Digital Revitalization or Useless Effort: The Impact of a Government-initiated E-commerce Platform on Local Specialty Sales*

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Abstract

This empirical study examines the impact of a Government-initiated E-commerce Platform (GEP) on local specialty sales, focusing on China's Pu'er tea market. Two-way fixed effects regressions were employed on data from 983 farmers, representing over more than 95% of local tea farming output over a five-year period. The results indicate that the launch of the GEP resulted in a 15.55% decrease in offline sales and a 16.65% increase in online sales. Further evidence suggests that the increase in online sales was primarily due to an expansion in product assortment, rather than an increase in the number of online sellers.

Keywords: *Government-initiated E-commerce Platform (GEP), Tea sales, Online channels*

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1 Introduction

The distinct advantages of E-commerce over traditional sales channels have resulted in an unparalleled increase in the adoption of this mode of trade across a diverse range of geographical locations. In particular, it eliminates the fixed costs inherent to entering new markets while also removing geographic limitations on trade. As indicated in a recent report (Intelligence 2024), E-commerce sales are projected to exceed 6 trillion USD in 2024, with digital retail accounting for 20.1% of total sales. As E-commerce platforms gain in popularity and usage, policymakers in developing economies are increasingly recognizing the transformative potential of E-commerce as a catalyst for agricultural productivity and rural economic development. For instance, in Indonesia, government agencies have facilitated the establishment of platforms such as RegoPantes by granting them access to local farmer databases, thereby reducing the time and effort required for farmers to become registered sellers on the site. These agencies have implemented educational initiatives and training modules with the objective of equipping farmers with the competencies necessary to engage in E-commerce transactions (Joiner and Okeleke 2019). In India, local governments have been promoting their own Open Network for Digital Commerce (ONDC) platform on a national scale since 2022. The platform offers a range of products, including groceries, food, and beverages, with the objective of competing with Amazon (Mandavia 2022). Similarly, E-commerce policy in China has been a subject of scrutiny in recent decades, shaped by guidelines issued by the central government. Notwithstanding governmental initiatives to facilitate the transition to E-commerce, farmers encounter obstacles such as elevated platform fees, information asymmetry, and entry barriers (Tadelis 2016). Despite their willingness to do so, it is frequently the case that agricultural products sold on conventional E-commerce platforms are sourced from a limited number of large retailers rather than farmers. In response to these challenges, regional authorities are seeking to provide incentives for farmers to shift their sales online. Indeed, an increasing number of local governments have recently established their own E-commerce platforms with the aim of facilitating this transition (Yue 2017; Chen et al. 2023).

Government-initiated E-commerce Platforms (GEPs) have been established and implemented in various locations.[1] Despite their growing presence, there is a notable gap in research on their effects on farmers' choice of sales channels and the resulting market dynamics. This paucity of studies can be attributed to two primary factors: the difficulty in obtaining observable and plausibly exogenous policy shocks for causal analysis, and the intensive nature of collecting detailed tea farming output and sales data from rural farmers. Most existing research relies on aggregated data, such as market-level information, which limits the ability to analyze individual-level impacts of policy. An exception is the study of Couture et al. (2021), which used micro-level data to analyze the impact of a national E-commerce expansion through a randomized controlled trial (RCT), revealing substantial benefits for rural farmers, such as reduced living costs. However, this study primarily focused on the impact of commercial E-commerce platforms entering rural areas, with most farmers using these platforms for purchasing rather than selling. The existing literature (e.g., Katz and Shapiro 1994; Shapiro and Varian 1999) generally predicts a "winner-take-all" (WTA) outcome. However, the role and effectiveness of GEPs in the market, distinct from traditional E-commerce leaders such as Amazon, eBay, Alibaba, and JD.com, remain unclear. This study aims to address these gaps in the literature.

To achieve this goal, our paper employs a granular micro-level dataset to conduct the inaugural study on the impact of launching a GEP on the sales of local specialty products in rural areas, with the aim of gaining insight into the underlying economic mechanisms. The present study is focused on Pu'er City in Yunnan Province, China. As the primary center for Pu'er tea farming in China, the local farmers in this city are responsible for approximately 90% of the total Pu'er tea farming output. Historically, local farmers have sold their tea in bulk to tourists or nearby government-established tea processing factories. In response to

1. In Web Appendix A.1, we provide a table listing a set of GEPs established by local governments across China from 2017 to 2023.

the central government's initiative to advance E-commerce, the local government introduced a digital platform in 2018, operated by the government, which enabled tea farmers to sell their tea directly. Upon receipt of orders via the digital platform, the government dispatches them to the farmers, who then process the tea leaves into cakes at a cost price of RMB 5 per kilogram through local cooperatives established by the government. The tea cakes are uniformly labeled and shipped to buyers.

One of the major empirical challenges is the online-offline problem (Johnson et al. 2017). Even though the platform began rolling out to local tea farmers in 2018, the majority of tea leaf sales continue to occur through offline channels. In order to evaluate the impact of the platform, it is essential to observe the volume of tea sales through both online and offline channels for each year. Our research involved a two-year survey implementation and data collection process conducted in six regions spanning two major Pu'er City tea-producing zones. The aforementioned regions adopted the platform offered by the local government in a successive manner between 2018 and 2020. The survey was conducted by six teams organized by the local government, each led by a village cadre or a local with expertise in tea farming. Moreover, the teams included local college and university students on vacation, as well as young, educated residents of the area. The general manager was responsible for ensuring coordination of the survey work and data cleaning. The data set, which encompasses more than 95% of local tea farmers, is highly representative. It includes data on tea farming, such as the acreage of trees and the annual output of different quality tea leaves. Most importantly, it also includes data on quantities sold in each sales channel for each household in each year during the sample period. This data presents a unique opportunity to study the causal impact of the introduction of the GEP on tea sales across various channels.

To assess the causal effects of GEP on online sales, two-way fixed effects (TWFE) regressions are employed. To control for unobservable household-level factors and time trends, our econometric model includes both household- and year-fixed effects. To address potential bias from village-specific variables that may change over time, standard errors are clustered at the village level. Furthermore, our model permits variation in the number of nearby tea processing factories, thereby enabling the capture of dynamic environmental changes. The analysis reveals a significant substitution effect. The average decrease in offline tea sales at the household level is 15.55%, while the average increase in online sales is 16.65%. In light of the potential biases associated with TWFE regressions, as evidenced in recent literature (De Chaisemartin and d'Haultfoeuille 2020; Jakiela 2021; Roth et al. 2023), we conduct diagnostic checks to guarantee that our findings accurately reflect the actual impact of the government platform launch on tea sales. To further address the potential issue of staggered introduction bias, we employ the interaction-weighted estimator developed by Sun and Abraham (2021) to avoid biases that may arise when previously treated observations are implicitly used as controls for newly treated observations. Furthermore, to substantiate the reliability of our empirical findings, we implement a series of tests to test the exogeneity and random assignment of the policy treatment and to guarantee that our estimation of the causal effect of the policy on tea producers' sales decisions is accurate. Two sets of spurious tests are employed. In the initial test, the year indices were randomized at the area and household levels in a placebo test, with the total number of treated years held constant. In the second test, we analyze households that engaged exclusively in offline tea sales throughout the study period. A significant effect within this subset of non-adopters would suggest the presence of latent variables influencing sales decisions. The results from both sets of tests confirm that the observed changes in channel selection are due to the introduction of GEPs in these areas.

To investigate the underlying mechanisms responsible for the substitution effect, we initially categorize farmers based on key metrics such as annual tea farming outputs and their farming area. The results indicate that the introduction of the GEP did not result in an overall increase in sales volume. However, the substitution effect remained statistically significant across different subsamples. This indicates that a pervasive substitution effect is occurring among tea farmers at varying tea farming output levels. It is noteworthy that when farmers are categorized based on their pre-GEP restrictions on online sales, a more pronounced substitution effect is observed among those who were previously more restricted in online tea sales. This finding underscores the role of the GEP as a cost-effective alternative to traditional online sales channels (e.g., JD.com, Taobao, and social media), which often impose barriers to entry to vet high-quality producers (Hałaburda and Yehezkel 2013; Rong et al. 2024). In contrast, local governments, which are more closely acquainted with local tea farmers and their product quality, are not compelled to impose entry costs or high costs to screen for high-quality merchants. Thus, the GEP may serve as a distinctive sales channel for high-quality yet affordable local specialties that may not have been accessible online prior to its introduction. To validate these findings, we examine the impact of the GEP on online sales through both the extensive margin, which is the farmers' decision to sell tea online, and the intensive margin, where farmers decide on what and how much to sell online. The results demonstrate that, while the GEP did not result in an increase in the number of online sellers, it did lead to a significant expansion in the quantity and variety of tea sold online. Those engaged in the sale of premium quality tea online have found it profitable to diversify their product range to include low-end items, thereby contributing to the expansion of the specialty tea market.

This study makes three contributions to the existing literature. First, we present a highly granular, data-driven analysis of the impact of GEPs on agricultural producers' channel choices. This diverges from existing studies, which frequently use aggregated datasets and prioritize consumer-centric outcomes. Secondly, we provide insights into the economic mechanisms driving the shift from offline to online sales, demonstrating that the primary catalyst is the intensive margin. The platform has provided farmers, particularly those in areas with nascent online activity, with an alternative and economically efficient distribution channel that favors a low-cost, high-volume strategy. Third, our results demonstrate the influence of the platform in diversifying the online product variety.

2 Relevant Literature

The objective of our study is to make a significant contribution to the existing literature by examining the following aspects that have been underexplored in previous research: the implications of the introduction of a GEP and its impact on supply-side market dynamics. Our study is situated within the specific context of China's Pu'er tea industry and aims to determine how the introduction of a GEP affects the sales decisions of local tea farmers. To this end, this literature review section provides a brief overview of existing studies to contextualize our contribution to this rapidly growing area of research.

2.1 Online Platform Implementation

Several studies have examined the impact of the introduction of new platforms in established markets. For example, Zervas et al. (2017) conducted an empirical analysis to assess the impact of Airbnb on hotel revenues in Texas. The results demonstrated a detrimental effect on hotel revenues in areas where Airbnb is operational. In a similar study, Berger et al. (2018) examined the impact of the entry of ride-sharing platforms like Uber on the income of traditional taxi drivers. The authors observed a 10% reduction in average earnings and a 9-11% decline in hourly wages for incumbent taxi drivers in comparison to their counterparts in control markets. In a more recent study, Farronato et al. (2023) provided interesting perspectives from a different angle, examining the role of network effects and platform differentiation in the context of a merger between two of the largest pet-sitting service platforms. The findings revealed that while users of the acquiring platform benefit from the merger due to network effects, users of the acquired platform are worse off because their preferred options are eliminated. In addition to these empirical studies, an important question in both the theoretical and empirical literature on platforms is whether there should be a single or multiple platforms. The existence of network effects on platforms may lead to the assumption that a single, large platform is the optimal outcome. This hypothesis has been proposed by Katz and Shapiro (1994) and Shapiro and Varian (1999). Cennamo and Santalo (2013) demonstrated that while the construction of a substantial user network is crucial in platform markets, the implementation of a winner-takes-all (WTA) rule by all platforms can impede platform performance. Consequently, platforms may also succeed by differentiating themselves from their larger competitors and carving out a niche through strategic positioning.

Expanding on these foundational studies, our research contributes to the growing literature examining the effects of online platform integration on pre-existing firms in mature markets. Using a unique and granular household-level dataset, we focus on the experience of tea farmers in China. Prior to the introduction of the government platform, these farmers predominantly sold their tea leaves through local cooperatives, with online platforms accounting for only a marginal share of their sales. In contrast to the existing literature, which primarily focuses on the impact of commercial platforms on regional markets and consumers, our unique dataset allows us to identify, for the first time, the impact of GEPs on rural agricultural producers. More specifically, the impact on their choice of what type of products to produce and sell through various online and offline channels. Our research provides a credible and robust estimate of the policy effect, thereby improving our understanding of how entry into online platforms could affect farmers' decisions. Given the increasing prevalence of E-commerce platforms worldwide, our findings also shed preliminary light on the instrumental role that GEPs could potentially play in the future, particularly in facilitating digital transformation for local producers.

2.2 Impact of E-commerce Platforms on Transaction Volumes

Our study also contributes to the existing literature on the impact of E-commerce platforms on transaction volumes. The majority of studies in this domain concentrate on the impact of alterations to platform policies or external shocks on transaction volumes within the platform. A substantial body of literature has been devoted to examining the implications of information asymmetry in E-commerce platforms. For example, early research by Jin and Kato (2006) demonstrated the significance of rating systems in E-commerce platforms, as they facilitate the identification of reputable sellers who are less likely to distribute counterfeit products. Subsequent studies by Hui et al. (2016) and Saeedi (2019) provided an analysis of the reputation system on eBay. As demonstrated by Hui et al. (2016), the implementation of buyer protection measures has the potential to enhance overall welfare, with an estimated increase of 2.9%. This is largely attributed to the enhancement of seller quality and the mitigation of adverse selection, which is achieved by accelerating the exit rate of low-quality sellers. Saeedi (2019) proposed that the removal of the reputation mechanism would result in an increase in the market share of low-quality sellers and a corresponding decline in prices. In more recent studies, Brynjolfsson et al. (2019) demonstrated that the introduction of machine translation has resulted in a reduction in language barriers, leading to a 10.9% increase in export volumes. Similarly, Chen and Tsai (2019) employed data from Amazon to demonstrate that when E-commerce platforms serve dual roles—as both platform owners and retailers—there is an incentive to misuse the power of algorithmic recommendations. Specifically, the researchers discovered that when Amazon is out of stock, identical products offered by third-party sellers are eight percentage points less likely to receive a recommendation. As indicated by Brynjolfsson et al. (2003), major online booksellers such as Amazon have the potential to enhance consumer surplus by offering consumers access to a more expansive product range. These large online retailers enhance consumer surplus by increasing product awareness and reducing transaction costs for products that are not stocked by brick-and-mortar retailers. In a study of the impact of the gig economy on product quality, Shin et al. (2023) employed a difference-in-difference methodology to investigate the effect of ride-sharing platforms on the availability and quality of waitstaff for local restaurants. Their findings indicate that the entry of these platforms leads to a reduction in both the availability and quality of waitstaff, which in turn results in a decline in customer satisfaction and the provision of lower-quality service.

Our study is distinguished by its investigation of the impact of the introduction of a novel E-commerce platform on sales volumes. This particular area has not been subjected to sufficient scrutiny in previous research. The majority of studies on platforms are constrained by data availability and often exclusively focus on online sales within a single platform, thereby neglecting the multi-channel reality of product sales that span different online platforms and offline channels. This potential for misinterpretation of empirical findings represents a significant limitation of prior research. Our approach, which relies on the use of supplier-side survey data, diverges from studies that rely on platform-scraped data, thereby providing a more comprehensive understanding of the influence of the entry of a GEP. In comparison to the existing literature, our study focuses on elucidating how a GEP enables farmers to sell their products online directly and how these platforms alter the balance between online and offline sales.

2.3 Market Dynamics in Competitive Landscapes

Additionally, our study contributes to the existing literature on market dynamics and competition. A substantial body of literature suggests that the introduction of a new competitor into an established market can lead to market expansion, particularly when the new entrant introduces innovative products or services. For example, the study by Cao et al. (2021) examined the impact of a new bike-sharing company's market entry on the volumes and revenues of incumbent firms in China. The researchers observed a 40.8% increase in trip volume and a marginal revenue increment of 0.041 RMB per ride for the incumbent firm. Although the incumbent firm experienced a certain degree of customer attrition, this was offset by an influx of new users. Reshef (2023) employed a quasi-experimental design to assess the ripple effects of new entries on incumbent restaurants listed on Yelp. The results demonstrate that markets exhibiting an increase in the number of restaurants experienced a 36% surge in consumer engagement and a 60% increase in platform revenues, relative to stagnant markets. It is noteworthy that this expansion proved advantageous for high-quality incumbents, whereas low-quality ones experienced a decline in revenue. Another example of this phenomenon is provided by Raj (2022), who evaluated how the release of a new album impacts the streaming demand for other artists on Spotify. The study indicates a 0.7% increase in unique listeners and a 0.2% rise in platform popularity subsequent to the release, thereby confirming the expansion tendencies of the market over the cannibalization of existing markets.

Although a substantial number of articles have examined demand-side market dynamics, there has been a paucity of research investigating changes in supply-side market structures and the supply chain. This is largely due to the constraints imposed by limited data availability. Our findings challenge the conventional view of market expansion through the adoption of the E-commerce platform. In contrast to previous research, which primarily focused on the increase in platform-based sales following the implementation of E-commerce promotion policies, our study comprehensively examines the joint effects of E-commerce promotion policies on tea farming output, online sales, and offline sales. Our findings indicate that the overall volume of tea sales does not exhibit an increase with the adoption of E-commerce. Instead, there seems to be a shift in sales from offline to online channels. Our study finds that the potential of a GEP is to diversify online product offerings while simultaneously enhancing margins for tea farmers.

3 Institutional Background

This section provides an overview of the tea farming output and sale of Pu'er tea. Subsequently, the central government's guidelines for promoting E-commerce sales of Pu'er tea are introduced, along with an analysis of how local governments customize the implementation of these policies in accordance with local needs.

3.1 A Brief Description of Pu'er Tea

The objective of this study is to examine the sales of Pu'er tea, a distinctive tea variety primarily cultivated in the six mountains surrounding Pu'er City in Yunnan Province. In 2008, Pu'er tea was granted geographical indication status by the Chinese government, thereby limiting its commercial designation and sale to specific regions within Yunnan. The study focuses on two major tea-producing counties in Pu'er City (County J and M), which are home to the world's largest ancient tea forest. In 2023, these areas were designated a World Heritage Site by UNESCO. Figure 1 illustrates the location of Yunnan within China and the key Pu'er tea zones. It also identifies the specific locations of County J and County M and the six areas surveyed. The data presented in this study primarily stems from extensive surveys conducted with residents of these areas.

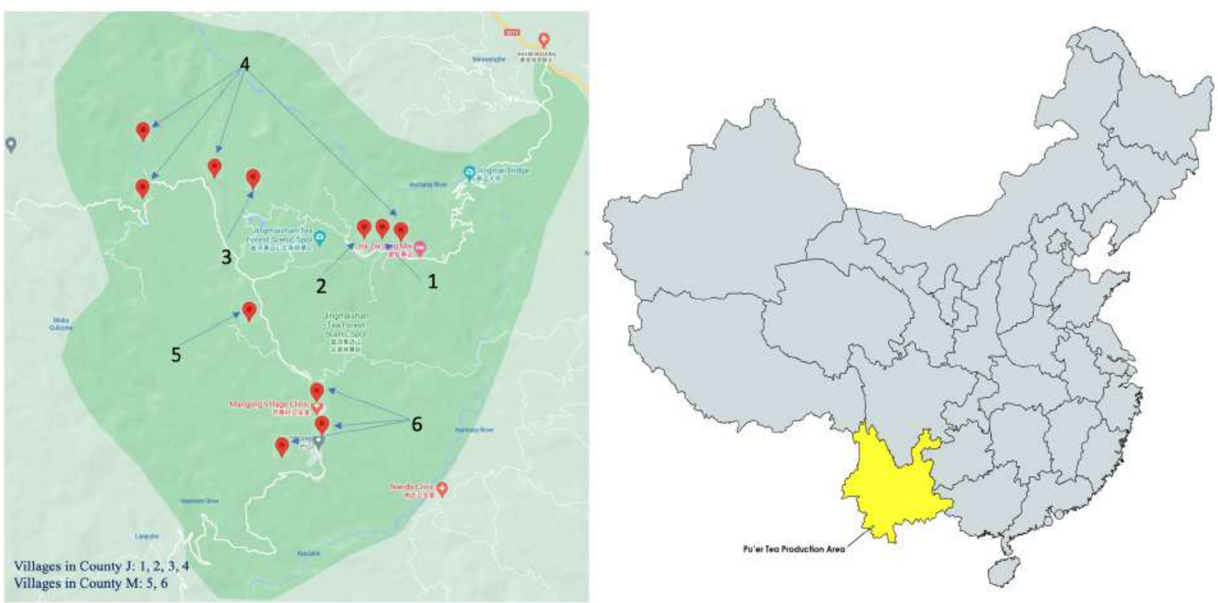


Figure 1: Geographical Location of Pu'er Tea Farming and Areas

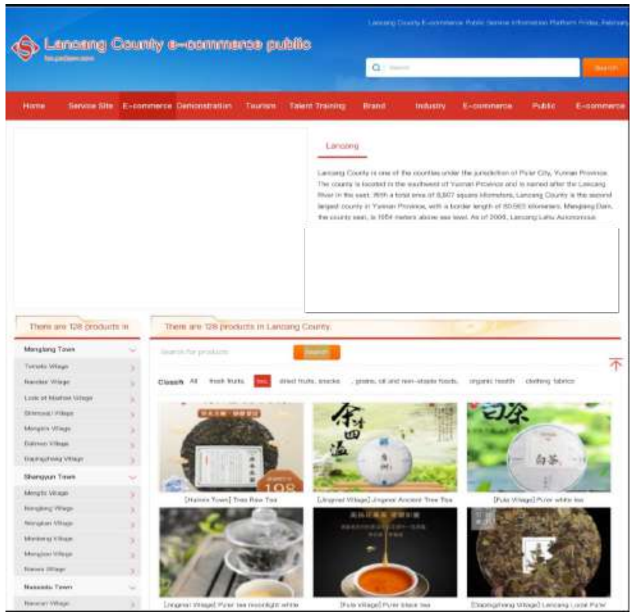
The dataset encompasses the farming output and sales data of three main tea varieties in the region: premium-quality, high-quality, and regular tea, collectively constituting over 98% of the local tea farming output during the study period. Premium-quality tea is distinguished by its derivation from the central buds of single ancient trees aged over 50 years, representing the highest grade. High-quality tea is a blend of leaves from multiple ancient trees, each over 20 years old. Regular tea, the most commonly produced, is harvested in spring from younger trees in plantation tea gardens.

3.2 Policy Treatment: Launch of the Platform

The Chinese government has implemented a series of policies with the objective of promoting the sales of specialty products in rural areas. These policies were issued by the Ministry of Commerce and the Ministry of Agriculture and Rural Affairs of the People's Republic of China (Commercial Construction Letter [2017] No. 597). The primary objective is to motivate local governments to develop or promote E-commerce platforms that facilitate direct sales of agricultural products by rural farmers to consumers, thereby enhancing the comprehensive service capacity of agricultural products on the Internet. To further this objective, local governments are encouraged to establish training facilities and offer online courses to teach farmers how to utilize various E-commerce platforms.

In response to the central government's policy initiative, the Lancang County E-commerce Public Platform was launched by the local government with the objective of facilitating online tea sales for farmers. It is noteworthy that the Lancang government was not the first local authority to implement such a platform subsequent to the issuance of the central policy. In Web Appendix A.1, we provide a table that lists E-commerce platforms that were established by local governments throughout China from 2017 to 2023 in response to the central government's initiative. This demonstrates that comparable platforms have been established in various locations throughout the country. Our article represents the inaugural investigation into the impact of these platforms.

The platform was established at the conclusion of 2017, with implementation commencing in 2018. Figure 2 presents a screenshot of the platform's website. Prior to the introduction of the platform, local tea farmers primarily engaged in the sale of loose tea leaves to tourists



Notes: The screenshot of “Lancang County E-commerce Public Platform” shows a user interface that allows customers to set specific regions based on conditions, located in the lower left corner. Additionally, the platform includes a display of tea products in the bottom right corner. The page was translated using Google Translate.

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

or directly to local tea processing factories. The advent of the platform enabled farmers to accept orders online and sell tea directly to consumers after compressing the leaves into cakes at cooperatives supported by the local government. This process comes at a minimal cost (5 RMB per kilogram) to the farmer, with the tea being labeled with the cooperative's brand. During this period, personnel from the local government were deployed to various regions to inform local tea farmers about the new platform. This ensured that all farmers were aware of this new sales channel and encouraged them to sell their tea on it. Additionally, the government established WeChat groups to facilitate communication among the farmers and to provide timely feedback on the usage of the platform.

One important aspect of the platform's implementation was its phased rollout, which allowed for gradual access to the platform across different regions.[2] From 2018 to 2020, the

2. In Web Appendix B, we present a detailed account of the temporal aspects associated with the adoption of the platform by farmers residing in a geographically diverse array of locations.

platform was introduced incrementally to each of the six areas in Counties J and M, providing an ideal empirical setting for our study. The staggered introduction across areas, confirmed as relatively random by the local government, allows us to effectively identify treatment effects using panel data, controlling for household- and year-fixed effects. In subsequent sections, we will further substantiate the randomness of the treatment with robustness checks.

During the period under consideration, tea farmers had the option of selling their tea online via social media or other E-commerce platforms, including JD.com and Tmall. Nevertheless, due to concerns regarding product quality and information asymmetry, these larger platforms frequently impose considerable entry costs for products with uncertain quality (Hui et al. 2023). This situation renders it exceedingly challenging for numerous small and medium-sized farmers to sell lower-end, inexpensive teas on these platforms. To better understand the difference between the GEP and other sales channels, Web Appendix C provides detailed information and a comparison with different online channels for tea sales.

4 Data Collection and Descriptive Statistics

This section describes the two administrative counties included in the sample, outlines the survey methodology, and details the measures taken to ensure the quality of the collected data. The latter half of this section presents the descriptive statistics related to the data.

4.1 General Description

To obtain data on tea farmers' household characteristics, farming output, sales, and sales channels, two administrative counties in the tea farming area, County J and County M, were selected as the subjects of our household survey. The geographical locations of both counties and their sub-areas are illustrated in Figure 1. County J is comprised of four distinct areas, encompassing an area of 66.9 square kilometers. The population of this county is 3,339 individuals residing in 801 households. A significant proportion of the population have been residents of the mountainous region for multiple generations. To the south of County J is County M, which is comprised of two areas and has a population of 2,645 individuals distributed across 639 households.

A household survey was conducted in Counties M and J in order to gather the data required for the study. A comprehensive survey of households was conducted in each area. The survey team was constituted jointly by the local government. In County J, 785 out of 801 households (98%) provided complete questionnaire responses. A total of 198 households in County M were surveyed and responded to the questionnaire. It is important to note that this does not indicate that County M exhibited a lower response rate. In contrast to County J, where tea farming is nearly ubiquitous among households, County M has only 202 households engaged in tea farming output. Nevertheless, our data collection encompasses at least 98% of all tea-producing households in County M. Overall, we are confident that our survey includes and receives careful responses from more than 98.01% of all tea-producing households, ensuring that our sample is representative of the local tea farmers in this area.

For each household, data were collected on variables including the amount of tea produced per year, the quantity of agricultural land accessible to each household, the annual output of different quality tea leaves, and the amount sold through online and offline channels. The following sections will provide further details on the methodology employed in the survey.

4.2 Data Collection

The survey was conducted 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 either an area cadre or a local expert with expertise in tea farming. Their objective was to oversee the collection of data within a specified geographical area. The teams were composed of college and university students on holiday break, 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 collected data for each team.

The data were collected through in-person interviews, with each team member responsible for engaging with multiple households. The sample consisted of 983 households from the six selected areas, each of which received 20 RMB as an incentive for participation. The survey encompassed a comprehensive range of topics, including household characteristics, tea farming methodologies, marketing avenues, and household revenue streams. Over 90% of respondents maintained a household notebook for the purpose of tracking relevant metrics, including tea picking, farming output, and sales. Upon completion of each household survey, the team leaders subjected the data to rigorous scrutiny to identify inconsistencies and ambiguities, which were then resolved prior to forwarding the collated information to the general manager for final aggregation. For illustrative purposes, Web Appendix D displays a photo of the interview process.

Prior to administering the survey, 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 over 95% of the regional tea farming output, exhibited a high degree of alignment with the statistics reported in various media outlets. A comparison was conducted between the data obtained from the survey and publicly accessible news reports. The comparison is based on two core metrics: the total output of tea and its corresponding market valuation (i.e., farming output level × price), spanning the period from 2016 to 2020. With regard to farming output, the mean yield in our dataset (964 tons) is found to fall well within the range specified by news sources (870-1,480 tons). Similarly, the computed average commercial value of tea farming output (495,733,250 RMB) is in close approximation to the values cited in media reports (500 million RMB).[3]

3. 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).

4.3 Summary Statistics

Table 1 presents a summary of the statistical data for the key variables. Tea sales channels are primarily categorized into offline and online. In the context of offline channels, tea farmers typically sell their tea leaves to nearby processing factories following the harvesting process. Prior to 2018, online sales were predominantly conducted via social media platforms due to the considerable costs associated with selling and operating on mainstream E-commerce platforms, which were prohibitively expensive for tea farmers. Subsequently, in 2018, the local government initiated a non-profit E-commerce platform, which led to the expansion of online sales channels to include both social media and E-commerce platforms. If we set 2018 as the timeline for the policy change and disregard the specific adoption time for farmers in each area accessing the GEP, it becomes evident that the online sales of all three grades of tea—premium-, high-quality, and regular—experienced a significant increase following 2018. In particular, the online sales of premium tea increased by 75.81%, high-quality tea by 81.07%, and regular tea by 112.26%. In contrast, the mean offline sales figures for all tea qualities exhibited a decline relative to the pre-treatment period, with decreases of 14.31%, 11.46%, and 4.65% for premium-, high-quality, and regular teas, respectively. It is noteworthy that despite the considerable substitution effects observed, online sales still account for less than half of the average household's total sales, even after 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 presented in Table 1, our sample also includes detailed time-varying information about each household in these six areas. Moreover, data have been gathered regarding the number of tea processing factories and freight companies situated in proximity to each area over the five-year period encompassed by the dataset. In Web Appendix E, we provide a further statistical summary of the data, disaggregated by household and area. This indicates stability in the size of tea farming lands and local infrastructural factors from before to after 2018. This stability implies a consistent market environment, and the data points to no expansion of tea plantations during the period of our study.

5 Econometric Model and Estimation Results

This section introduces an econometric model designed to identify the impact of launching the GEP on tea sales. We begin by presenting the empirical model and discussing the underlying assumptions for identification. We then report the estimates of the baseline model. Finally, we conduct a series of robustness tests to check for potential treatment endogeneity and show that the estimates are robust.

5.1 Econometric Model

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

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

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, which equals 1 if the area where household i resides had access to the government platform for four or more calendar months in year t. $mode_{i,j,t}$ is a binary indicator that captures the sales channels. It equals 1 if the amount of tea leaves of quality j has been sold by household i in period t 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 unobserved household traits and time trends on the estimates is captured by the 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 to avoid biased estimation that could result from some households only producing a single type of tea. The variable, ζ, captures this effect. The variable η_j indicates the quality-level fixed effects. The household-quality, time-varying, unobserved 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 government platform, designated as the treatment variable $D_{i,t}$. The second difference is obtained across the mode of sale. That is to say, the change in online sales before and after the treatment is compared to the change in offline sales before and after the treatment. By calculating these differences, we can estimate the effect of the treatment on both offline and online sales through the parameters γ and θ as long as $D_{i,t}$ is randomly assigned.

5.2 Baseline Results

The estimates derived from our baseline specification are presented in Columns (1), (2), and (3) of Table 2. Column (1) depicts the model estimates devoid of any fixed effects. Column (2) incorporates year-fixed effects into the econometric model, and Column (3) introduces household and quality fixed effects in addition to year-fixed effects. The estimated coefficients are statistically significant at the 1% level, indicating that the policy had an impact on a household's decision 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 $100\times(\exp(\gamma)\text{-}1)\%$. Similarly, online sales experience an average increase or decrease of

$100\times(\exp(\gamma+\theta)$-1)% after obtaining access to the platform. Using the estimated coefficients from Column (3) of Table 2, it is evident that, on average, online sales experience an increase of 16.65 percent (i.e., 100 times the exponential of the difference between 0.323 and 0.169) after the area gains access to the government platform. Conversely, offline sales drop by an average of 15.55% (i.e., $100\times(\exp(-0.169)-1)$%) after the area gains access to the government platform. 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 government platform and various social media and private E-commerce platforms.

Table 2: Effect of Government Platform on Sales

Dependent Variable:	Log(sales): $q_{i,j,t}$					
	Without Clustering			**With Clustering**		
	(1)	(2)	(3)	(4)	(5)	(6)
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)
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 $\times$ 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)
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. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In Columns (4), (5), and (6), error terms are clustered at the area level.

While panel data allows us to better isolate the treatment effect by controlling various fixed effects, we exercise caution in regard to potential correlations in the error term resulting from unobserved area-specific factors that vary over time. In accordance with our baseline specifications, the unit of analysis is household-quality-year sales (both online and offline). However, our treatment, defined as gaining access to the GEP, occurs at the area level rather than the individual level. In response, we cluster standard errors at the area level for our baseline model and all subsequent models where this discrepancy appears. The estimates for the baseline specification, with standard errors clustered at the area level, are presented in Columns (4), (5), and (6) of Table 2. After clustering standard errors at the area level, our estimated treatment effect maintains statistical significance 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 time-varying factors at the area level are correlated with both the treatment (access to the government platform) and the outcome (tea sales). To illustrate, consider a scenario in which farmers become more productive over time. In such a case, an erroneous conclusion might be drawn, attributing the surge in online sales to the introduction of the government platform. Nevertheless, the observed increase in online sales may be attributed to the expansion of farming output. It is therefore essential to address these concerns in order to accurately estimate the impact of the government platform on online and offline sales. To this end, 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 operating in each area. These controls enable us to separate the policy's impact from other time-varying area-specific factors that could influence 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 incorporating area-level controls, we recognize the possibility of unobserved area-specific, time-varying factors that may be associated with both the treatment and outcome variables. For example, if certain areas adopt smartphone technology at a faster rate than others, those with higher smartphone adoption rates may demonstrate increased online sales. Failure to account for these unobserved time-varying differences across areas could result in biased treatment effect estimates. To address this, we introduce area-specific trends into Equation 2. In particular, 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 reported are presented in Web Appendix F. The first two columns of Table F.1 that online sales increase by an average of 18.41%, while offline sales decrease by an average of 16.22% when controls for time-varying area-specific factors in Equation 2 are applied. The last two columns include additional controls for household-level farming output and area characteristics in Equation 3, respectively. Our findings are consistent across specifications indicating that there are no significant trend differences across counties.

5.4 Robustness Check 2: Treatment Endogeneity

The existence of unobserved variables that exert simultaneous influence on both the treatment and the outcome may also result in endogeneity bias in our estimates. This bias could erroneously attribute the effects of these unobserved factors to the treatment itself (Angrist and Pischke 2009). To enhance the causal interpretation of our estimates, it is essential to ensure that the timing of the government platform's introduction is not correlated with unobserved time-varying factors at the area level that could simultaneously impact tea sales. While the local government confirmed that no explicit criteria or special considerations were used to determine which area gained access to the platform first, we conduct further tests to ensure the randomization.

The initial step is to ascertain whether the probability of obtaining access to the government platform is contingent upon area-level characteristics, such as the extent of agricultural output, the number of tea processing facilities, or the number of shipping companies. In accordance with the methodology proposed by Zervas et al. (2017), we examine the relationship between access to the government platform and year-fixed effects. The detailed results are presented in Web Appendix G. As indicated in Table G.1, the results confirm that area-specific time-varying factors, including the total amount of tea produced, the number of factories, and the number of shipping companies, that may be correlated with the timing of platform adoption have been incorporated.

To further ensure the robustness of our findings, we propose a series of placebo tests. These tests aim to check whether the treatment effect we estimate captures the true effect of the government's policy intervention and not other confounding factors that are correlated with both the treatment and the farmer's choice of online or offline sales channels.

In our first placebo test, we randomize the years in which a household or area has access to the platform, keeping the total number of years of access fixed. The results of this test are presented in Columns (1) and (2) of Table G.2 of Web Appendix G. In Column (1), we re-shuffle treatment at the area level. For example, if an area had access to the government platform in 2019 and 2020 (two years of access), then we randomly select two years between 2016 and 2020 and assign a value of one to a new variable, termed 'placebo treatment,' for these selected years. The placebo treatment is applied consistently across all households within a given area. In Column (2), the treatment status is reshuffled for each household, rather than each area. Once we have created the placebo treatment, we then estimate the effect of this placebo treatment on offline and online sales. The results of both columns indicate that the placebo treatment does not exert a statistically significant effect on a household's online or offline sales at the 10% 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 approximately 9% of the total sample falls into this category. If the impact of the GEP on tea sales across different channels is exclusively due to the platform's introduction, it would be expected that these non-online sellers would remain uninfluenced by the policy change. The results, shown in Column (3) of Table G.2 in Web Appendix G, align with this hypothesis. We find that the introduction of 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), TWFE estimation 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 incorporates additional robustness checks to prevent the 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 from regressing the treatment indicator on the household-, year-, and quality-fixed effects. The treatment effect is thus 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 Web Appendix I.1, we present a comprehensive examination of the robustness of our findings, employing the procedures outlined by Jakiela (2021) to illustrate the weights for both treated and untreated units. It is suggested that only 15% of treated units exhibit negative weights. For context, Jakiela (2021) observed that approximately 25% of treated units had negative weights, yet the treatment effect remained robust after removing these observations. As our estimate of the Average Treatment Effect (ATE) is a weighted sum of outcomes, it is unlikely that these negligible negative weights will introduce bias. As an additional robustness check, the model was recalculated, this time excluding treated units with negative weights. Table I.1 of Web Appendix I.1 demonstrates that the substitution effect post-platform launch remains significant.

5.5.2 Interaction Weighted Estimator

To circumvent 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). IW estimator is robust to heterogeneous treatment effects in models with staggered treatment and can be used even in the absence of a never-treated group. In accordance with the methodology proposed by Sun and Abraham (2021), our sample was divided into distinct cohorts based on the year in which each household gained access to the platform. In the context of our study, this results in the formation of three distinct cohorts (2018, 2019, and 2020) along with a cohort that has not been exposed to the treatment.

In Web 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 online and offline sales effects, we find that the GEP resulted in an average 14.44% decrease in offline sales and a 12.52% increase in online sales. Figure H.1 shows the estimated effects across cohorts. We find a consistent effect across cohorts, suggesting a significant positive impact on online sales

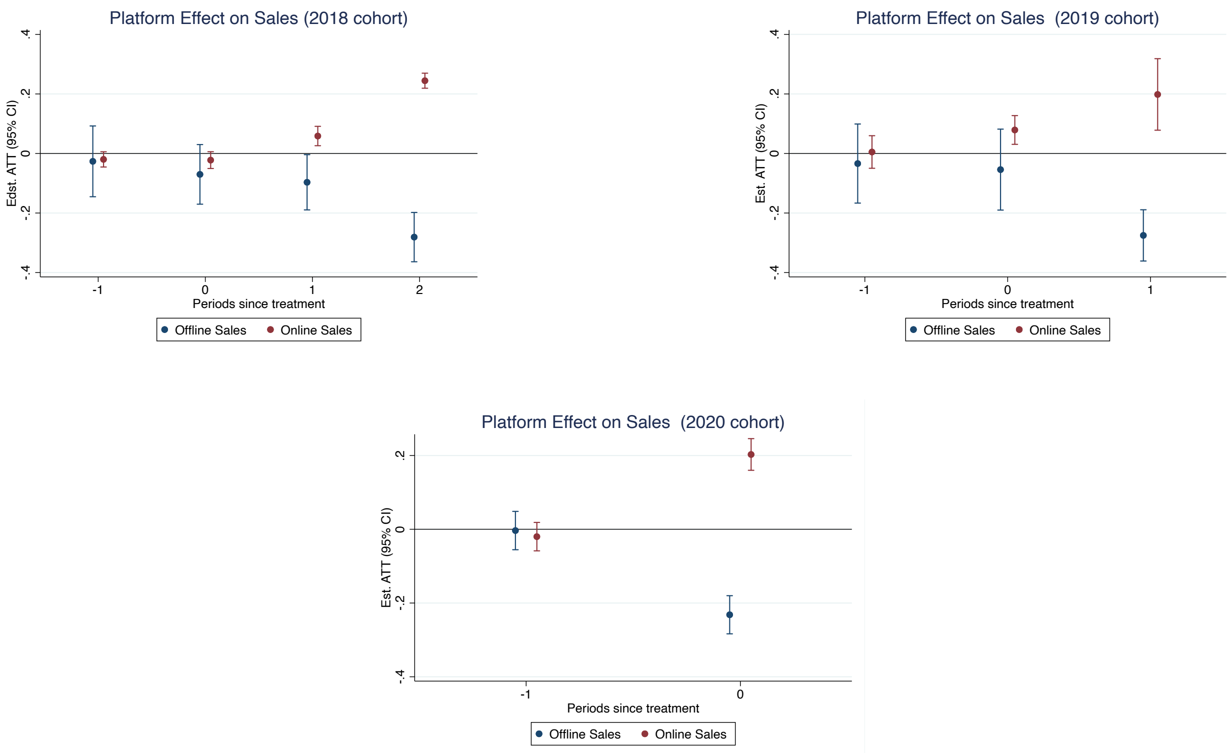


Figure 3: Average Treatment Effects by Cohort

Notes: The above figure illustrates the impact of the government platform on online and offline tea sales for different cohorts. The blue dots indicate the effect on offline sales, while the red dots show 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 pretrends), we also provide additional checks in Web Appendix H to further validate the assumption of parallel trends.

and a negative impact on offline sales after platform implementation.

6 Heterogenous Treatment Effects

To gain insight into the influence of the policy, our study examines how the GEP could impact diverse household types with differing levels of tea farming output. Our analysis assesses the heterogeneous treatment effects across three key dimensions: farming output, quality, and pre-treatment sales channels, providing a comprehensive understanding of the policy's impact on different household groups.

6.1 Effects Across Different Output Levels

The policy may have differential effects on households with varying levels of agricultural output. In particular, the impact of the platform may vary for farmers with high and low output levels. To address this issue, the households in our sample have been grouped into three quantile-based output categories: low output (with an annual yield ranging from 0 to 405 kg), medium output (an annual yield between 406 and 870 kg), and high output (an annual yield exceeding 870 kg). Subsequently, separate regression analyses are performed for each of these sub-groups to investigate two distinct dimensions of impact: the aggregate effect and the specific effect of the GEP's launch on the substitution from offline sales to online sales.

The findings presented in Table 3 indicate that the introduction of the GEP does not result in a significant impact on the overall volume of tea sales. Notwithstanding, there is a significant shift from offline to online sales, particularly among the largest tea farmers who transition a more substantial proportion of their sales to the online platform in comparison to their medium and small counterparts. Overall, the implementation of the GEP did not result in an increase in agricultural outputs. The cultivation of tea is constrained by a number of factors, including the size of the tea gardens and the number of ancient tea trees. These constraints, particularly the age required for trees to produce high-quality leaves, impede rapid expansion. Land ownership shifts among households also revealed minimal changes, which further demonstrates that total farming output remained consistent before and after the treatment. Given that the overall volumes remain unchanged, the shift from offline to online sales for all producer sizes suggests a strategic optimization in sales channels, facilitated by the GEP. This provides evidence that the GEP may also enhance farmer welfare.

Table 3: Heterogeneous Effects of GEP 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. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Error terms are clustered at the area level.

6.2 Effects Across Different Product Qualities

Furthermore, the introduction of the GEP is likely to affect the sales volumes of tea products of varying qualities, both online and offline. The quality of tea can be classified into three categories: premium, high, and regular. Regressions are performed on each subgroup, as illustrated in Table 4. In accordance with our previous findings, the introduction of the platform does not yield a statistically significant effect on the overall sales volume. Nevertheless, a statistically significant increase in online tea sales is observed in each subgroup following the launch of the GEP. Subsequent calculations indicate that online sales of regular tea have increased by 11.97%, high-quality tea by 15.60%, and premium-quality tea by 21.65%. While the premium-quality tea segment demonstrates the most substantial percentage increase in online sales, this is predominantly attributable to its markedly smaller pre-launch online sales volume in comparison to regular tea. Conversely, despite online sales of regular tea rising by just under 10%, in terms of volume (kg/year), it exhibited the most significant increase in online sales.

Table 4: Heterogeneous Effects of GEP 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. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Error terms are clustered at the area level.

6.3 Effects Across Different pre-GEP Mode of Sales

To gain further insight into the role of the GEP, we examine its impact on farmers, categorizing them based on the markets where they sell their tea prior to the introduction of the GEP. The farmers are initially divided into two groups based on their pre-GEP online sales channels. The initial cohort comprises farmers who engage exclusively in online tea sales via social media. In contrast, the second group comprises farmers who used commercial platforms for tea sales prior to the establishment of the GEP.

A significant proportion of farmers in the second group also sold their tea on social media platforms. However, we find that most farmers who sell their tea on social media do not sell on commercial platforms. We posit that this is due to the fact that commercial E-commerce platforms frequently implement entry barriers with the objective of screening high-quality merchants Hałaburda and Yehezkel (2013); Rong et al. (2024). This has the effect of preventing farmers in rural areas from selling low-end products online. Therefore, we believe the barriers to online sales are lower for the second group compared to the first.

Table 5 illustrates the impact of the GEP across varying quality tiers of tea—including regular, high-quality, and premium— among farmers who utilized only social media for sales versus those who used commercial platforms prior to the implementation of the GEP. In Columns (1) and (2), the results show that the increase in online sales of regular tea is statistically significant for those who previously engaged in sales on social media. However, this significance does not extend to farmers who have used commercial platforms. In contrast, Columns (3)-(6) illustrate that the increase in online sales of high- and premium-quality tea is statistically significant (at the 10% level) for both farmer groups. These results are consistent with our expectations and suggest that the GEP has effectively lowered the entry barriers for selling regular quality tea on online platforms by providing a low-cost alternative to commercial platforms. This effect is particularly significant for farmers who previously sold exclusively on social media and were hindered by the high entry barriers associated with commercial platforms. For regular tea, where margins are lower as the high transaction costs of commercial platforms often make sales less profitable.

7 Exploring Potential Mechanisms

In this section, we build on the insights of Section 6 to investigate the mechanisms behind the GEP's impact on online sales, focusing on both extensive and intensive margins. The extensive margin considers the increase in farmers selling online post-GEP launch, which may be attributed to the platform and related policies, such as training. The intensive margin examines changes in the volume and variety of tea sold by existing online sellers, who, with a new government platform available, can operate at reduced costs and may thus lead to more online transactions.

Table 5: Heterogeneous Effects of GEP on Sales by Pre-treatment 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. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Error terms are clustered at the area level.

7.1 Extensive Margin: Effects on Online Mode Adoption

First, we construct a new binary variable, $Adopt_{i,t}$, which takes the value of one if farmer i engages in the sale of at least one type of tea via an online marketplace during period t, and takes the value of zero otherwise. In Column (2) of Table 6, we expand the definition of adopting online channels to a more refined outcome variable $Adopt_{i,j,t}$. This binary variable indicates whether farmer i sells tea of quality j online during period t. In Column (3), we further introduce another alternative outcome variable, $Adopt^{f}_{i,t}$, which is equal to 1 if t is the first year that farmer i has sold tea of any quality of tea online.

Table 6 presents the estimated results, which indicate that the introduction of the GEP has no statistically significant effect on the outcome variable across all specifications. This suggests that the policy had no significant impact on the decision to adopt online sales channels. Even after the introduction of the GEP, farmers who were selling their tea primarily in offline markets continued to do so. Online sales channels such as JD.com and Taobao, along with social media outlets like WeChat stores, were already in existence prior to the implementation of government platform so one explanation for this could be that there are

Table 6: Effect of Government Platform on Adoption of Online Sales

Dependent Variable:	$Adopt_{i,t}$	$Adopt_{i,j,t}$	$Adopt^f_{i,t}$
	(1)	(2)	(3)
Platform Access	0.008	0.003	0.004
	(0.010)	(0.004)	(0.020)
Observations	4,915	14,745	4,915
Household FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.717	0.174	0.310

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

other factors preventing farmers from engaging with E-commerce. For example, some farmers could have lack of experience with using mobile phones or have already established strong relationships with local buyers. Consequently, the resistance exhibited by farmers against online sales channels due to these reasons cannot be effectively addressed by the introduction of GEP.

7.2 Intensive Margin: Effects on Product Diversity

This section further examines the extent to which the platform contributes to an increase in the diversity of tea types offered online, which may subsequently lead to an overall increase in online sales. Typically, the mass sale of regular-quality tea on conventional E-commerce platforms offers marginal returns, leading farmers to focus on selling higher-priced tea online. In this context, we hypothesize that the government's platform may offer a cost-effective channel for selling low-priced tea online.

Figure 4 presents some model-free evidence that corroborates the aforementioned scenario. The dataset reveals four distinct combinations of tea types produced by the farmers. The four distinct combinations of tea types produced by the farmers are as follows: (1) premium-quality tea only, (2) regular and high-quality tea, (3) regular and premium-quality tea, and (4) premium- and high-quality tea. The use of different colors indicates the combinations of tea types that are sold online by the farmers. It indicates that a greater proportion of farmers are selling their lower-end products online after gaining access to the platform. For example, prior to 2018, there were 283 households engaged in the cultivation and sale of both regular and premium-quality tea. Of the 283 households, 175 engaged in the sale of both regular and premium tea via online channels while 86 only offered premium tea for sale online, 8 exclusively sold regular tea online, and 14 households conducted all transactions offline. Subsequently, after 2018, there were 250 households that sold both regular and premium-quality tea online. Of these, 30 sold only premium tea, while 3 sold only regular tea. This indicates that a considerable number of households that previously only sold premium-quality tea online (or did not sell online at all) are now selling regular tea online following the platform's launch.

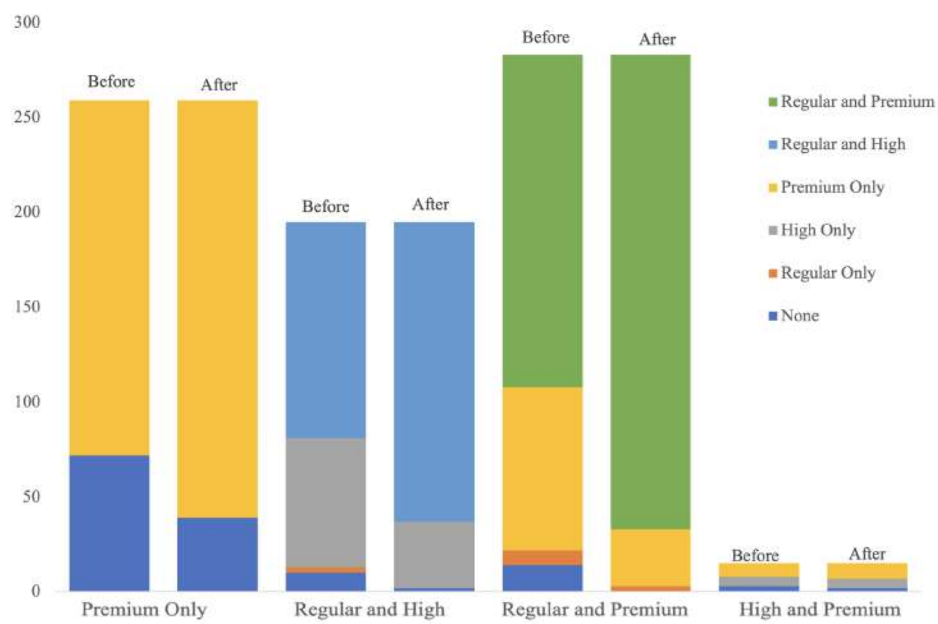


Figure 4: Qualities Sold Online Before/After Launching the Platform

In order to ascribe the observed changes in Figure 4 to the introduction of the platform as opposed to other potential factors, we conducted additional regression analysis looking at online varieties. A control variable, $V_{i,t}$, is introduced to represent the diversity of tea types (i.e., different qualities) sold online by household i in period t. The regression results obtained with this variable are presented in Table 7. Columns (1) and (2) shows the impact of the GEP on the variety of tea ($V_{i,t}$) sold online. Specifically, Column (1) considers farmers who were already engaged in online sales of regular tea varieties prior to the GEP's launch, while Column (2) focuses on those who had not engaged in any online sales of regular tea before the GEP. In Column (3), we analyze $V_{i,t}$ as a potential mediating factor. By incorporating interaction terms into the regression model, we examine the combined effect of the diversification of tea types and the GEP's launch on the total volume of online tea sales.

Table 7: Effect of Government Platform on Varieties Sold Online

Dependent Variable:	Online Variety		Online Sales
	Regular Tea in Online Sales	**Regular Tea Not in Online Sales**	
	(1)	(2)	(3)
Platform Access	-0.055	0.064***	-0.491***
	(0.045)	(0.021)	(0.035)
Online Variety = 1			4.288***
			(0.055)
Online Variety = 2			5.287***
			(0.060)
Platform Access × Online Variety = 1			0.595***
			(0.043)
Platform Access × Online Variety = 2			0.664***
			(0.054)
Observations	1,665	3,250	4,915
Household FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.519	0.674	0.975

Notes: Standard errors are indicated in parentheses. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results presented in Table 7 are in accordance with our hypothesis. Gaining access to the GEP increases the varieties of tea sold online particularly for farmers who were previously only selling exclusively higher quality tea online before the policy. An estimated coefficient of 0.064 (significant at the 1% level) indicates that approximately one in 16 households increase the diversity of tea types sold after gaining access to the GEP. Column (3) additionally demonstrates that diversifying the tea types has a positive impact on the total online sales volume, even after controlling for household- and year-fixed effects. Specifically,we find a significant rise in online sales with an increase in variety. Therefore, we can reasonably infer that the changes in online diversity serve as a reliable mediator. They contribute to the proposed intensive margin: the platform's introduction offers a more cost-effective channel for low-quality tea, enriching the diversity of online tea products and elevating the overall tea sales volume.

8 Conclusion

The accelerated growth and dissemination of E-commerce have prompted significant interest from policymakers, who seek to leverage it as a policy instrument to enhance the livelihoods of rural agricultural producers. The present study examines the impact of implementing a GEP that focuses on local specialty products. The empirical results indicate that while such a platform may not result in a significant increase in overall sales, it serves as a crucial catalyst for market development by reducing transaction costs, thereby increasing the quantity and variety of products sold online and enhancing profitability by enabling rural producers to access a broader consumer base.

This study makes a significant contribution to the fields of agricultural and industrial economics by offering a novel perspective for policy evaluation. The data, gathered through face-to-face interviews, is representative and uniquely capable of illustrating the trade-offs tea farmers make between various sales channels for the first time. This allows for a comprehensive understanding of the policy's full impact. In addition to measuring the impact on overall sales volumes, our econometric modeling identifies how the policy affects the distribution of sales between online and offline channels. If farmers are rational, a more optimal allocation of online and offline sales would also indicate that farmers are deriving greater profits from the policy.

Secondly, the observation of decisions across multiple sales channels provides a comprehensive foundation for mechanism analysis. The data effectively identifies that the shift in sales channel distribution is not driven by an increase in the number of online tea farmers, but rather by an increase in the variety of lower-end teas sold online, which has driven overall online sales. The prevailing theoretical perspective tends to assume that large platforms possess inherent advantages in terms of sales. Our empirical findings corroborate this theoretical development. While large platforms benefit from network advantages, policymakers frequently neglect the constraints imposed by information asymmetry and high marketing costs, which impede the sale of distinctive, quality-uncertain products. Government intervention can bridge this gap. Local governments, more so than large platforms or social media, possess a superior understanding of producers' backgrounds and can guarantee the quality of products sold on the platform, thus facilitating the online circulation of these specialty products at lower costs.

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Web Appendix

Digital Revitalization or Useless Effort: The Impact of a Government-initiated E-commerce Platform on Local Specialty Sales

Table of Contents

A List of Locations in China that have Launched GEPs from 2017 to 2023

Table A.1 presents a comprehensive list of locations in China that have launched Government-initiated E-commerce Platforms (GEPs) from 2017 to 2023. The data set includes information on the province, the specific location, the year of establishment, and the name of each platform. It encompasses a diverse array of regions, encompassing major cities like Harbin in Heilongjiang and smaller counties such as Jinzhong in Shanxi and Linzhi in Tibet. It serves to illustrate the government's endeavors to facilitate the expansion of E-commerce infrastructure across a multitude of provinces, including autonomous regions such as Ningxia and Inner Mongolia. It is noteworthy that while the table enumerates the identified GEPs, there may exist additional platforms due to the ongoing nature of the initiatives, which are not reflected in this table.

Table A.1: Government-initiated E-commerce Platforms in China since 2017

Province	**Location**	**Setup Year**	**Name of the Platform**
Tianjin	Tianjin	2018	Tianjin Yinongtao
Chongqing	Qijiang District	2018	Caiba.com
Hebei	Shijiazhuang	2018	Zanhuang County E-commerce Public Service Center
Shanxi	Jinzhong	2017	Zuoquan Commerce Public Service Center
Heilongjiang	Harbin	2019	Xiao Kang Long Jiang
Jilin	Tonghua	2019	Huinan E-commerce Public Service Center
Liaoning	Tieling	2021	Tieling E-commerce Public Service Center
Jiangsu	Xuzhou	2018	Peixian E-commerce Public Service Center
Zhejiang	Lishui	2020	Suichang County E-commerce Public Service Center
Anhui	Tongling	2019	Songyang County E-commerce Public Service Center
Fujian	Quanzhou	2018	Anxi E-commerce Public Service Center
Jiangxi	Fuzhou	2019	Nancheng E-commerce Service Center
Shandong	Linyi	2022	Lanling E-commerce Public Service Center
Henan	Zhoukou	2019	Shangshui E-commerce Public Service Center
Hubei	Xiaogan	2020	Yunmeng County E-commerce Public Service Center
Hunan	Loudi	2018	Central Hunan Rural Business
Guangdong	Huizhou	2018	E-commerce Public Service Center in Long Men County
Hainan	Hainan	2021	Hainan Rural Revitalization Network
Sichuan	Luzhou	2016	Guangdianyunshuang
Guizhou	Guiyang	2022	Kaiyang County E-commerce Public Service Center
Shaanxi	Yulin	2018	Qingjian County E-commerce Public Service Center
Qinghai	Golog Tibetan Autonomous Prefecture	2021	Maduoxian Commerce Public Service Center
Inner Mongolia	Ordos	2020	Wushen Banner E-commerce Public Service Center
Guangxi	Hezhou	2018	Zhaoping County E-commerce Public Service Center
Tibet	Linzhi	2022	Motuo E-commerce Public Service Center Platform
Ningxia	Guyang	2017	Pengyang E-commerce Service Center
Ningxia	Hetian	2023	Hetianyuese

Notes: The table lists Government-initiated E-commerce Platforms (GEPs) identified during our research. New platforms may have been established in response to ongoing government initiatives, which may not be reflected in the table.

B Timing of Adopting the GEP

Table B.1 provides a detailed account of the adoption dates of Government-initiated E-commerce Platforms (GEPs) across various geographical areas, identified by their respective area codes. The table includes the area codes (J1, J2, J3, J4, M1, M2) and the corresponding dates of platform access. To illustrate, area J1 accessed the platform in June 2019, while area J2 did so in September 2018. In a similar vein, Area J3 accessed the platform in October 2020, while Area J4 did so in November 2019. The table also indicates that Areas M1 and M2 accessed the platforms in November 2018 and April 2020, respectively. The table thus serves to highlight the staggered nature of GEP adoption across different areas over time.

Table B.1: Timing of Platform Adoption

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

C Alternative Online Sales Channels

Table C.1 provides a comprehensive overview of the costs associated with different online sales channels. For example, JD.com and Tmall require all sellers to possess a registered business license, which presents a significant challenge for small, rural farmers. Moreover, these platforms impose high commissions and annual fees, which reduce the profitability of online tea sales. Farmers must also bear the costs associated with increasing product visibility on these platforms. While social media channels do not directly charge commission fees or have entry requirements, they present soft barriers to entry. For instance, live streaming on social media often incurs technical fees, and leveraging influencers for sales involves paying them a substantial commission. Compared to these platforms, GEPs may emerge as a viable alternative for farmers seeking online market access without the burdensome costs associated with commercial platforms and social media.

Table C.1: Comparison of Online Sales Channel Costs

	Government Platform	Social Media	E-commerce	
			JD.com	**Tmall**
Commission Fee	0	0	5%	2%
Technology Fee	0	3%-8%	5%-8%	2%-5%
Annual Fee	0	0	30,000 RMB	12,000 RMB
Marketing Cost	0	Advertising Cost	0.01 RMB/click	0.01 RMB/click
Entry Requirements	No	No	Registered License	Registered License with 1 Million RMB for 2 years

Notes: Marketing Cost in the fourth row refers to the fees sellers pay (e.g., Cost per Click) based on the traffic generated by users clicking on the shop.

D Illustration of Interview and Data Collection Process

Figure D.1 provides a visual representation of the interview and data collection process conducted by the research team. The image depicts a group of research team members engaged in an interactive session with local farmers on the left side of the image. The research team members are seated around a table, engaged in discussion and information gathering at what is presumably a local farmer's residence. The right side of the image presents a close-up of a notebook utilized by local farmers. This notebook contains handwritten records delineating various types of tea, sales volumes, and prices. According to the accompanying text, after verifying this information, the research team members enter the data into distributed forms. These forms categorize the information based on 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

E Household- and Area-related Statistics

As showcased in Table E.1, we summarize the household- and area-related variables. It indicates stability in the size of tea farming lands and local infrastructural factors from before to after 2018. This stability implies a consistent market environment, and the data points to no expansion of tea plantations during the period of our study.

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

The estimation results of the equation are presented in Table F.1. The estimated treatment effects, after incorporating the additional controls, are consistent with the results obtained from the baseline specification. In particular, the data indicate that online sales experience an average increase of 18.41% following the establishment of access to the government platform in a given area. Conversely, offline sales experience an average decrease of 16.22% post-access to the platform. In Column (3), we control for household-level farming output (volume), while in Column (4), we control for both volume and area characteristics, such as the number of factories and the number of shipping companies. These results are quantitatively consistent with our previous findings, suggesting that no noticeable trend differences exist across the counties.

Table F.1: Effect of Government Platform 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. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Error terms are clustered at the area level.

G Robustness Check 2: Treatment Endogeneity

As indicated in Table G.1, the results of the analysis demonstrate that the proposed model is already capable of explaining approximately 76% of the observed variation in platform adoption. Subsequently, area-specific, time-varying factors that may be correlated with the timing of platform adoption are incorporated, including the total amount of tea produced, the number of factories, and the number of shipping companies. No statistically significant coefficients were observed for these factors, and their inclusion did not enhance the explanatory power of the regression, indicating that the timing of treatment is uncorrelated with area-specific time-varying factors.

Table G.1: Likelihood of Access to the Government Platform

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. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. 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.

We also report the results of placebo tests to enhance the interpretation of the treatment. In our first placebo test, we randomize the years in which a household or area has access to the platform, keeping the total number of years of access fixed. The results of this test are presented in Columns (1) and (2) of Table G.2. In Column (1), we re-shuffle treatment at the area level. For example, if an area had access to the government platform in 2019 and 2020 (two years of access), then we randomly select two years between 2016 and 2020 and assign a value of one to a new variable, termed 'placebo treatment,' for these selected years. The placebo treatment is applied consistently across all households within a given area. In column (2), the treatment status is reshuffled for each household, rather than each area. Once we have created the placebo treatment, we then estimate the effect of this placebo treatment on offline and online sales. The results of both columns indicate that the placebo treatment does not exert a statistically significant effect on a household's online or offline sales at the 10% 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 approximately 9% of the total sample falls into this category. If the impact of the GEP on tea sales across different channels is exclusively due to the platform's introduction, it would be expected that these non-online sellers would remain uninfluenced 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. Significance levels are denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Error terms are clustered at the area level.

H Robustness Check 3: Parallel Trends

To further ensure that our estimated effects are causal in nature, we show that online and offline sales in different areas would have developed in the same way (parallel trends) in the absence of the government platform. First, we can plot the evolution of online and offline sales in different areas according to the year in which they first gained access to the platform (cohorts). We can see in figure H.1 that both online and offline sales show similar trends in the pre-treatment periods, with online sales increasing and offline sales decreasing over this time. This suggests that in the absence of the government platform, online sales would have increased at roughly similar rates in all the different areas and that any additional increase in online sales beyond this is due to the introduction of the platform.

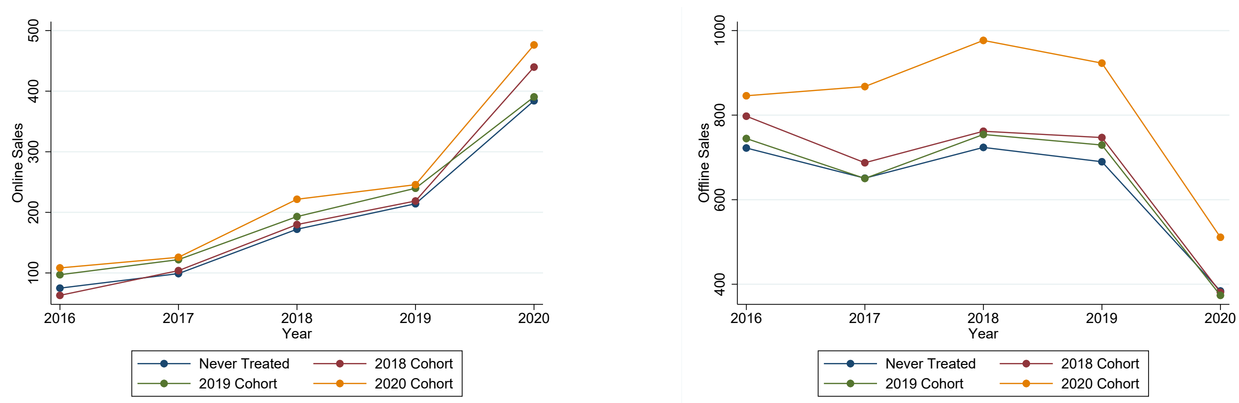

Figure H.1: Average Treatment Effects by Cohort

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

We further confirm this result by estimating the marginal effects of time (trend) on online sales across cohorts and then testing whether these estimated trends differ across cohorts. These estimated trends are reported in H.1. Using a Wald test, we fail to reject the null hypothesis that these pre-trends are equal, providing further evidence that the evolution of online sales is the same across cohorts prior to the launch of the government platform.

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

I Robustness Check 4: Bias Correction Related to Two-way Fixed Effects (TWFE) Estimators

I.1 Negative Treatment Weights

Our analysis accounts for the staggered adoption of the platform across different villages. To control for various household-specific, period-specific, and quality-specific shocks, we employ 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 across units. In this section, following Jakiela (2021), we show that our treatment effect estimates remain unbiased after controlling for household-, quality-, and year-fixed effects.

We base our analysis on the following equation:

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

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

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

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 thus 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.

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

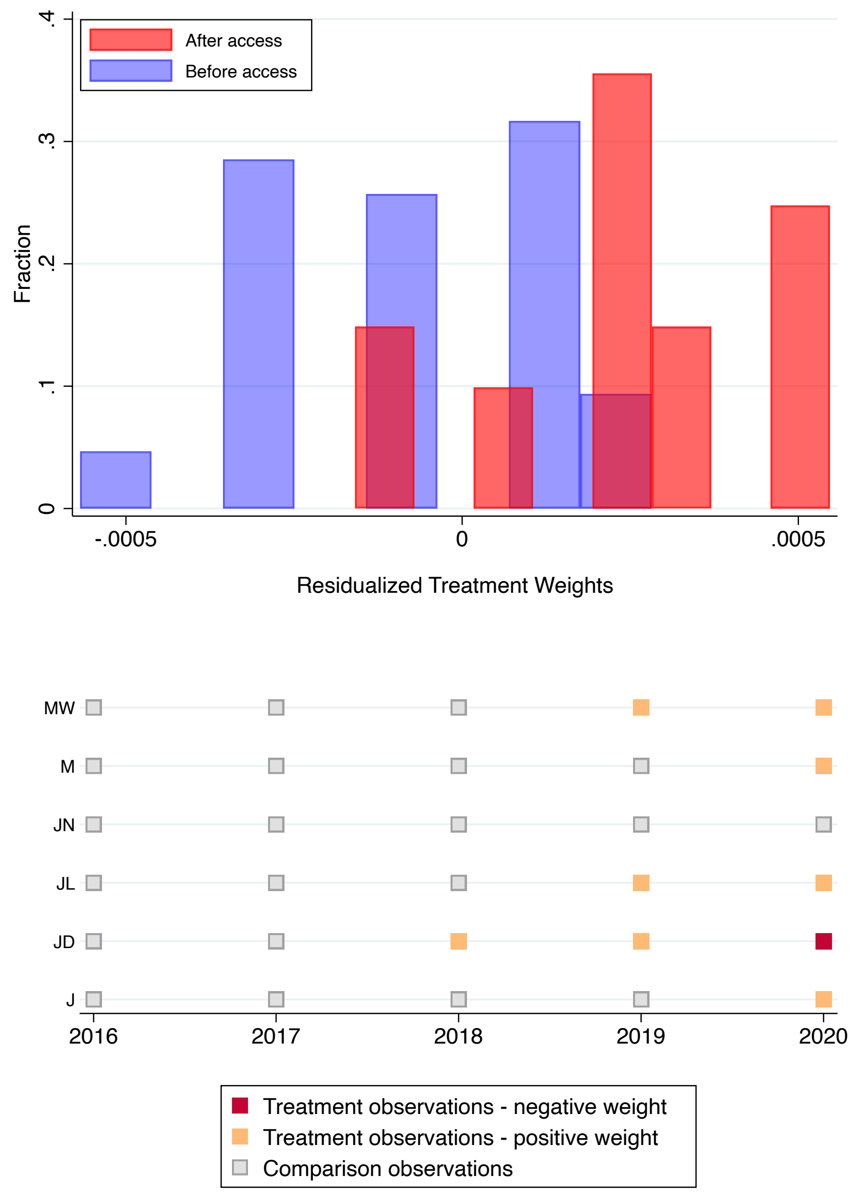

Figure I.1: Weights of Two-Way Fixed Effects.

Table I.1: Effect of Government Platform 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 × 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. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Error terms are clustered at the area level.

each observation. Figure I.1 displays these weights for treated and untreated units. The figure shows only 15% of treated units have negative weights. For context, Jakiela (2021) observed that around 25% of treated units had negative weights, yet the treatment effect remained robust after removing these observations. Since our Average Treatment Effect (ATE) estimate is a weighted sum of outcomes, these negligible negative weights are unlikely to introduce bias.

As a further robustness check, we recalculated our model excluding treated units with negative weights. The revised results in Table I.1 affirm a significant substitution effect post-platform launch: offline sales decreased by approximately 13.93%, and online sales increased by roughly 14.8%.

I.2 Interaction Weighted Estimator

To circumvent the potential for bias inherent in two-way fixed effect 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). This estimator is robust to heterogeneous treatment effects in models with staggered treatment and can be used even in the absence of a never-treated group. In accordance with the methodology proposed by Sun and Abraham (2021), our sample was divided into distinct cohorts based on the year in which each household gained access to the platform. In the context of our study, this results in the formation of three distinct cohorts (2018, 2019, and 2020) along with a cohort that has not been exposed to the treatment. We first estimate the cohort-time average treatment effect on treated units (CATT) using a two-way fixed effects specification that interacts cohort indicators with a relative period indicator. These relative period indicators represent the number of periods that each cohort has been treated and are included to allow for treatment effects that vary over time. In the case of a static model, an alternative estimator of CATT can be implemented, whereby cohort indicators have interacted with a binary treatment indicator. The following equation is estimated:

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

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 are calculated on the basis of the sample share of each cohort in each relative period. Ultimately, the IW estimate of the treatment effect is computed through a weighted average of CATT, using the weights obtained in the preceding step. The IW estimates are presented in Table I.2. The results of our analysis, which employ the IW two-way fixed effects estimator, indicate that the impact of the government platform on tea sales is consistent with our baseline findings. In particular, the estimated coefficient for platform access is -0.156, while the estimated coefficient for the interaction between platform access and online sales is 0.274. The estimated coefficients were converted into online and offline sales effects, which yielded a 14.44% decrease in offline sales and a 12.52% increase in online sales. These estimated treatment effects are statistically and economically significant and are consistent with the baseline estimates, supporting the hypothesis that farmers began shifting their sales from offline to online channels after receiving access to the government platform.

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. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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 (09.2018) is included in cohort 1. Areas M1 (11.2018) and J1 (06.2019) are included in cohort 2. Areas J4 (11.2019) and M2 (04.2020) are included in cohort 3. Area J3 (10.2020) is not included in the study and serves as a control group.