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

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A List of GEPs in China from 2017 to 2023

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

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

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

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

B Comparative Institutional Context: Entry Costs and Operational Complexity

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

B.1 Financial Entry Barriers

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

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

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

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

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

B.2 Operational Complexity and Required E-commerce Skills

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

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

References

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C Timing of Adopting the GEP

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

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

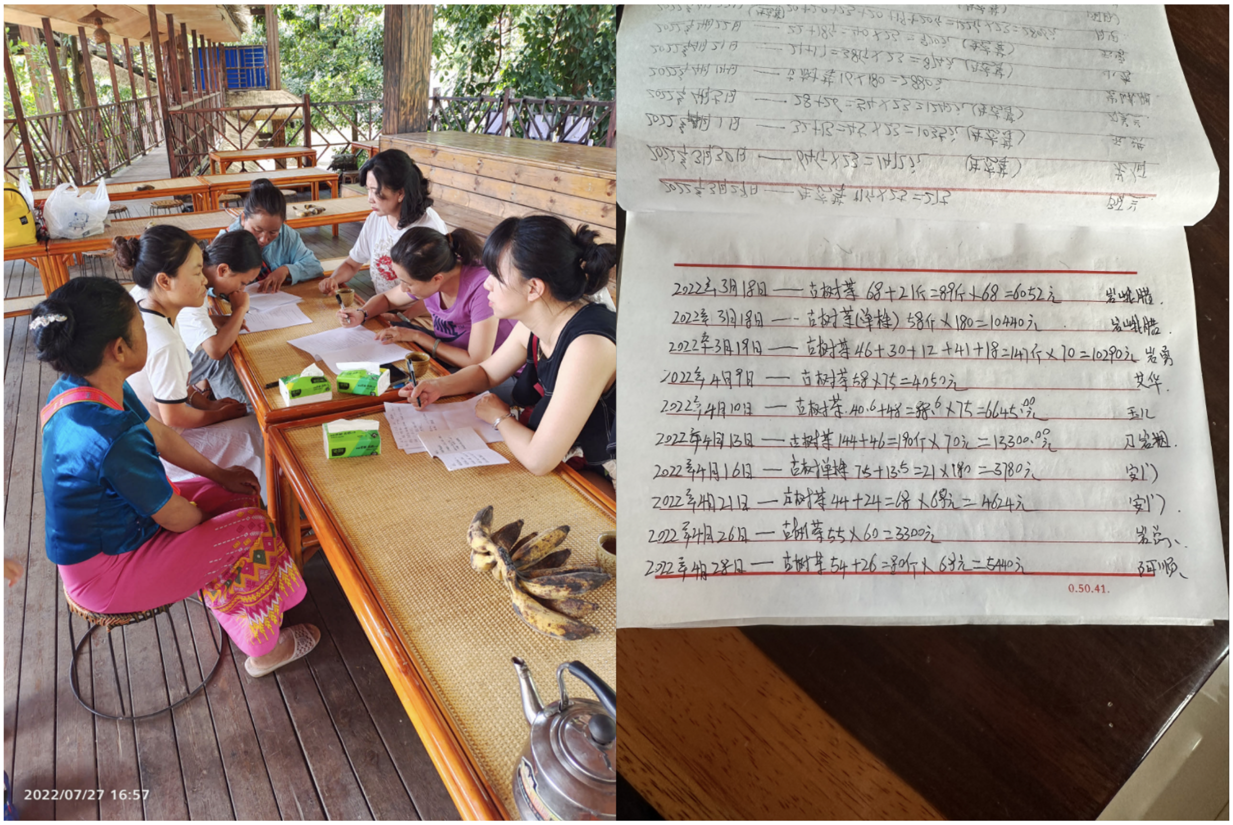
Area Code	**Platform Access Date**
J1	Jun 2019
J2	Sep 2018
J3	Oct 2020
J4	Nov 2019
M1	Nov 2018
M2	Apr 2020

D Data Collection Process

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

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

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



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

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

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

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

E Household- and Area-related Statistics

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

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

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

Notes: We report the standard deviation in parentheses.

F Robustness Check 1: Unobserved Trends and Environmental Changes

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

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

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

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

G Robustness Check 2: Treatment Endogeneity

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

Table G.1: Likelihood of GEP Access

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

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

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

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

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

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

H Robustness Check 3: Parallel Trends

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

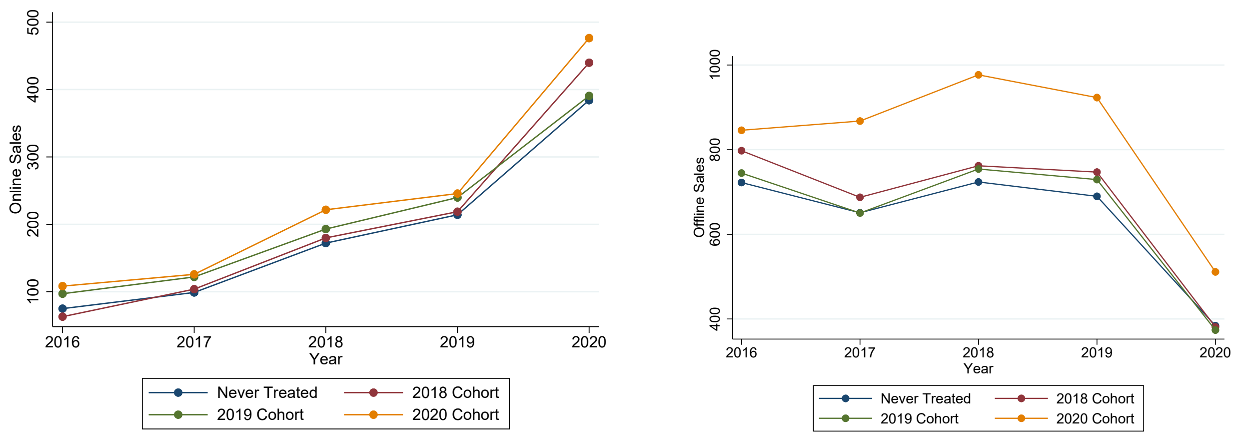


Figure H.1: Offline and Online Sales Trends

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

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

Table H.1: Estimated Pre-trends by Cohort

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

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

I Robustness Check 4: Bias Correction Related to TWFE Estimators

I.1 Negative Treatment Weights

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

We base our analysis on the following equation:

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

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

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

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

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

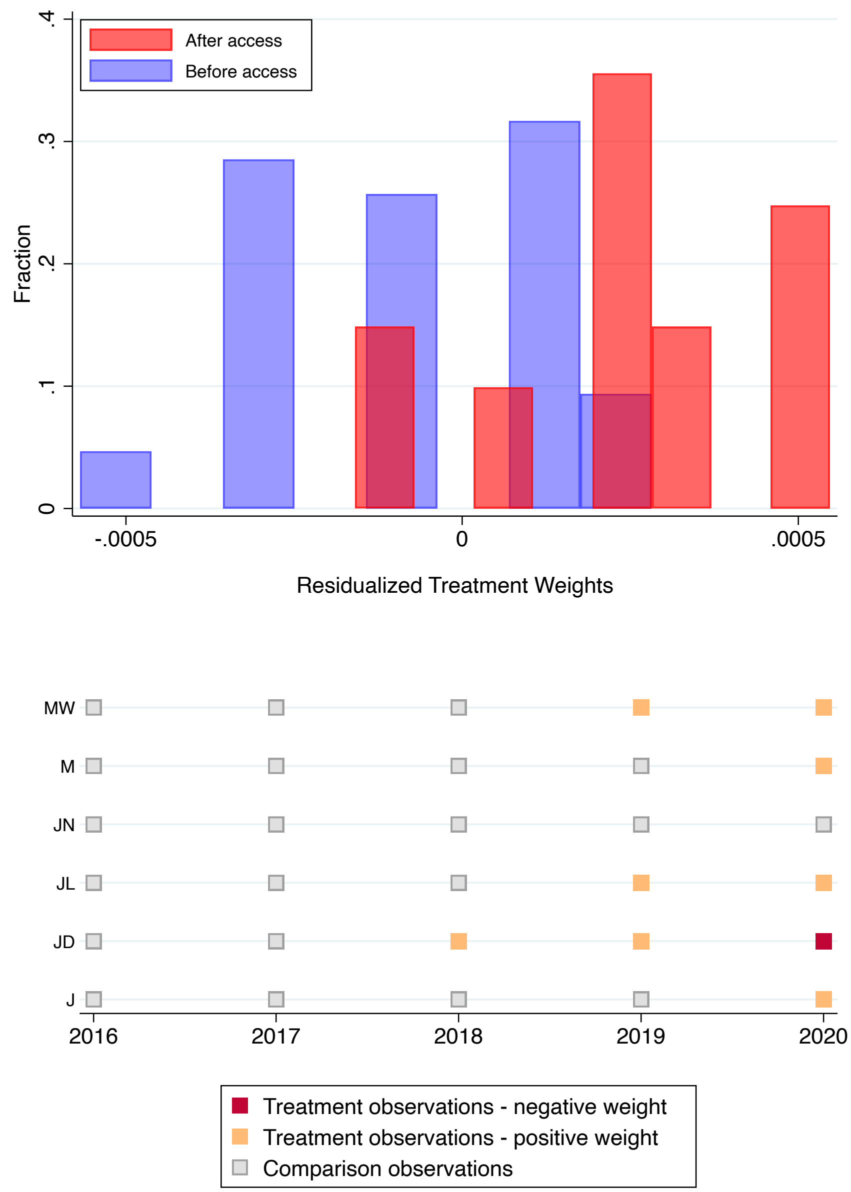


Figure I.1: Weights of Two-Way Fixed Effects.

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

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

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

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

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

I.2 Interaction Weighted Estimator

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

The following equation is estimated:

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

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

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

Table I.2: Interaction Weighted TWFE Estimates

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

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

J Additional Evidence on Product Mix

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

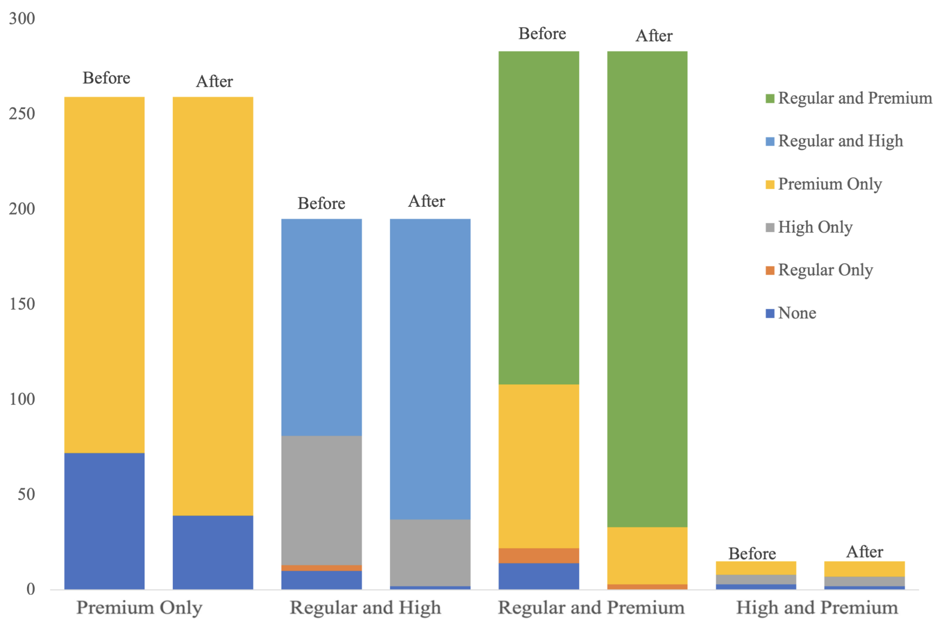


Figure J.1: Qualities Sold Online Before and After GEP access

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

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

K Effects Across Different Pretreatment Channel of Sales

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

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

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

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

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

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

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

L Reconciling the Effect of GEP access

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

L.1 Reconciling the Log Effects

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

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

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

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

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

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

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

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

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

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

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

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

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

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

L.2 Quantitative Approximation with Zero Observations

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

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

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

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

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

M Additional Mediation Analysis

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

M.1 Mediating Role of Shipping Companies on Online Sales

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

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

Table M.1: Mediating Role of Shipping Companies

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

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

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

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

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

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

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

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

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

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

N Follow-up Survey and Results

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

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

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

N.1 Survey Estimation Results

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

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

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

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

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

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

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

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

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

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

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

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

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

N.2 Survey Instrument (English Translation)

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

- (d) No online sales at present

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

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

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

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

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

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

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

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

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