Qualities		**Regular**		**High**		**Premium**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Platform Access	-0.008	-0.169***	-0.007	-0.127*	-0.010	-0.166***	-0.011	-0.219**
	(0.008)	(0.035)	(0.009)	(0.051)	(0.008)	(0.028)	(0.013)	(0.077)
Platform Access × Online Sales		0.323***		0.240**		0.311***		0.415*
		(0.078)		(0.092)		(0.049)		(0.175)
Online Sales	-0.392***	-0.482***	-0.398***	-0.469***	-0.319***	-0.407***	-0.461***	-0.579***
	(0.027)	(0.038)	(0.031)	(0.047)	(0.056)	(0.063)	(0.079)	(0.128)
Zero Output	-5.438***	-5.429***	-6.003***	-5.972***	-4.977***	-4.945***	-5.003***	-4.962***
	(0.069)	(0.065)	(0.047)	(0.040)	(0.142)	(0.142)	(0.078)	(0.057)
Observations	29,490	29,490	9,830	9,830	9,830	9,830	9,830	9,830
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Quality FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.965	0.965	0.976	0.976	0.977	0.977	0.972	0.973

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7 Exploring Potential Mechanisms

We now investigate the mechanisms through which the GEP affects farmers' sales, focusing on the extensive margin (whether more farmers sell online) and the intensive margin (how the online presence of farmers expands). On the extensive margin, we examine the increase in the number of farmers selling online after gaining access to the GEP. This increase is likely driven by the introduction of the platform and its accompanying public services (e.g., training and regional branding support).

7.1 Extensive Margin: Effects on Online Mode Adoption

We first look at the extensive margin: Does GEP access induce farmers who weren't selling online to start doing so? To assess the impact, we estimate three different adoption outcomes. First, we define an overall online adoption indicator ($Adopt_{i,t}$), which equals one if farmer i sells any tea online in year t, and zero otherwise. Column (1) of Table 5 shows that farmers who had no prior experience selling tea online before the introduction of the GEP are significantly more likely to start selling tea online after gaining access, with an estimated effect of 22.774% (significant at the 1% level).

In Columns (2) and (3), we further refine our analysis by examining adoption decisions using alternative metrics. In Column (2), the dependent variable ($Adopt_{i,j,t}$) equals one if farmer i sells tea of quality j online during year t. The results show a statistically significant increase of 7.551% (significant at the level 1%) in the probability that farmers adopt online sales for each tea quality category. Column (3) uses an alternative definition by estimating the effect of the platform on the timing of online adoption. Here, we use the dependent variable ($Adopt^{f}_{i,t}$), which equals 1 only if year t is the first year the farmer adopts online tea sales. The results indicate that farmers without previous online sales experience show a significant increase of 21.778% (significant at the 1% level) in the probability of making their first online sale after gaining access to the platform. These estimates suggest that the policy lowered entry barriers for households that had been offline, either by closing knowledge gaps about online sales or by helping them meet the onboarding requirements of commercial platforms.

Table 5: Effect of GEP Access on Adoption of Online Sales

Dependent Variable:	Overall Online Adoption ($Adopt_{i,t}$)	Online Adoption by Quality ($Adopt_{i,j,t}$)	First-time Online Adoption ($Adopt^{f}_{i,t}$)
	(1)	(2)	(3)
Platform Access	0.228***	0.076***	0.218***
	(0.049)	(0.017)	(0.030)
Observations	745	2235	745
Household FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.548	0.205	0.357

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. The differences in observations across columns are due to conditioning on farmers who had no online sales experience before the introduction of the GEP. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7.2 Intensive Margin: Effects on Number of Online Channels

Next, we consider an intensive-margin mechanism: Does the GEP help farmers expand their online presence across multiple channels? Specifically, we monitor the number of online channels each household utilizes. Before the policy, most online activity took place on social media, as large commercial platforms (e.g., Taobao or JD) often required deposits, fees, and higher operational capacity. In contrast, social media has lower entry requirements (see Online Appendix B for a detailed comparison). In line with a mechanism that reduces fixed and capability barriers through training, cooperative processing, and access to the GEP, we anticipate diversification into multiple online channels once access is granted.

The estimates in Table 6 show two patterns. First, among households without online sales prior to the policy, access to the GEP increases the probability of adopting one additional online channel by 22.780%. Columns (2) to (5) further explain which channels are adopted. Restricting to households with specific pretreatment channel restrictions, access to the GEP increases the in-sample adoption rate of social media by 23.407% and the in-sample adoption rate of online platforms by 11.625%. Among households with no prior online sales, program access is associated with a higher likelihood of adopting social media channels, with no detectable change in the adoption of online platforms.

Table 6: Effects of GEP Access on Online Channel Adoption

Dependent Variable	Number of Channels	Adopt Social Media		Adopt Platform	
	Offline Only	**Offline Only**	**Excluding Social Media**	**Offline Only**	**Excluding Platform**
	(1)	(2)	(3)	(4)	(5)
Platform Access	0.228***	0.232***	0.234***	-0.004	0.116*
	(0.057)	(0.050)	(0.051)	(0.012)	(0.053)
Observations	745	745	760	745	4,095
Household FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
R^2	0.562	0.548	0.547	0.351	0.437

Notes: Standard errors are indicated in parentheses. Standard errors are clustered at the area level. "Excluding Social Media" refers to farmers who have no online sales and those who previously sold only on the platform before the policy was implemented. "Excluding Platform" refers to farmers who have no online sales and those who previously sold only on social media prior to the implementation of the GEP. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results from Columns (2) to (5) convey an insight: When households first move online, they always prioritize the social media channel, even when the GEP is available. This is evident from the much larger coefficients for social media adoption relative to platform adoption. In the subsample estimates, the coefficient increase is 0.234 for adopting social media versus 0.116 for adopting the platform channel. Overall, the evidence suggests that the estimated impact of gaining access to the GEP primarily stems from cross-channel spillovers of the bundled public service package, including training, cooperative processing, packaging, and regional branding, rather than from the immediate, direct use of the GEP storefront alone. Therefore, even if the storefront were not maintained, farmers would continue to benefit from these public services and sustain profitable online sales through existing private channels. In addition, the adoption sequence aligns with the capacity and credibility constraints. Farmers typically begin by selling their products through informal, low-cost social media platforms; then, processing and branding services reduce participation costs and enhance credibility, enabling a gradual expansion into more formal marketplaces, including platform storefronts. This aligns with evidence that reducing participation barriers reshapes the market structure and entry in LMICs (Goyal, 2010; Bergquist and Dinerstein, 2020), and with findings that platform assurances and third-party certification mitigate adverse selection in online markets (Jin and Kato, 2006; Saeedi, 2019).

7.3 Intensive Margin: Effects on Product Diversity

We also analyze product diversity on the intensive margin: Do farmers sell a wider range of tea qualities online after gaining access to the GEP? Since the market for regular tea tends to have thin margins in traditional online commercial markets, we hypothesize that the government's package of services - cooperative processing at minimal cost, regional public branding, training, and a commission-free sales channel - makes it cost-effective to list lower-priced varieties online, while also allowing entry into higher-end segments for households previously absent from them. In Online Appendix J, we present some model-free evidence that corroborates this hypothesis.

Table 7: Effects of GEP Access on Online Varieties

Dependent Variable	Online Varieties	Online Regular		Online High/Premium	
	Offline Only	**Offline Only**	**Excluding Regular**	**Offline Only**	**Excluding High/Premium**
	(1)	(2)	(3)	(4)	(5)
Platform Access	0.227^{***}	0.003	0.058^{*}	0.224^{***}	0.258^{***}
	(0.052)	(0.006)	(0.027)	(0.050)	(0.058)
Observations	745	745	3,250	745	795
Household FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
R^2	0.558	0.342	0.358	0.546	0.568

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. The dependent variables "Online Regular" and "Online High/Premium" indicate whether the farmer is selling regular tea online and high/premium tea online, respectively. "Excluding Regular" refers to farmers who did not sell any regular-quality tea online prior to the policy. "Excluding High/Premium" refers to farmers who did not sell any high-quality or premium-quality tea online prior to the policy. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7 summarizes these two aspects of product diversity. First, we examine the number of varieties sold online and show that GEP access increased the overall variety of online tea products. Second, our results on adoption by quality show a clear reallocation along both ends of the spectrum. At the lower end, households that did not sell regular tea online before the policy are 5.759% more likely to do so after gaining access, even though the effect is nil for the previously offline group taken as a whole. At the upper end, households with no online sales and those without prior high/premium listings are 22.355% and 25.799% more likely, respectively, to sell high/premium tea online after gaining access.

These results show that GEP access broadens the online selection across both high-end and low-end products. We also observe a pattern in product adoption: Among households without prior online activity, the first products listed after gaining access to the GEP are mostly high- and premium-quality tea, while among households already selling online, access is followed by additional listings of regular tea. This pattern aligns with our expectations: Higher-grade teas have higher markups, making them the first natural products to go online. In contrast, regular tea usually has smaller online-offline price differences and is not prioritized without additional support. Since the GEP reduces online costs for selling regular tea through cooperative processing and compact packaging under regional public branding, it can help farmers list some of their regular output online and earn additional income.[5]

These intensive-margin responses match two strands of existing evidence. First, by lowering participation and operating costs for small producers, the public digital infrastructure can broaden market access and reallocate where transactions occur (Fernandes et al., 2019; Couture et al., 2021). Second, reputation and certification alleviate quality uncertainty in online settings (Jin and Kato, 2006; Saeedi, 2019). In our context, standardized processing and regional public branding play a role analogous to third-party certification, reducing credibility costs for regular tea and supporting the listing of higher-end products by previously excluded households. Quality-side adjustments in response to access to distant buyers are also consistent with experimental evidence on product upgrade under export-market access (Atkin et al., 2017). The documented expansion of variety is consistent with our aggregate results. With the short-term inelasticity of the tea supply (fixed plot sizes and age requirements for tea trees), digital integration changes what is sold online rather than expanding total output (Foster and Rosenzweig, 2004). The public e-commerce service thus functions less as an online platform and more as an enabling infrastructure that lowers costs for a

5. In Online Appendix K, we present additional evidence supporting this mechanism. When we restrict the sample to farmers who were already selling online before gaining access to GEP, we find that GEP access is associated with increased online sales across nearly all channel types. The exception is the subgroup already qualified to sell on commercial marketplaces before the program: For these farmers, GEP access has a non-significant incremental effect. They typically operate on a larger scale, meet qualifications for commercial platforms, and are almost universally active on social media; therefore, the GEP storefront does not significantly increase margins or profits. These findings collectively demonstrate that the GEP offers a cost-effective alternative channel, enabling farmers who previously could not profitably sell lower-grade teas on commercial platforms to market these products online.

broader set of product varieties.

7.4 Mediating Role of Online Channels and Product Variety

To determine whether the observed margins are the primary channels driving the substitution pattern, Table 8 presents mediation regressions with the dependent variable defined as the log of household–year level online sales aggregated across qualities. Column (1) repeats the baseline specification used in Table 2 for the aggregated online sales. Columns (2) and (3) add the number of online channels used by the household and the number of product varieties listed online separately. Column (4) jointly adds the number of online channels and product varieties together.

Table 8: Mediating Role of Online Channels and Product Variety

Dependent variable:	Total Online Sales			
	(1)	(2)	(3)	(4)
Platform Access	0.081*	0.032	0.034	0.020
	(0.035)	(0.055)	(0.032)	(0.038)
Number of Channels		2.357***		1.217***
		(0.086)		(0.056)
Number of Varieties			2.579***	1.971***
			(0.062)	(0.036)
Zero Output	-2.387***	-0.953***	-1.031***	-0.610***
	(0.191)	(0.105)	(0.102)	(0.064)
Observations	4,915	4,915	4,915	4,915
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.777	0.884	0.926	0.946

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Our results align with a mediated substitution mechanism. In Column (1), access to the GEP significantly boosts overall online sales.[6] When we add the two potential mediators,

6. Differences between the baseline coefficient in Table 2 and the overall coefficient in Table 8 result mechanically from the model specifications (i.e., log-of-parts vs. log-of-sum); we document this relationship formally

each one enters positively and is highly significant on its own; both remain positive and statistically significant when included together, indicating they are not strongly collinear and each explains different variation. As we add these mediators, the coefficient on GEP access shrinks toward zero and becomes statistically insignificant by Column (4). At the same time, model fit improves markedly once the number of online channels and the number of product varieties are included. This pattern supports the idea that GEP access primarily increases online sales by expanding the number of online channels and broadening the range of product offerings available online. In Online Appendix M, we present parallel analyses using aggregate offline sales as the outcome. We also control for the number of shipping companies to ensure that the increase in online sales is not simply due to simultaneous growth in local shipping capacity. We find that including shipping companies as a control does not change our results in this section. Meanwhile, an increase in online channels and a greater variety of online products are also associated with greater declines in offline sales; including them significantly reduces the coefficient related to access to the GEP.[7]

8 Conclusion

This paper examines the impact of a government-initiated e-commerce program on the sales of rural producers, considering both offline and online channels. Using a staggered county rollout in Pu'er, China, and a near-census household panel of 983 tea producers from 2016 to 2020, we employ TWFE models to distinguish between online and offline responses at the household-year-quality level. We show clear evidence that access to the GEP reallocates sales

in Online Appendix L.

7. To supplement the mediation analysis, we conducted a brief household survey to describe how online behavior changed with access to GEP. Details are provided in Online Appendix N. The responses clearly indicate a shift from little to no online activity to sustained online sales. After adopting GEP, the selection of online products expands, primarily with regular teas, and farmers diversify the channels they use to sell their products online. The adoption of GEP is common, with producers often multi-homing on WeChat, short-video platforms, and live-streaming platforms, as well as traditional e-commerce platforms, alongside the GEP. When asked whether and why profits increased, respondents highlighted that the local GEP, in general, helps increase their profits. A commission-free marketplace and bundled public services, including training, cooperative branding, and standardized processing and packaging, are key factors for increasing profit.

across channels. Online sales increase by approximately 16.649%, while offline sales decrease by approximately 15.549% after gaining access, resulting in no overall change in total sales in the short to medium term. This pattern remains consistent when using alternative estimators that account for staggered treatment.

Mechanisms operate on both margins. On the extensive margin, program access increases the likelihood that previously offline households start selling online. On the intensive margin, sellers broaden their online footprint across channels, typically entering via social media formats and then adding online platforms, and expand the range of tea qualities they offer. Adoption occurs at both ends of the quality spectrum: households that had not listed regular tea begin doing so, and households without prior premium listings add higher-grade products. Mediation tests reveal that the policy effect is primarily transmitted through two pathways: increased online sales channels and expanded online product variety.

Our policy implications are as follows. First, when supply is inelastic in the short run, the presence of public digital services and the GEP can shift transactions from offline to online channels, thereby increasing participation on the extensive margin. This mechanism works by reducing fixed and capability costs through training, shared processing and packaging, standardized quality control, and public regional brands. In LMICs, these features are especially crucial for smallholders facing thin margins, limited buyer recognition, and restricted access to professional e-commerce operations. Second, the public sector should complement rather than replace private marketplaces. Effective complements include community processing facilities, seller training, and basic digital infrastructure for collection and delivery. These efforts could lead to an increase in the variety of online products and encourage households to adopt multichannel strategies. In summary, digital public services initially change what is sold and where it is sold. Long-term growth and income improvements can occur when additional investments reduce supply-side constraints, allowing farmers to earn higher profits from online sales.

9 Declaration of generative AI and AI-assisted technologies in the writing process

During manuscript preparation and revision, the authors used ChatGPT (GPT-4o and GPT-5 Thinking) solely for grammar and language editing. All ideas, analyses, and conclusions are the authors' own. The authors verified and edited any AI-assisted suggestions and take full responsibility for the final content.

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Online Appendix for "Digital Revitalization or Useless Effort? Public E-commerce Support and Local Specialty Sales"

Table of Contents

A List of GEPs in China from 2017 to 2023

Table A.1 offers a current and detailed list of China's regions where local governments have established e-commerce public service centers between 2017 and 2023. The table shows the variety of local efforts and illustrates the widespread government-backed rural digitization initiatives across China. The listed platforms mainly serve as public service centers to help local producers access and use existing commercial e-commerce marketplaces, rather than functioning as independent, profit-driven platforms. The table highlights the government's focus on improving rural digital infrastructure, branding support, and training services, reflecting the broader goals of the National Rural E-commerce Comprehensive Demonstration Program launched in 2014 and significantly expanded in 2017 (Ma et al., 2023; Li et al., 2025).

Table A.1: Government E-commerce Public Service Centers in China since 2017

Province	Location	Setup Year	Name of Public E-commerce Service Center	Link
Tianjin	Tianjin	2018	Tianjin Yinonghe	http://tj.365960.cn/catalog/11000000.html
Gansu	Minle	2019	Min Le You Pin	https://mldszx.com.cn/productlist.php
Henan	Xixian	2019	Xi County E-commerce Public Service Center	hhttp://www.xixiandianshang.cn/index.html
Gansu	Tanchang	2018	E-commerce of Tanchang	http://www.tanchangds.com/index.jsp
Shanxi	Xixian	2017	Xixian County E-commerce Public Service Center	http://xxdsfwzx.com/techan.aspx?ClassID=78
Chongqing	Qijiang District	2018	Chongqing Qijiang Caiba Trade Co., Ltd.	http://www.cb023.com/
Liaoning	Tieling	2021	Tieling E-commerce Public Service Center	http://data.ehoneycomb.net/data/index/index/city_id/13.html
Jiangsu	Jiangyin	2019	Jiangyin E-commerce Public Service Platform	http://jiangyinds.com/product
Anhui	Laian	2017	Laian E-commerce Public Service Center	http://www.laecps.com/list-teseguan-2.html
Fujian	Quanzhou	2018	Anxi E-commerce Public Service Center	http://www.axswfj.com/
Shandong	Linyi	2022	Lanling Electronic Commerce Public Service Center	http://www.lanlingds.com/
Henan	Zhoukou	2019	Shangshui E-commerce Public Service Center	http://shop.shangshui.agdata.cn/wssc.html
Guangdong	Chaozhou	2018	Chaozhou E-commerce Public Service Center	https://www.czecc.com/index.php/commerce/shop.html
Hainan	Hainan	2018	Hainan Rural Revitalization Network	https://shop.hainanfp.com/index
Heilongjiang	Jiamusi	2017	Jiamusi Specialty Website	http://jiamusi.kuaimicheng.com/techan.html
Hunan	Xiangyin	2016	Xiangyin County E-commerce Public Service Center	https://xiangyin.hnbotong.net/goods/all?page=2
Guizhou	Guiyang	2022	Kaiyang County E-commerce Public Service Center	http://www.seonky.cn/?product/
Shaanxi	Yulin	2018	Qingjian County E-commerce Public Service Center	https://www.91jindi.com/index.php?homepage=15667062990&file=sell
Qinghai	Maduo	2021	Maduoxian Commerce Public Service Center	https://www.maduodianshang.com/
Inner Mongolia	Ordos	2020	Wushen Banner E-commerce Public Service Center	https://wsq.we1010.cn/specialty.html
Guangdong	Longmen	2018	Longmen County E-commerce Public Service Center	http://longmen.hunge.vip/goods
Qinghai	Huzhu	2021	Huzhu E-commerce Public Service Center	http://www.huzhuds.com/specialty?tabIndex=1
Guangxi	Shangsi	2017	Shangsi E-commerce Public Service Center	http://www.ssdszx.com/pr.jsp?_pp=0_318_0_-1&pcp=2
Xinjiang	Hetian	2021	Hetianyuese	http://hetian.pandahigo.com/

Notes: The above table lists government-initiated e-commerce public service centers identified through our research, reflecting the broad implementation of China's National Rural E-commerce Comprehensive Demonstration Program. These centers primarily assist small-scale producers in rural areas in accessing and effectively utilizing existing commercial e-commerce platforms. All listed website links were accessible as of June 2025. Additional centers may exist beyond those listed here, considering the ongoing and expanding nature of government initiatives.

B Comparative Institutional Context: Entry Costs and Operational Complexity

The Lancang GEP differs structurally from major commercial e-commerce platforms and social media commerce channels. Two factors are important for smallholder adoption and policy design: (i) financial entry costs and (ii) operational complexity and required skills, comparing each with official rulebooks and program manuals. Throughout, we rely on platform rulebooks and large-agency reports rather than trade blogs to benchmark costs and frictions.[1]

B.1 Financial Entry Barriers

Large platforms usually require refundable deposits, platform fees, and per-transaction service fees. In Tmall Global, the official rulebook specifies a refundable security deposit and an annual technical service fee with two tiers (30,000 or 60,000 RMB). In addition, there are technical service fees per transaction that generally range from 2% to 5%, depending on the category (Tmall Global, 2024). JD Worldwide applies a flat transaction service fee of 0.9% to POP merchants and utilizes a tiered deposit scheme that increases with sales and category (JD Worldwide, 2025a,b). In contrast, Taobao (C2C) requires a refundable consumer protection deposit, the amount of which depends on the category under the Consumer Protection Service Agreement (Taobao, 2024). Beyond formal fees, participating in these platforms typically involves ongoing expenses for paid traffic and promotions. Evidence from the Taobao Village study by the World Bank highlights high advertising and promotion costs, intense competition, and lack of skills as the main challenges faced by E-shop owners (World Bank, 2019).

Short videos and social media platforms like Douyin have low formal access fees but

1. Fee schedules vary by category and over time; we report rulebook ranges and archive all cited URLs with access dates to ensure verifiability.

depend on creator interaction. The official Douyin rules show (i) technical service fees for the platform by category, usually ranging from 1 to 5%, and (ii) affiliate commissions from merchants within its Jingxuan Alliance: 1 to 50% for general plans, with higher caps (up to 80%) under targeted plans (Douyin E-commerce, 2025a,b). In practice, gaining significant visibility often requires paid advertising and creator commissions, making indirect costs substantial even when headline fees are low.

In our setting, by design, the Lancang GEP does not impose deposits, listing fees, or commissions on local farmers (according to government policy and our fieldwork protocols). Public finance and screening replace monetary entry screens, reducing barriers for smallholders and shaping the empirical patterns we study.

B.2 Operational Complexity and Required E-commerce Skills

Operating stores on large commercial platforms such as Tmall, JD, and Taobao requires comprehensive skills in merchandising, customer service, fulfillment, promotion, and data-driven operations. On social media platforms such as Douyin, content creation, live stream hosting, and creator management are also required. Evidence from China, based on large samples, suggests that skill gaps are the primary obstacles. E-commerce retailers cite the lack of skills as one of the top three barriers, along with advertising costs and competition (World Bank, 2019). In low and middle-income countries LMICs, training and incubation are repeatedly identified as necessary complements to access to the digital market (Vidal and Faz, 2020).

Unlike commercial and social media channels, the GEP reduces operational complexity through a government-led model that bundles training, cooperative processing/packaging, and regional branding. In this setup, farmers are relieved of the burden of advertising, packaging design, and storefront competition, allowing them to focus on production while the program handles market-facing tasks. Instead, the local government centrally manages product promotion and brand development, marketing all agricultural products under the rural cooperative brand. In addition, the cooperative system allows farmers to convert their tea leaves into low-cost, market-ready standardized tea cakes, handling processing, packaging, and branding on their behalf. This integrated service framework substantially reduces skill demands for online sales; Farmers do not need to master performance marketing, live streaming, or complex digital operations.

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C Timing of Adopting the GEP

Table C.1 provides a detailed overview of when different areas adopted the government-initiated e-commerce platform (GEP), identified by their respective area codes. The table lists the area codes (J1, J2, J3, J4, M1, M2) along with their respective platform access dates. For example, area J1 accessed the platform in June 2019, while area J2 did so in September 2018. Similarly, Area J3 accessed the platform in October 2020, and Area J4 in November 2019. The table also shows that Areas M1 and M2 accessed the platforms in November 2018 and April 2020, respectively. Overall, the table highlights the staggered pattern of gaining access to the GEP in different areas over time.

Table C.1: Timing of GEP Access in Each Area

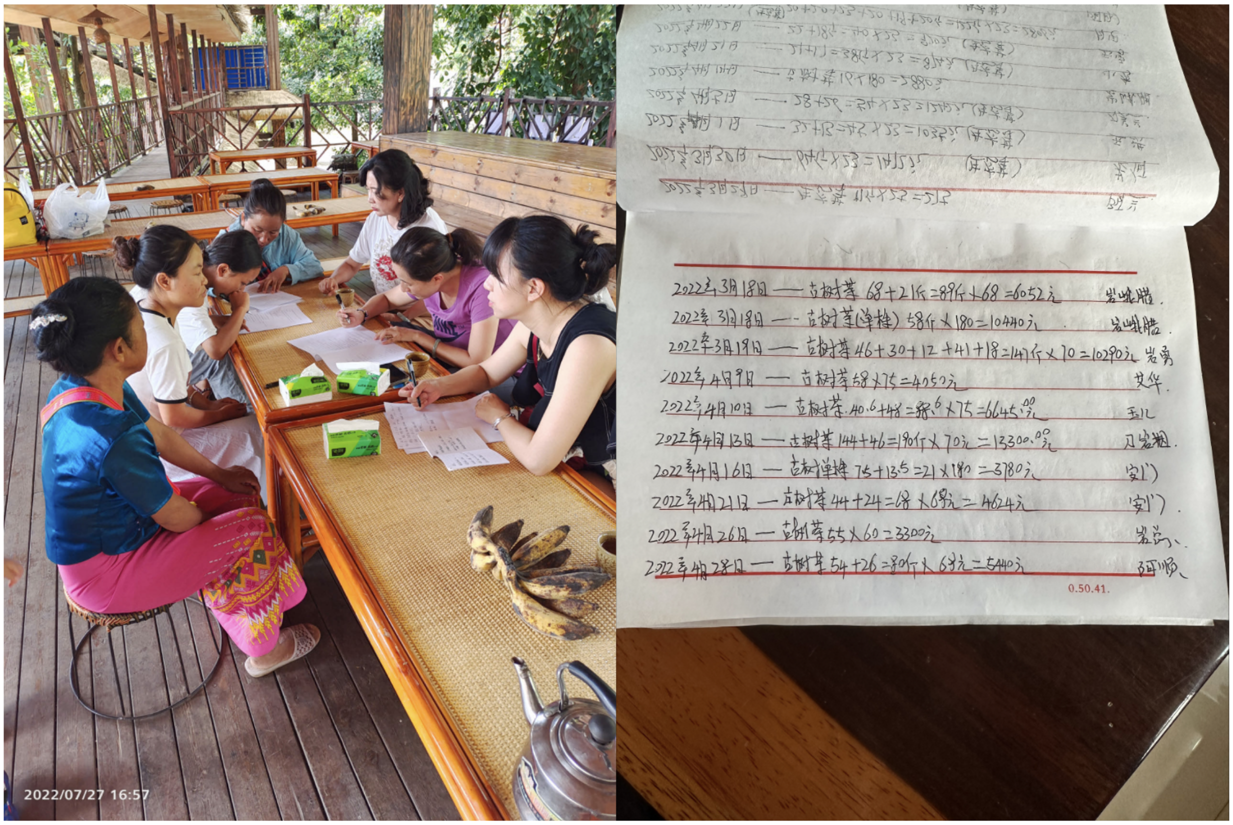
Area Code	**Platform Access Date**
J1	Jun 2019
J2	Sep 2018
J3	Oct 2020
J4	Nov 2019
M1	Nov 2018
M2	Apr 2020

D Data Collection Process

The survey was carried out in two counties, designated as J and M, by a total of six specialized teams. The teams were selected by the local government and led by an area cadre or a local expert with expertise in tea farming. Their objective was to oversee the collection of data within a specified geographic area. The teams were composed of college and university students on vacation, as well as academically qualified local youth. A general manager was appointed to oversee the coordination of the survey and the subsequent consolidation of the data collected for each team.

Data were collected through in-person interviews, with each team member responsible for engaging with multiple households. The sample consisted of 983 households in the six selected areas, each of which received 20 RMB as an incentive to participate in the study. The survey encompassed a wide range of questions, including household characteristics, tea farming methods, marketing channels, and sources of household income. More than 90% of the respondents kept a household notebook to track relevant metrics, such as tea picking, farming output, and sales. Upon completing each household survey, the team leaders subjected the data to rigorous scrutiny to identify inconsistencies and ambiguities, which were then resolved before forwarding the collected information to the general manager for final aggregation and analysis.

Figure D.1 provides a visual overview of the interview and data collection process conducted by the research team. The image shows a group of researchers and team members engaging in an interactive session with local farmers on the left side. Team members are seated around a table, participating in discussions and gathering information at what appears to be a local farmer's home. On the right side, a close-up shows a notebook used by local farmers, featuring handwritten records of various types of tea, sales volumes, and prices. According to the accompanying text, after verifying this information, the researchers input the data into distributed forms. These forms organize the information by different sales channels for various types of tea each year.



Notes: The above images show our team's interactive sessions with local residents. The left photo captures our follow-up group gathering information at a local farmer's home. The right photo displays a notebook used by local farmers to record accounts, detailing the types of tea, sales volumes, and prices. After verification, team members log the data into our distributed forms based on different sales channels for various types of tea each year.

Figure D.1: Survey Engagement: Data Collection among Local Farmers

Before administering the survey, the team managers participated in comprehensive training sessions to ensure the integrity of the data. Following a comprehensive examination of the collected data, it was determined that the farming output and sales data, which represent more than 95% of the regional tea farming output, exhibited a high degree of alignment with the statistics reported in various media outlets. A comparison was made between the data obtained from the survey and publicly accessible news reports. The comparison is based on two core metrics: total tea output and its corresponding market value (that is, the level of agriculture output $\times$ price), covering the period 2016 to 2020. Regarding farming output, the mean yield in our dataset (964 tons) falls well within the range specified by news sources (870-1,480 tons). Similarly, the calculated average commercial value of the tea production output (495,733,250 RMB) is close to the values cited in the media reports (500 million RMB).[2]

2. Sources for regional-level farming output and commercial values are as follows: https://www.chinanews.com.cn/cul/2014/08-26/6529253.shtml (accessed on 27 August 2023); http://www.puernews.com/zthd/pejmsgcysw/03110090482853688837 (accessed on 27 August 2023); https://m.puercn.com/show-8-44415.html (accessed on 27 August 2023).

E Household- and Area-related Statistics

Table E.1 summarizes the household and area-level variables in our data. The results show that plot sizes, as well as local infrastructure, did not change significantly before and after 2018. This suggests that local market conditions remained relatively stable during our sample period, aside from the introduction of the GEP and its associated public services.

Table E.1: Summary Statistics for Household- and Area-level Variables

	Before 2018	**After 2018**
Acres of Tea Trees	17.00	16.87
	(7.76)	(7.77)
Acres of Tea Gardens	34.70	34.56
	(11.34)	(11.31)
Operating Factories	14.12	15.71
	(7.30)	(7.72)
Shipping Companies	3.22	4.07
	(1.26)	(1.28)

Notes: We report the standard deviation in parentheses.

F Robustness Check 1: Unobserved Trends and Environmental Changes

In this section, we extend our baseline specification by adding household and area-level controls as well as county-specific time trends. The results of the estimation are shown in Table F.1. The estimated treatment effects, after including the additional controls, align with the results of the baseline specification. Specifically, the data show that online sales increase by an average of 18.4122% after gaining access to the GEP. In contrast, offline sales decrease by an average of 16.222% after access to the platform. In Column (3), we control for household-level farming output (volume), while in Column (4), we account for both volume and area characteristics, such as the number of factories and shipping companies. These findings are consistent with our previous results, indicating that the increase in online sales can be largely attributed to the GEP rather than changes in production technology or the local market.

Table F.1: Effect of GEP Access on Sales with Additional Controls

Dependent Variable:	Log(sales): $q_{i,j,t}$			
	Time-varying Controls		**County-specific Trends**	
	(1)	(2)	(3)	(4)
Online Sales	-0.522***	-0.513***	-0.522***	-0.513***
	(0.035)	(0.061)	(0.035)	(0.061)
Platform Access	-0.183***	-0.177**	-0.183***	-0.181**
	(0.038)	(0.047)	(0.036)	(0.048)
Platform Access × Online Sales	0.356***	0.346**	0.356***	0.346**
	(0.084)	(0.099)	(0.084)	(0.099)
Zero Output	-5.153***	-5.154***	-5.153***	-5.154***
	(0.087)	(0.087)	(0.087)	(0.087)
Log(Volume)	0.052***	0.052***	0.052***	0.052***
	(0.005)	(0.005)	(0.005)	(0.005)
Number of Operating Factories		0.002		0.013
		(0.004)		(0.008)
Number of Shipping Companies		0.006		-0.005
		(0.014)		(0.020)
Number of Factories × Online Sales		-0.003		-0.003
		(0.004)		(0.004)
Number of Companies × Online Sales		0.010		-0.010
		(0.019)		(0.019)
Observations	29,490	29,490	29,490	29,490
Quality FE	YES	YES	YES	YES
Household FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
County Specific Trend	NO	NO	YES	YES
R^2	0.966	0.966	0.966	0.966

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G Robustness Check 2: Treatment Endogeneity

As shown in Table G.1, the results indicate that the proposed model explains approximately 76% of the observed variation in the adoption of the platform. Next, area-specific, time-varying factors that can be linked to the timing of platform adoption are added, including the total tea production, the number of factories, and the number of shipping companies. No statistically significant coefficients were found for these factors, and their inclusion did not improve the explanatory power of the regression, suggesting that the timing of treatment is not related to area-specific and time-varying factors.

Table G.1: Likelihood of GEP Access

Dependent Variable:	Access to the GEP	
	(1)	(2)
2018	0.333**	0.241
	(0.149)	(0.167)
2019	0.667***	0.571***
	(0.149)	(0.169)
2020	1.000***	0.876***
	(0.149)	(0.177)
Volume of Tea Produced		-0.033
		(0.070)
Number of Factories		-0.005
		(0.007)
Number of Shipping Companies		0.057
		(0.036)
Observations	48	48
R^2	0.763	0.779

Notes: Standard errors are indicated in parentheses. This table reports the estimated coefficients when regressing treatment status (access to the platform) on year-fixed effects and area-level characteristics. Including area-specific characteristics does not increase the explanatory power of the model once we control for year effects. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We also present the results of the placebo tests to better interpret the treatment. In our first placebo test, we randomized the years during which a household or area had access to the platform, while keeping the total number of years of access unchanged. These results are shown in Columns (1) and (2) of Table G.2. In Column (1), we shuffle treatment at the area level. For example, if an area had access to the GEP in 2019 and 2020 (a two-year period), we randomly select two years between 2016 and 2020 and assign a value of one to a new variable called "placebo treatment" for those years. The placebo treatment is applied uniformly to all households in that area. In Column (2), treatment status is reshuffled for each household instead of each area. After creating the placebo treatment, we estimate its effect on offline and online sales. Both columns indicate that the placebo treatment has no statistically significant impact on online or offline sales of households at the 10% significance level. In the second placebo test, we estimate Equation 1 in our manuscript using a subset of households that have never participated in online sales during the entire sample period. Our data indicate that about 9% of the total sample falls into this group. If the impact of the GEP on tea sales across different channels is solely due to the introduction of the platform, these non-online sellers should remain unaffected by the policy change.

Table G.2: Placebo Tests: Effect of Placebo Treatment on Sales

Dependent Variable:	Log(sales): $q_{i,j,t}$		
	Re-shuffled Treatment		**Non-adopters**
	Area Level	Household Level	
	(1)	(2)	(3)
Platform Access	-0.067	-0.002	-0.017
	(0.084)	(0.020)	(0.013)
Platform Access × Online Sales	0.123	0.014	
	(0.162)	(0.029)	
Online Sales	-0.426***	-0.396***	
	(0.064)	(0.021)	
Zero Output	-5.438***	-5.439***	-4.689***
	(0.068)	(0.069)	(0.108)
Observations	29,490	29,490	2,610
Household FE	YES	YES	YES
Quality FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.964	0.965	0.948

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

H Robustness Check 3: Parallel Trends

To further ensure that our estimated effects are causal, we demonstrate that online and offline sales across different areas would have followed similar patterns (parallel trends) in the absence of the GEP. First, we plot the evolution of online and offline sales based on the year they first gained access to the platform (cohorts). As shown in Figure H.1, both online and offline sales exhibit similar trends in the pretreatment periods, with online sales increasing and offline sales decreasing during this time. This indicates that without the GEP, online sales would have increased at roughly similar rates across different areas, and any additional growth in online sales beyond this is attributable to the introduction of the platform.

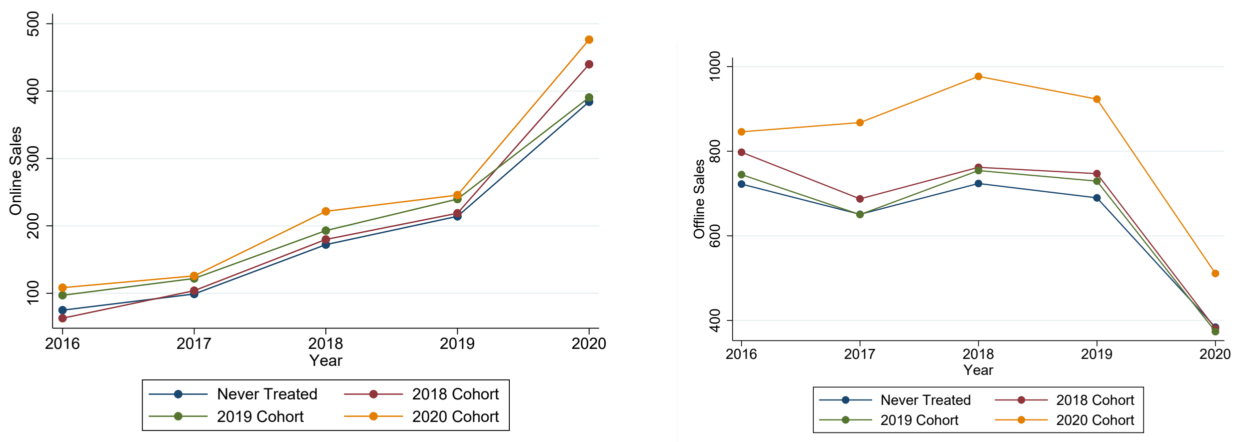


Figure H.1: Offline and Online Sales Trends

Notes: The above figure plots the evolution of online and offline sales for different cohorts.

We further verify this result by estimating the marginal effects of time (trend) on online sales across cohorts and then testing whether these estimated trends differ among cohorts. These estimated trends are shown in Table H.1. Using a Wald test, we fail to reject the null hypothesis that these pre-trends are equal, providing additional evidence that the evolution of online sales is consistent across the different cohorts before they gained access to the GEP.

Table H.1: Estimated Pre-trends by Cohort

Dependent Variable:	Cohort Mean Online Sales: $\bar{q}_{c,online,t}$			
	Never Treated	2018 Cohort	2019 Cohort	2020 Cohort
	(1)	(2)	(3)	(4)
Marginal Effect of t	48.623***	58.433***	47.985***	56.653***
	(15.753)	(15.753)	(15.753)	(15.753)

Notes: Standard errors are indicated in parentheses. The dependent variable is the average online sales in each cohort over time. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

I Robustness Check 4: Bias Correction Related to TWFE Estimators

I.1 Negative Treatment Weights

Our analysis examines the staggered adoption of the platform across different villages. To control for household-specific, year-specific, and quality-specific shocks, we include fixed effects. However, literature such as De Chaisemartin and d'Haultfoeuille (2020) and Jakiela (2021) warns of potential bias in treatment effect estimates when effects vary over time or between units. In this section, following Jakiela (2021), we show that our treatment effect estimates remain unbiased after including household-, quality-, and year-fixed effects.

We base our analysis on the following equation:

$$q_{i,j,t} = \alpha + \gamma D_{i,t} + \delta mode_{i,j,t} + \theta D_{i,t} \times mode_{i,j,t} + \zeta Z_{i,j,t} + \mu_i + \eta_j + \psi_t + \epsilon_{i,j,t}, \tag{I.1}$$

where $\hat{\theta}^{TWFE}$, the OLS estimator for treatment effect θ, can be derived using the Frisch-Waugh-Lovell theorem:

$$\hat{\theta}^{TWFE} = \sum_{ijt} q_{ijt} \left(\frac{\hat{\epsilon}_{i,j,t}}{\sum_{i,j,t} \hat{\epsilon}^2_{i,j,t}} \right), \tag{I.2}$$

with $\hat{\epsilon}_{i,j,t}$ representing the residual from regressing the treatment indicator on the household-, year-, and quality-fixed effects. The treatment effect is therefore a weighted sum of the outcome variable, with the weights being the residualized treatment weights. Jakiela (2021) states that bias occurs when treated units have negative treatment weights and when treatment effects vary.

To detect such biases, we check whether treated units have negative weights and then test for homogeneity of treatment effects. Following Jakiela (2021), we regress our treatment indicator on the fixed effects to obtain the residualized treatment $\hat{\epsilon}_{i,j,t}$. We then construct the treatment weights $\sum_{i,j,t} \hat{\epsilon}^2_{i,j,t}$ for each observation. Figure I.1 displays these weights

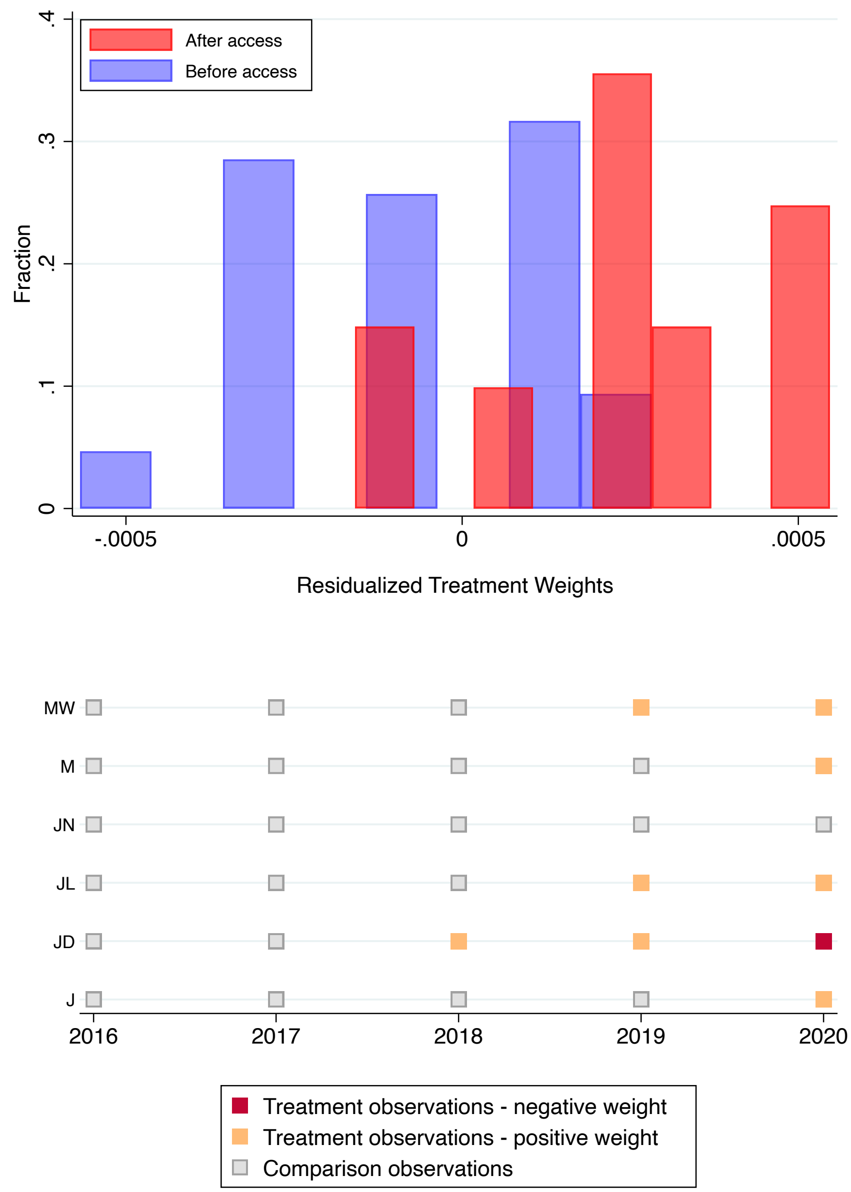


Figure I.1: Weights of Two-Way Fixed Effects.

Table I.1: Effect of GEP access on Sales (Negative Treatment Weights Excluded)

Dependent Variable:	Log(sales): $q_{i,j,t}$		
	(1)	(2)	(3)
Online Sales	-0.474^{***}	-0.474^{***}	-0.482^{***}
	(0.036)	(0.036)	(0.037)
Platform Access	-0.127^{*}	-0.160^{*}	-0.150^{**}
	(0.061)	(0.073)	(0.050)
Platform Access $\times$ Online Sales	0.282^{**}	0.282^{**}	0.288^{**}
	(0.109)	(0.109)	(0.111)
Zero Output	-5.482^{***}	-5.482^{***}	-5.429^{***}
	(0.077)	(0.077)	(0.068)
Constant	5.738^{***}	5.746^{***}	5.715^{***}
	(0.096)	(0.098)	(0.057)
Observations	28,284	28,284	28,284
Quality FE	NO	NO	YES
Household FE	NO	NO	YES
Year FE	NO	YES	YES
R^2	0.955	0.956	0.965

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

for treated and untreated units. Figure I.1 shows these weights for treated and untreated units. The figure indicates that only 15% of the treated units have negative weights. For context, Jakiela (2021) found that about 25% of the treated units had negative weights, yet the treatment effect remained strong after removing these observations. Since our Average Treatment Effect (ATE) estimate is a weighted sum of outcomes, these small negative weights are unlikely to cause bias.

As a further robustness check, we recalculated our model excluding treated units with negative weights. The revised results in Table I.1 confirm a significant substitution effect after GEP access: offline sales decreased by approximately 13.929%, and online sales increased by approximately 14.798%.

I.2 Interaction Weighted Estimator

To further address potential bias in two-way fixed effects estimators, we also used the interaction-weighted (IW) fixed effects estimator, as suggested by Sun and Abraham (2021) and Callaway and Sant'Anna (2021). This estimator is robust to varying treatment effects in models with staggered treatment timing and can be applied even when there is no never-treated group. Following the approach of Sun and Abraham (2021), we divided our sample into distinct cohorts based on the year each household started using the platform. In our study, this creates three cohorts (2018, 2019, and 2020) plus a group that was never treated. We first estimate the effect of the average treatment effect over time in the treated units (CATT) using a two-way fixed effects model that interacts with cohort indicators with a relative period indicator. These relative period indicators show how many periods each cohort has been treated, allowing treatment effects to change over time. For a static model, an alternative estimate of CATT can be used, where cohort indicators interact with a binary treatment indicator.

The following equation is estimated:

$$
\begin{aligned}
q_{i,j,t} = \alpha + \sum_{e \notin C} \sum_{l=-1}^{2} \gamma_{e,l} \left(\mathbb{1}\{E_i = e\} \cdot D_{i,t}^{l} \right) + \delta mode_{i,j,t} + \\
\sum_{e \notin C} \sum_{l=-1}^{2} \theta_{e,l} \left(\mathbb{1}\{E_i = e\} \cdot D_{i,t}^{l} \right) \times mode_{i,j,t} + \\
\zeta \times Z_{i,j,t} + \beta' X_{i,t} + \mu_i + \eta_j + \psi_t + \epsilon_{i,j,t}
\end{aligned}
\tag{I.3}
$$

where $E_i \in \{2018, 2019, 2020, \infty\}$ denotes the year that household i first gained access to the platform (treatment), C is the set of households that were never treated and $D_{i,t}^{l}$ is an indicator for household i being l periods away from treatment in period t.

Subsequently, the weights were calculated based on the sample share of each cohort in each relative period. Ultimately, the IW estimate of the treatment effect is derived by weighting the average of the CATT using the weights obtained in the previous step. The IW estimates are shown in Table I.2. The results of our analysis, which uses the IW two-way fixed effects estimator, suggest that the impact of the GEP on tea sales aligns with our baseline findings. Specifically, the estimated coefficient for platform access is -0.156, while the estimate for the interaction between platform access and online sales is 0.274. These coefficients were converted into effects on online and offline sales, resulting in a 14.444% decrease in offline sales and a 12.524% increase in online sales. Both estimated treatment effects are statistically and economically significant, supporting the hypothesis that farmers shifted their sales from offline to online channels after gaining access to the GEP.

Table I.2: Interaction Weighted TWFE Estimates

Dependent Variable:	Log(sales): $q_{i,j,t}$		
	(1)	(2)	(3)
Online Sales	-0.474^{***}	-0.474^{***}	-0.482^{***}
	(0.043)	(0.043)	(0.045)
Platform Access (γ)			
Cohort 1, $t_0 - 1$	-0.104	-0.056	-0.026
	(0.060)	(0.070)	(0.046)
Cohort 1, t_0	-0.062	-0.107	-0.070
	(0.060)	(0.063)	(0.039)
Cohort 1, $t_0 + 1$	-0.083	-0.044	-0.097^{**}
	(0.060)	(0.024)	(0.036)
Cohort 1, $t_0 + 2$	-0.263^{***}	-0.224^{***}	-0.281^{***}
	(0.053)	(0.019)	(0.032)
Cohort 2, $t_0 - 1$	-0.041	-0.086	-0.034
	(0.109)	(0.118)	(0.052)
Cohort 2, t_0	-0.056	-0.017	-0.054
	(0.112)	(0.106)	(0.053)
Cohort 2, $t_0 + 1$	-0.273^{**}	-0.234^{**}	-0.275^{***}
	(0.092)	(0.085)	(0.034)
Cohort 3, $t_0 - 1$	0.079	0.118^{***}	-0.003
	(0.051)	(0.024)	(0.020)
Cohort 3, t_0	-0.145^{**}	-0.106^{***}	-0.232^{***}
	(0.047)	(0.016)	(0.020)
Interaction Weighted	-0.129^{***}	-0.098^{***}	-0.156^{***}
	(0.053)	(0.028)	(0.028)
Platform Access $\times$ *Online Sales* (θ)			
Cohort 1, $t_0 - 1$	0.007	0.007	0.007
	(0.054)	(0.054)	(0.054)
Cohort 1, t_0	0.046	0.046	0.048
	(0.051)	(0.051)	(0.052)
Cohort 1, $t_0 + 1$	0.153^{**}	0.153^{**}	0.155^{**}
	(0.051)	(0.051)	(0.052)
Cohort 1, $t_0 + 2$	0.515^{***}	0.515^{***}	0.525^{***}
	(0.041)	(0.041)	(0.043)
Cohort 2, $t_0 - 1$	0.036	0.036	0.039
	(0.079)	(0.079)	(0.079)
Cohort 2, t_0	0.130	0.130	0.133
	(0.072)	(0.072)	(0.072)
Cohort 2, $t_0 + 1$	0.463^{***}	0.463^{***}	0.473^{***}
	(0.051)	(0.051)	(0.054)
Cohort 3, $t_0 - 1$	-0.019	-0.019	-0.016
	(0.039)	(0.039)	(0.040)
Cohort 3, t_0	0.425^{***}	0.424^{***}	0.435^{***}
	(0.039)	(0.039)	(0.042)
Interaction Weighted	0.268^{***}	0.268^{***}	0.274^{***}
	(0.042)	(0.042)	(0.044)
Zero Output	-5.479^{***}	-5.480^{***}	-5.424^{***}
	(0.073)	(0.073)	(0.066)
Constant	5.733^{***}	5.722^{***}	5.718^{***}
	(0.097)	(0.083)	(0.061)
Observations	29,490	29,490	29,490
Quality FE	NO	NO	YES
Household FE	NO	NO	YES
Year FE	NO	YES	YES
R^2	0.956	0.956	0.965

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. The areas are divided into cohorts based on the year in which they were treated. For this study, the term "treatment" is defined as having access to the platform for a minimum of four consecutive calendar months within a given year. Area J2 (as of 09.2018) is included in Cohort 1. Areas M1 (as of 11.2018) and J1 (as of 06.2019) are included in Cohort 2. Areas J4 (as of 11.2019) and M2 (as of 04.2020) are included in Cohort 3. Area J3 (as of 10.2020) is not included in the study and serves as a control group. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J Additional Evidence on Product Mix

Figure J.1 summarizes the model-free household counts based on the bundles of quality tea sold by farmers. It also shows, within each bundle, the set of qualities they sell online before (before 2018) and after gaining access to the GEP (2018 onward). The distribution reflects a shift toward listing lower-priced products online once the public e-commerce service becomes available.

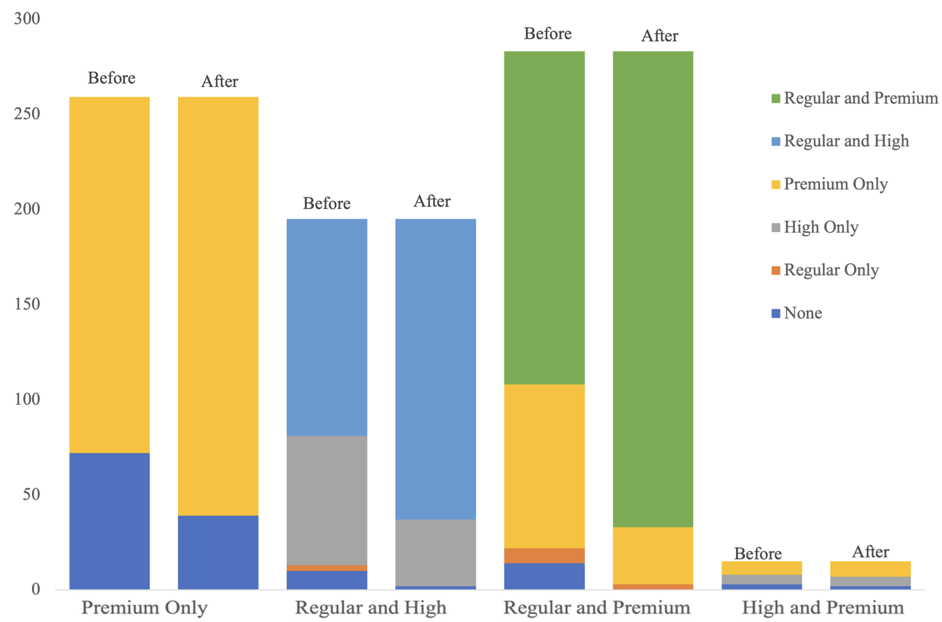


Figure J.1: Qualities Sold Online Before and After GEP access

Notes: Bars display the number of households by four production bundles: (1) premium only, (2) regular and high, (3) regular and premium, and (4) high and premium. Within each bundle, colors indicate which qualities are available for sale online. "Before" refers to pre-2018, and "After" indicates 2018 onward. Online sales include transactions through the GEP, commercial platforms, and social media channels. For households producing both regular and premium tea, the number of households selling regular tea online increases after gaining access, while the number of households selling only premium tea online decreases.

The shift is most pronounced among households that produce regular and premium tea. Before 2018, of the 283 such households, 175 sold both types online, 86 sold only premium-quality tea, 8 sold only regular tea, and 14 sold neither. After 2018, 250 sold both types online, 30 sold only premium-quality tea, and 3 sold only regular tea (none remained offline). The decline in premium-only and offline-only segments, together with the growth of the "both channels" segment, is consistent with the GEP lowering the costs of selling lower-priced regular tea online (e.g., through cooperative packaging and public branding). This compositional shift aligns with our regression results, which show higher online sales for both regular and premium teas.

K Effects Across Different Pretreatment Channel of Sales

To gain further insight into the role of the GEP, we examine its effect on farmers by dividing them based on the markets where they sold their tea before the GEP was introduced. Farmers are initially divided into two groups based on their online sales channels prior to treatment. The first group consists of farmers who only sold tea online through social media. The second group includes farmers who used commercial platforms for tea sales before gaining access to the GEP.

A large portion of farmers in the second group also sell their tea through social media platforms. However, we observe that most farmers who sell on social media do not use formal e-commerce platforms. We believe this is because commercial e-commerce platforms often set entry barriers to filter out high-quality merchants. These barriers effectively prevent farmers in rural areas from selling low-end products online. Therefore, we hypothesize that the barriers to online sales are lower for farmers selling high-quality or premium-quality tea compared to selling regular tea on online platforms.

Table K.1 illustrates the impact of access to the GEP on tea quality, including regular, high-quality, and premium-quality, among farmers who used only social media for sales, compared to those who used commercial platforms before the introduction of the GEP. In Columns (1) and (2), the results indicate that the increase in online sales of regular tea is statistically significant for farmers who previously sold through social media. However, this significance does not apply to farmers who use commercial platforms. In contrast, Columns (3)-(6) reveal that the increase in online sales of high- and premium-quality tea is statistically significant (at the 10% level) for both groups.

Overall, the table shows that the only exception is the subgroup that was already qualified to sell on commercial marketplaces before the program: for these farmers, GEP access has minimal additional impact. They tend to operate on a larger scale, possess the necessary qualifications, and are almost always active on social media; thus, the public storefront does not significantly boost their margins or profits. These findings support our previous findings: the GEP provides a low-cost alternative channel for farmers who previously could not profitably sell lower-end teas on commercial platforms, allowing them to sell their products online.

Table K.1: Heterogeneous Effects of GEP Access on Sales by Pretreatment Online Channels and Quality

Dependent Variable:	Regular Tea Sales		High-quality Tea Sales		Premium-quality Tea Sales	
	Social Media	**Platform**	**Social Media**	**Platform**	**Social Media**	**Platform**
	(1)	(2)	(3)	(4)	(5)	(6)
Platform Access	-0.103***	-0.236**	-0.171***	-0.246**	-0.193**	-0.418
	(0.012)	(0.064)	(0.039)	(0.074)	(0.048)	(0.310)
Platform Access × Online Sales	0.208***	0.314	0.316**	0.435**	0.412***	0.542*
	(0.030)	(0.164)	(0.080)	(0.130)	(0.075)	(0.249)
Online Sales	-0.589***	-0.385**	-0.509***	-0.477**	-0.719***	-0.406**
	(0.037)	(0.093)	(0.085)	(0.167)	(0.123)	(0.108)
Zero Output	-5.868***	-6.254***	-5.067***	-5.343***	-5.073***	-5.418***
	(0.058)	(0.032)	(0.095)	(0.093)	(0.081)	(0.148)
Observations	7,510	610	7,510	610	7,510	610
Household FE	YES	YES	YES	YES	YES	YES
Quality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R^2	0.974	0.982	0.978	0.980	0.974	0.976

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

L Reconciling the Effect of GEP access

This section clarifies why, in our manuscript, the effect of GEP access on online sales reported in Table 2 (0.166) exceeds the corresponding estimate in Table 8 (0.081). Both tables capture the same underlying effect, but they do so under different aggregation and functional-form choices. Once these differences are made explicit, the numerical gap is expected.

L.1 Reconciling the Log Effects

We index households by i, years by t, and product qualities by j. Let $q_{ijt} \geq 0$ denote household i's sales of quality j in year t. We define $\text{Online}_{ijt} \in \{0, 1\}$ as a binary online-channel indicator and $\text{Platform}_{it} \in \{0, 1\}$ as a binary indicator for access to the GEP. We write the total online sales volume as

$$Z_{it} \equiv \sum_j q_{ijt}^{\text{online}} = \sum_j q_{ijt} \cdot \text{Online}_{ijt}.$$

At the quality level (Table 2), we estimate Equation L.1, a "log of parts" specification in which the effect of access to the GEP on online sales is $\beta \equiv b_0 + c_0$. The estimating equation is

$$\log\bigl(q_{ijt} + 1\bigr) = \alpha + b_0 \,\text{Platform}_{it} + c_0 \bigl(\text{Platform}_{it} \times \text{Online}_{ijt}\bigr) + d_0 \,\text{Online}_{ijt} + \text{FEs} + \varepsilon_{ijt}. \quad \text{(L.1)}$$

The marginal effect of access to the platform on online sales in Equation L.1 is $\beta \equiv b_0 + c_0$.

At the household-year aggregate (Table 9), we estimate Equation L.2, a "log of sum" specification where b_1 captures the effect of access to the GEP on $\log(1 + Z_{it})$. The estimating equation is

$$\log\bigl(Z_{it} + 1\bigr) = a_1 + b_1 \,\text{Platform}_{it} + \text{FEs} + u_{it}, \quad \text{(L.2)}$$

so b_1 is the effect of the access to the platform on $\log(1 + Z_{it})$.

Equations L.1 and L.2 are not algebraically equivalent because they apply the concave link $\log(1+\cdot)$ to different objects: $\log(1+\text{part})$ versus $\log\left(1+\sum \text{parts}\right)$. Concavity implies mechanical compression when moving from the former to the latter. To see this, suppose that the platform scales the sales of each quality online by the same factor e^{β} (with $\beta = b_0 + c_0$): $q_{ijt}^{\text{online}} \mapsto e^{\beta} q_{ijt}^{\text{online}}$. Let $Z \equiv Z_{it}$ denote the total volume of online sales before access to the platform. The induced change in the aggregate dependent variable is

$$\Delta(\beta;\ Z) = \log\bigl(1 + e^{\beta} Z\bigr) - \log(1+Z) = \log\Bigl(1 + \bigl(e^{\beta}-1\bigr)\frac{Z}{1+Z}\Bigr). \tag{L.3}$$

Because $Z/(1+Z) \in (0,1)$, we have $\Delta(\beta;\ Z) < \beta$ for every $Z > 0$, with strict inequality unless $Z \to \infty$. Thus, even if the quality-level log effect equals β, the aggregate "log of sum" effect is strictly smaller. For small to moderate β, a first-order expansion of Equation L.3 yields

$$\Delta(\beta;\ Z) \approx \beta \cdot \frac{Z}{1+Z}. \tag{L.4}$$

Taking expectations on the household-year distribution of Z, we have

$$b_1 \;\approx\; \beta \cdot \mathbb{E}\left[\frac{Z}{1+Z}\right]. \tag{L.5}$$

L.2 Quantitative Approximation with Zero Observations

Table 8 in the manuscript includes that 2,266 out of 4,915 household-year aggregates have zero online sales. Under the approximation of Equation L.4, the mapping between the log effect at the quality level β and the aggregate log effect b_1 is $b_1 \approx \beta \cdot \mathbb{E}\bigl[Z/(1+Z)\bigr]$. If, as the data suggest, $\frac{Z}{1+Z}$ is essentially 0 when $Z = 0$ and is close to 1 for most non-zero observations, then

$$\mathbb{E}\left[\frac{Z}{1+Z}\right] \leq (1-p_0)\cdot 1 + p_0 \cdot 0 = 1 - \frac{2266}{4915} = 0.539.$$

Using the new estimates $\beta \approx 0.166$ and $b_1 \approx 0.081$,

$$\frac{b_1}{\beta} = \frac{0.081}{0.166} = 0.488,$$

which is very close to $\mathbb{E}[Z/(1+Z)] \approx 0.5$. Hence, the attenuation from the quality–level estimate to the aggregate estimate is quantitatively explained by the mass of zeros and the concavity $\log(1+\cdot)$ embodied in Equation L.4.

M Additional Mediation Analysis

This section complements Section 7.4 in the manuscript by exploring two mechanism questions. First, we examine whether changes in local logistics—measured by the presence of shipping companies—mediate the program's effect on online sales. If local logistics are also a key pathway, including shipping company counts should reduce the GEP coefficient and improve model fit, even before adding online channel breadth or online product variety. Second, we verify whether the mediation pattern is symmetric when the outcome shifts from total online sales to total offline sales: If the local GEP shifts transactions across channels, the same mediators should explain the offline declines.

M.1 Mediating Role of Shipping Companies on Online Sales

Table M.1 reports household–year regressions with the log of total online sales as the dependent variable. All columns include household- and year-fixed effects, as well as an indicator for zero output; standard errors are clustered at the area level. Column (1) presents the baseline specification. Column (2) adds the count of shipping companies to capture contemporaneous changes in local logistics capacity. Columns (3) and (4) separately add the two hypothesized mediators—number of online channels and number of online product quality varieties—while column (5) includes both mediators jointly alongside shipping companies.

The evidence does not support shipping companies as a mediator. Adding shipping companies in column (2) leaves the GEP coefficient essentially unchanged, and the shipping company coefficient is small and statistically insignificant. The model fit also remains the same, indicating that logistics alone does not add explanatory power. In contrast, when we add the number of online channels in Column (3) or online varieties in Column (4), each mediator enters strongly and positively. The model R-squared coefficient increases significantly (to 0.884 and 0.926), and the GEP coefficient decreases toward zero (0.029 and 0.037, both statistically indistinguishable from zero). In Column (5), both mediators remain

Table M.1: Mediating Role of Shipping Companies

Dependent variable:	Total Online Sales				
	(1)	(2)	(3)	(4)	(5)
Platform Access	0.081*	0.095*	0.029	0.037	0.017
	(0.035)	(0.046)	(0.062)	(0.030)	(0.039)
Shipping Companies		0.084	-0.019	0.020	-0.018
		(0.078)	(0.066)	(0.013)	(0.031)
Number of Channels			2.358***		1.218***
			(0.085)		(0.055)
Number of Varieties				2.578***	1.971***
				(0.062)	(0.035)
Zero Output	-2.387***	-2.388***	-0.952***	-1.031***	-0.609***
	(0.191)	(0.188)	(0.106)	(0.102)	(0.065)
Observations	4,915	4,915	4,915	4,915	4,915
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.777	0.777	0.884	0.926	0.946

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

highly significant, while the shipping-company coefficient remains small and insignificant, and the GEP coefficient further decreases to 0.017. Overall, these patterns suggest that the expansion of online channels and the increase in online varieties, rather than changes in the presence of local shipping companies, are the primary pathways through which the program boosts online sales.

M.2 Mediating Role of Online Channels and Product Variety on Offline Sales

Table M.2 repeats the mediation design with the log of total offline sales as the dependent variable. Column (1) reports the baseline; Column (2) adds shipping companies; Columns (3) and (4) separately add the number of online channels and the number of online varieties; Column (5) includes both mediators jointly.

The results mirror the online analysis in two ways. First, shipping companies do not influence the effect: including them in Column (2) leaves the GEP coefficient basically

Table M.2: Mediating Role of Online Channels and Product Variety on Offline Sales

Dependent variable:	Total Offline Sales				
	(1)	(2)	(3)	(4)	(5)
Platform Access	-0.061*	-0.062*	-0.051	-0.059*	-0.052
	(0.026)	(0.029)	(0.030)	(0.029)	(0.030)
Shipping Companies		-0.006	0.010	-0.003	0.010
		(0.036)	(0.037)	(0.033)	(0.038)
Number of Channels			-0.364***		-0.409***
			(0.064)		(0.079)
Number of Varieties				-0.126***	0.078*
				(0.027)	(0.037)
Zero Output	-4.895***	-4.895***	-5.117***	-4.962***	-5.104***
	(0.115)	(0.115)	(0.111)	(0.120)	(0.116)
Observations	4,915	4,915	4,915	4,915	4,915
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.833	0.833	0.837	0.833	0.837

Notes: Standard errors are indicated in parentheses. Error terms are clustered at the area level. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

unchanged, and the shipping coefficient is small and not significant, with no improvement in model fit. Second, online mediators predict offline declines. When added separately, more online channels and greater online variety are each linked to lower offline sales, and adding either reduces the size and significance of the GEP coefficient. In the combined model, channels stay negative and highly significant, while the variety coefficient becomes small and positive. Including both mediators renders the GEP coefficient statistically indistinguishable from zero, indicating that the offline drop is primarily explained by the combined growth in online channels and product variety.

N Follow-up Survey and Results

We conducted an additional survey study through WeChat groups created by the local government in 2025. We invited all registered tea producers in the two counties to participate voluntarily through WeChat. Each completed questionnaire received an RMB 10 cash incentive. Respondents should complete the questionnaire independently, according to their own circumstances. We collected 228 online questionnaires. After removing a small number of invalid cases[3], we retained 202 valid surveys for analysis.

We acknowledge that the survey data may be influenced by non-random selection and recall biases. The survey was conducted approximately seven years after the first launch of the GEP, while our main panel spans the years 2016–2020. In addition, participation was likely favored by producers who were more active in online sales. Therefore, we do not rely on the survey for causal analysis. Instead, we use it as supplementary descriptive evidence to help interpret and contextualize the main results, such as illustrating pre- versus post-adoption patterns, the relative importance of specific online channels, and the makeup of product grades sold online.

To assist respondents with Question 1 (location), the instrument included a map highlighting the relevant administrative areas and their codes, making it easier for farmers to identify their area when answering. The original questionnaire was administered in Chinese; an English translation (used for analysis) is provided in Section N.2.

N.1 Survey Estimation Results

Table N.1 summarizes the differences before and after from the household survey ($N = 202$). These patterns align with our main findings in Section 7. Diff values in Column (3) are estimated as the coefficient on the post-period indicator in a two-period household fixed-

3. We excluded questionnaires with inconsistent answers between the pre- and post-sections or where more than one-third of the items were missing

effects model, which in this context equals the average within-household change from before to after. Standard errors are clustered at the area level to account for heteroskedasticity and within-area correlation.

Panel A shows a significant shift toward online sales: the shares reporting *Never* and *Occasionally* decrease by 35.6% and 49.5% respectively, while *Often* increases by 77.7%. and *Almost all* goes up by 7.4%. Consistent with this reallocation, the likelihood of having no online sales drops from 39.1% to 3.5% (a 35.6% decrease; SE = 0.034). All effects are statistically significant at the 1% level. GEP access also significantly increased the range of tea varieties sold online. The largest growth was observed for regular tea (58.9%, SE = 0.035), followed by premium-quality tea (47.6%, SE = 0.035) and high-quality tea (36.1%, SE = 0.034) (Panel B), indicating that the main varieties are most strongly adopted when farmers use online platforms. Adoption of local GEP starts almost fully (96.0%, SE = 0.014), and farmers also multi-home on private channels - especially WeChat Business / Groups (40.1%) and short video / livestream platforms (51. 0%), along with market participation in Taobao/Mall (53.5%) and Pinduoduo (45.0%).[4]

Table N.2 summarizes the impacts of the GEP on profit (Q12) and the potential mechanisms (Q13) of our household survey. We acknowledge that the survey likely overrepresents more online-active farmers and may therefore be subject to selection bias. Our goal here is to highlight the mechanisms among adopters: beyond attracting additional customers, complementary public services bundled with GEP access, such as processing, packaging, training, and public branding, play a key role in facilitating the shift online. Among the 195 valid Q12 responses, 74.9% report that profits increased, 19.5% report that profits increased to some extent, and 5.6% report no obvious change; no respondent reports a decrease or declines to answer. For respondents who report profit gains, the most frequently cited mechanisms are expansion of customer reach through the commission-free marketplace, the cooperative/regional public brand, platform training that improved e-commerce skills, and standardized

4. The high GEP usage rate reflects the program's 7-8 year duration; any farmer who completed at least one transaction through the GEP during this period is counted as a user.

Table N.1: Changes in Online Sales Frequency, Product Mix, and Channels

	Before mean	After mean	Diff
	(1)	(2)	(2)
Panel A. Online Sales Frequency			
Never (Yes=1)	0.391	0.035	-0.356***
			(0.034)
Occasionally (Yes=1)	0.515	0.020	-0.495***
			(0.037)
Often (Yes=1)	0.094	0.871	0.777***
			(0.038)
Almost all (Yes=1)	0.000	0.074	0.074***
			(0.019)
Panel B. Product Grades Sold Online			
Regular tea (Yes=1)	0.376	0.965	0.589***
			(0.035)
High-quality tea (Yes=1)	0.604	0.965	0.361***
			(0.034)
Premium-quality tea (Yes=1)	0.376	0.851	0.475***
			(0.035)
Panel C. Online Channels			
No online sales (Yes=1)	0.391	0.035	-0.356***
			(0.034)
WeChat Business/Groups (Yes=1)	0.564	0.965	0.401***
			(0.035)
Short-video / Live-stream (Yes=1)	0.302	0.812	0.510***
			(0.035)
Taobao/Tmall (Yes=1)	0.000	0.535	0.535***
			(0.035)
Pinduoduo (Yes=1)	0.000	0.450	0.450***
			(0.035)
Gov. E-commerce Platform (Yes=1)	0.000	0.960	0.960***
			(0.014)
Observations	202	202	404

Notes: Standard errors are in parentheses. Errors are clustered at the area level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table N.2: How the GEP Affects Profits: Q12 Distribution and Q13 Reasons

Item	Count	Share	95% CI
Panel A. Q12 distribution ($N = 195$)			
(a) Platform increased profit	146	0.749	
(b) Profit increased to some extent	38	0.195	
(c) No obvious change	11	0.560	
(d) Profit decreased	0	0.000	
(e) I do not want to tell	0	0.000	
Panel B. Q13 reasons among $Q12 \in \{a, b\}$ ($N = 184$)			
(a) Commission-free marketplace expands reach	181	0.984	[0.949, 0.996]
(b) Platform training improved e-commerce skills	177	0.962	[0.920, 0.983]
(c) Cooperative/regional public brand raised awareness	179	0.973	[0.934, 0.990]
(d) Standardized processing & compressed packaging cut costs	175	0.951	[0.906, 0.976]
(e) Better prices on the GEP than offline	90	0.489	[0.415, 0.564]

Notes: In total, we received 202 valid responses; 195 households reported adopting online sales only after the GEP was introduced. Shares are fractions of the panel-specific denominators. Confidence intervals are 95% binomial intervals computed with `prop.test` in R (continuity correction).

processing and compressed packaging that reduced costs; roughly half also cite better prices on the GEP.

N.2 Survey Instrument (English Translation)

Survey: Impact of a Government-initiated E-commerce Platform on Tea Farmers (for research use)

Q1. Which area do you live in? [Single choice]

- (a) County J – Area 1
- (b) County J – Area 2
- (c) County J – Area 3
- (d) County J – Area 4

- (e) County M – Area 5
- (f) County M – Area 6

Q2. How many years have you been engaged in tea cultivation? [Single choice]

- (a) Less than 5 years
- (b) 5–10 years
- (c) 11–20 years
- (d) More than 20 years

Q3. What is the size of your tea plantation?[5] [Single choice]

- (a) Less than 5 mu
- (b) 5–10 mu
- (c) 11–20 mu
- (d) More than 20 mu

Q4. What is your average annual sales volume of tea? [Single choice]

- (a) 0–405 kilograms (low output)
- (b) 406–870 kilograms (medium output)
- (c) 871 kilograms or above (high output)

Q5. Before the government e-commerce platform was introduced, how often did you sell tea online? [Single choice]

- (a) Never (no online sales at all)
- (b) Occasionally (small amount of online sales per year)
- (c) Often (continuous/regular online sales)
- (d) Almost all sales are online

5. Units: 1 mu $\approx$ 0.067 hectares.

Q6. After the government e-commerce platform was introduced, how often do you currently (within these three years) sell tea online? [Single choice]

- (a) Never
- (b) Occasionally
- (c) Often
- (d) Almost all sales are online

Q7. Before the government e-commerce platform was introduced, which grades of tea did you sell online? [Multiple choice]

- (a) Regular tea
- (b) High-quality tea
- (c) Premium-quality tea
- (d) No online sales at that time

Q8. After the government e-commerce platform was introduced, which grades of tea do you currently sell online? [Multiple choice]

- (a) Regular tea
- (b) High-quality tea
- (c) Premium-quality tea
- (d) No online sales at present

Q9. If you sell on the government e-commerce platform, which grades of tea do you sell there online? [Multiple choice]

- (a) Regular tea
- (b) High-quality tea
- (c) Premium-quality tea

- (d) No online sales at present

Q10. Before the government e-commerce platform was introduced, which online channels did you mainly use to sell tea? [Multiple choice]

- (a) No online sales
- (b) WeChat Business or WeChat groups
- (c) Short-video / live-streaming platforms (e.g., Douyin/Kuaishou)
- (d) Traditional e-commerce platforms (e.g., Taobao/Tmall)
- (e) Group-buying e-commerce platforms (e.g., Pinduoduo)
- (f) Other online channels

Q11. After the government e-commerce platform was introduced, which online channels do you currently (within these three years) use to sell tea? [Multiple choice]

- (a) No online sales
- (b) WeChat Business or WeChat groups
- (c) Short-video / live-streaming platforms (e.g., Douyin/Kuaishou)
- (d) Comprehensive e-commerce platforms (e.g., Taobao/Tmall)
- (e) Group-buying e-commerce platforms (e.g., Pinduoduo)
- (f) Government e-commerce platform
- (g) Other channels

Q12. If you are currently (within these three years) selling online, do you think the government e-commerce platform has helped increase the profit from your tea sales? [Single choice]

- (a) Yes, profit increased significantly
- (b) Yes, profit increased to some extent

- (c) No, no obvious change
- (d) No, profit decreased
- (e) I do not want to tell

Q13. If you believe the platform helped increase profit, what are the main reasons? [Multiple choice]

- (a) The platform provides a commission-free online marketplace that expands my sales reach
- (b) Training organized by the platform improved my e-commerce skills
- (c) Using a cooperative or regional public brand improved product awareness
- (d) Using cooperative services for standardized processing and compressed packaging reduced my sales costs
- (e) I can obtain better prices on the government platform than offline