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Transforming consumption: How *E*-commerce reshape online shopping behavior and household spending

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A R T I C L E I N F O

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Staggered difference-in-differences

A B S T R A C T

The high savings, low consumption dilemma among Chinese rural households remains a persistent development challenge. Emerging digital e-commerce adoption may recalibrate this imbalance. This study presents the first systematic examination of how *Rural E-commerce Demonstration Counties* (REDC) program influences rural household consumption patterns, leveraging data from the China Household Finance Survey (CHFS) spanning 2013 to 2021 combined with geospatial Points of Interest (POI) data sourced from navigation platforms. Our staggered difference-in-differences estimates reveal that the REDC program increased rural households' online shopping participation rate by 1.9 percentage points on the extensive margin. At the intensive margin, the program expands consumption options without reducing offline consumption. The mechanism analysis indicates that government investment in logistics serves as the primary channel for the increase in online shopping, accompanied by a concomitant increase in local labor supply that could be associated with more opportunities in logistics. Furthermore, we verify the digital inclusive function of e-commerce through heterogeneity analysis and find that households with limited resources benefit more from the REDC program. Our findings advance understanding of how targeted e-commerce policies reshape households' consumption patterns, offering developing countries actionable insights for designing digital inclusion programs.

1. Introduction

Developing economies worldwide face the persistent challenge of stimulating household consumption amidst disproportionately high savings rates. From the perspective of lifecycle hypothesis (Modigliani & Cao, 2004), such excessive precautionary savings suggest welfare losses through distorted intertemporal consumption allocation. Neoclassical growth theory further indicates potential capital misallocation when savings persistently outstrip productive investment opportunities (Solow, 1956). This dual efficiency concern—micro-level household welfare versus macro-level capital productivity—establishes the economic significance of consumption behavior analysis. Boosting consumption is crucial to enhancing rural welfare, expanding domestic demand, and driving broader economic growth.

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China's experience epitomizes this global paradox, with World Bank data indicating average national savings rates of 44.4 % compared to 22.4 % in OECD countries in 2023.[1] Nevertheless, a divergence between urban and rural residents persists despite narrowed income disparities. While national consumption growth averaged 7.3 % annually from 2012 to 2022,[2] in 2021, per capita consumer expenditure was 30,307 yuan for urban residents and 15,916 yuan for rural residents—nearly double among urban populations.[3] This study investigates how digital platforms might recalibrate the savings-consumption equilibrium in rural China, providing insights applicable to developing economies combating similar demand-suppression dynamics through technological leapfrogging.

E-commerce is a leading form of digital transformation in contemporary society. To stimulate rural consumption and encourage online shopping, the government has introduced substantial initiatives to advance rural e-commerce. Since 2015, the annual “No. 1 Central Document” has promoted the *Rural E-commerce Demonstration Counties* policy. This policy exemplifies a collaborative effort between governmental and market forces to establish a public e-commerce service system, a three-tiered logistics network across counties, towns, and villages, as well as comprehensive training and marketing frameworks. These initiatives aim to explore institutional mechanisms and policy frameworks essential for rural e-commerce advancement.

The implementation of national e-commerce policies tailored to rural areas has spurred rapid growth in rural e-commerce, significantly increasing rural residents' incomes and facilitating the development of essential infrastructure, including logistics networks. From 2014 to 2021, the *Rural E-commerce Demonstration Counties* initiative received over 27 billion yuan from central government, establishing 2400 county-level e-commerce service centers and logistics hubs, along with 148,000 village-level logistics service stations. These initiatives have raised incomes for 6.18 million impoverished farmers and played a crucial role in alleviating rural poverty.[4]

How to effectively leverage digital technology and e-commerce to stimulate household consumption growth and upgrade, while promoting urban-rural economic integration, is an important topic that is underestimated. This paper analyzes whether the *Rural E-commerce Demonstration Counties* program increases the probability of households engaging in online shopping and raises per capita online spending. Our study presents several key findings. Firstly, the program increased the probability of households shopping online by 1.9 %, and this result remains robust after a series of robustness checks. Heterogeneity analysis suggests that the program's impact is equally distributed across urban and rural area, which may narrow the digital divide. Secondly, the program has supported residents with lower levels of physical and human capital by organizing training sessions and improving logistics, thus assisting them in overcoming inefficiencies in market access and transaction barriers. Furthermore, we find that while the program has expanded consumption channels, it has not crowded out offline consumption. Finally, due to the lower search costs, reduced fixed costs, and diminished contractual frictions inherent in e-commerce, the program has reduced transaction costs and improved consumption efficiency. The time saved through online shopping has further increased residents' labor supply. Using POI data, our findings indicate that the policy gradually exerts a positive impact on the number of logistics points at the town level, while no significant effect is observed at the subdistrict or township levels. Effectively resolving the “last mile” challenge in the downward distribution of consumer goods could substantially enhance the policy's influence on household online shopping.

This paper makes several significant contributions to the existing literature. First, while prior studies predominantly examine rural e-commerce's impacts on poverty alleviation (Peng et al., 2021; Qin & Fang, 2022), online entrepreneurship (Zhao et al., 2024), or subjective well-being (Wei et al., 2024), we shift the focus to household consumption behavior. Leveraging nationally representative household finance surveys (CHFS 2013–2021), we provide the first micro-level evidence that e-commerce policies directly increase online shopping participation and expenditure. This behavioral approach addresses measurement limitations in subjective well-being studies and complements income-centric poverty analyses by capturing consumption channel diversification—a critical yet understudied dimension of material welfare.

Second, we advance the literature by systematically analyzing how specific government expenditures under the REDC program stimulate online shopping, whereas prior work predominantly focuses on whether the policy affects downstream outcomes like entrepreneurship (Dong et al., 2024; Zhao et al., 2024). Leveraging procurement information from the China Government Procurement Network, we identify four initiating-end policy instruments: (1) county-level logistics infrastructure, (2) e-commerce training systems, (3) public service platforms, and (4) marketing support. Additionally, we utilize POI data to verify that the development of logistics infrastructure, as evidenced by the expansion of delivery stations at the township level, functions as the primary mechanism. This supply-side analysis complements existing recipient-end studies by revealing how targeted fiscal allocations alleviate rural market access constraints.

Finally, our methodological innovation lies in the multi-source data integration framework, incorporating nationally representative micro-level China Household Finance Survey data spanning 2013–2021(CHFS), and spatial-geographic Point of Interest data (POI). The breadth and timeliness of this dataset enable the study to examine the policy's impact on household consumption not only in rural areas but also at the county level. This paper distinguishes itself from existing studies, such as those by Qin and Fang (2022) and Qin et al. (2023), which are primarily limited to data from county-level statistical yearbooks. We explore how e-commerce development influences online consumption behaviors and how these shifts subsequently reshape household consumption structures, driven

[1] Accessed from the website:https://data.worldbank.org.cn/indicator/NY.GDS.TOTL.ZS?locations=OEhttps://data.worldbank.org.cn/indicator/NY.GDS.TOTL.ZS?locations=CN

[2] Accessed from the website:https://data.worldbank.org.cn/indicator/NE.CON.PRVT.KD.ZG?end=2022&locations=CN&start=1996&view=chart

[3] Accessed from the website: https://www.stats.gov.cn/xxgk/jd/sjjd2020/202201/t20220118_1826611.html

[4] Accessed from the website:http://chinawto.mofcom.gov.cn/article/ap/p/202206/20220603316032.shtml

by evolving consumption habits. Our use of comprehensive nationwide POI data allows us to identify which specific types of logistics operations are most impacted by the program and to determine the particular administrative level—whether subdistrict, town, or township—at which these effects are most pronounced.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature and presents a theoretical framework on the impact of rural e-commerce development on consumption. Section 3 examines the policy background, offering an overview of the policy, detailing its implementation steps, and outlining the primary uses of funding. Section 4 presents the research design, explaining the sample and model construction, and includes a brief descriptive analysis of the relationship between the policy and household online shopping behavior. Section 5 presents the empirical results, including the main regression analysis, robustness checks, heterogeneity analysis, and mechanism tests. Section 6 offers further discussion and analysis, building on the results from Section 5 to explore the policy's impact on household consumption structure and the potential substitution effects between online and offline consumption. Finally, Section 7 concludes the study and provides policy implications.

2. Literature review and theoretical framework

E-commerce generally refers to commercial activities centered around the exchange of goods, facilitated by information and communication technologies. It can be categorized into online sales, online consumption, and related support services, including logistics and internet infrastructure. This paper primarily focuses on household online shopping and its associated support services.

Although the penetration of e-commerce is crucial for promoting household online shopping and improving consumption patterns, comprehensive evaluations of the *Rural E-commerce Demonstration Counties* (REDC) program remain lacking. Previous works have extensively discussed the impact of the REDC program on economic development. The program has been shown to significantly boost per capita income and GDP across different regions, highlighting its effectiveness in promoting rural economic growth and poverty alleviation (Qin et al., 2023; Qin & Fang, 2022). The importance of digital infrastructure and human capital investment in enhancing rural income through e-commerce has also been emphasized (Peng et al., 2021). Furthermore, recent research documents the program's dual entrepreneurial outcomes: improved e-commerce business survival (Zhao et al., 2024) and expanded women's participation in rural entrepreneurship (Dong et al., 2024).

By evaluating the REDC program, this paper seeks to examine the overall impact of e-commerce development on household consumption and identify the underlying mechanisms. In the following sections, we first review how e-commerce enhances consumer welfare to highlight its advantages and policy rationale. Then, we analyze how e-commerce policies promote households' consumption through improving logistics infrastructure and enhancing digital literacy, and present our theoretical framework.

2.1. How e-commerce enhances consumer welfare

Compared to traditional offline shopping, e-commerce significantly enhances consumer welfare by offering greater product variety, higher time efficiency, and lower prices.

Firstly, e-commerce provides consumers with significantly greater product variety by eliminating physical shelf-space limitations inherent to brick-and-mortar stores. This greater product availability enhances consumer welfare, especially in rural areas where offline shopping opportunities are limited (Couture et al., 2021). Fan et al. (2018) further demonstrate that e-commerce reduces spatial consumption inequality by enabling smaller and more remote cities to access a wider variety of goods through lower fixed costs and reduced distance sensitivity in online trade. Existing studies have quantified the welfare gains from increased product diversity using scanner data (Broda & Weinstein, 2006; Redding & Weinstein, 2020) and data from the digital platform (Brynjolfsson et al., 2025).

Secondly, e-commerce saves time and costs associated with in-store shopping by removing geographical barriers. Studies using transaction data reveal that e-commerce generates consumer surplus through lower transportation costs (Dolfen et al., 2023) and time savings reallocated to offline activities (Relihan, 2022). Conversely, physical store entry reduces local consumers' online purchasing and price sensitivity, underscoring e-commerce's convenience value (Forman et al., 2009).

Lastly, e-commerce lowers prices and reduces price dispersion, thereby increasing consumer surplus (Bakos, 1997). This effect is driven by a reduction in search and communication costs: product ranking and review systems help consumers evaluate quality more easily, while search and matching algorithms improve the efficiency of locating desired products (Choi & Suh, 2005). Brynjolfsson and Smith (2000) found that internet prices for books and CDs were 9–16 % lower than in traditional stores, and that online retailers adjusted prices far more frequently due to lower menu costs.

2.2. The role of rural e-commerce policy in shaping household consumption

The welfare gains identified in Section 2.1 have motivated policy interventions to accelerate rural e-commerce adoption, where addressing logistical barriers and improving digital literacy are key to expanding online consumption.

First, overcoming logistical barriers is essential for promoting rural e-commerce adoption, as these barriers significantly impede the efficient delivery of goods to rural consumers. Couture et al. (2021) show that addressing logistical challenges through measures like building transport infrastructure and improving delivery networks can effectively enhance e-commerce access and reduce costs for rural households.

Second, enhancing digital literacy and skills is vital for expanding online consumption in rural areas, aligning with policy efforts to bridge the digital divide and promote inclusive development. Peng et al. (2021) highlight that digital skills training significantly boosts rural income by enabling residents to effectively use e-commerce platforms. Huang et al. (2022) further emphasize that education and digital skills are key factors in ICT adoption and e-commerce use, noting that training programs and intergenerational support can help overcome barriers for older and less educated farmers.

To overcome logistical barriers and enhance digital literacy, the REDC allocates funds to build four key systems: (1) *E*-commerce Public Service Systems, (2) Logistics and Supply Chain Systems, (3) E-commerce Training Systems, and (4) Promotion Marketing Systems. As Section 3.2 demonstrates, this targeted investment framework directly addresses both foundational infrastructure needs and human capital development.

Building on the literature review as well as the REDC's policy design, we develop a theoretical framework to inform our empirical investigation (see Fig. 1).

3. Policy background

3.1. The implementation of REDC program

The *Rural E-commerce Demonstration Counties* (REDC) program operates on an "application-approval" basis, providing support as illustrated in Fig. 2. Counties submit applications, and upon approval by the Ministry of Commerce, they receive financial support to develop local e-commerce. The central government allocates approximately 20 million yuan to each demonstration county. After two years, outcomes are evaluated using a scoring system; if a county's score does not meet the required standards, funding is reduced, and counties deemed unqualified may be required to repay the funds. By 2020, the policy had achieved full coverage of all 832 impoverished counties. At the provincial level, the five provinces with the highest number of REDC counties are the Tibet Autonomous Region, Sichuan Province, Yunnan Province, Shaanxi Province, and Guizhou Province, collectively accounting for 682 demonstration counties—approximately 37 % of the national total.[5] By the end of 2021,[6] the program had supported a total of 1841 counties and districts, covering all 832 impoverished counties, with cumulative central government funding exceeding 27 billion yuan.

3.2. Primary uses of REDC policy funds

The government encourages local authorities to explore various support mechanisms, including service procurement, government equity investment, public-private partnerships (PPP), performance-based rewards, and interest subsidies. These approaches aim to leverage fiscal funds to attract social capital to participate in rural e-commerce initiatives.[7] In practice, each demonstration county has adopted different policy measures to support county-level e-commerce projects, resulting in varying levels of effectiveness. This section compiles data from the China Government Procurement Service Information Platform, detailing the specific usage of funds in 125 REDC counties from 2014 to 2021.

As shown in Fig. 3, the signing of government procurement contracts[8] for the first batch of REDC counties was concentrated within 1–2 years after they were designated as demonstration counties, with contract amounts typically around 15 million yuan. The fiscal funds provided by the policy enabled local governments to implement various support measures, such as expanding consumer facilities, improving the e-commerce development environment, and reducing costs for farmers to engage in e-commerce, we divide the measures into the following four aspects:

1. *E*-commerce public service systems

A well-functioning public service center plays a critical role in driving the development of the e-commerce industry at the county level. In the county e-commerce system, the construction of public service centers typically focuses on integrating resources from various sectors to establish training programs, logistics systems, rural service stations, rural product marketing, and supply chain networks. These centers aim to address challenges related to entrepreneurship training, creating a supportive e-commerce environment, facilitating the sale of agricultural products, and promoting consumer goods, thereby making it easier for nearby villagers to buy and sell products.

2. Logistics and supply chain systems

Achieving the "last mile" of courier services to rural areas and the "first mile" of agricultural product distribution is crucial to resolving the logistics challenges rural areas face when participating in e-commerce activities. This includes the construction of a three-tier logistics system spanning counties, towns, and villages, as well as the development of warehousing centers, product supply chains, and traceability systems.

[5] The list of Rural *E*-commerce Demonstration Counties from 2014 to 2021 is derived from documents issued by the State Council's Office of Poverty Alleviation, the Ministry of Commerce, and the Ministry of Finance. The designation of impoverished counties is based on the list of 832 counties published in 2014 by the National Rural Revitalization Administration.

[6] See Appendix 2 for detailed information about the development goals and key support areas of the REDC policy across years.

[7] See Appendix 2 for detailed information about the implementation of REDC program

[8] See appendix 1 for the contracts of different kinds.

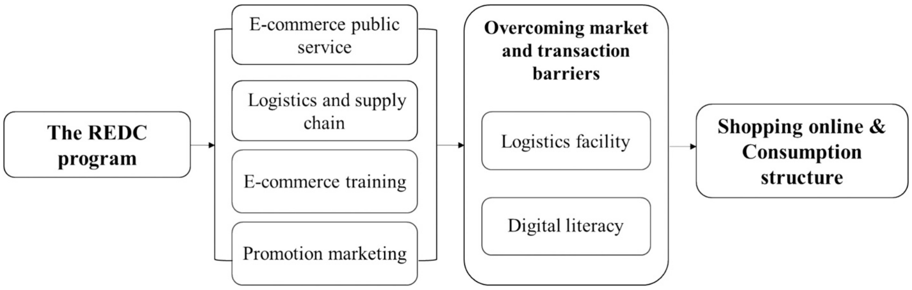


Fig. 1. Theoretical Framework.

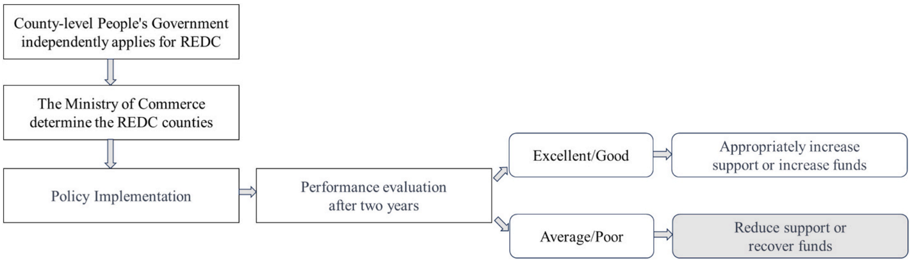


Fig. 2. Implementation Process of the Rural *E*-commerce Demonstration Counties Program.

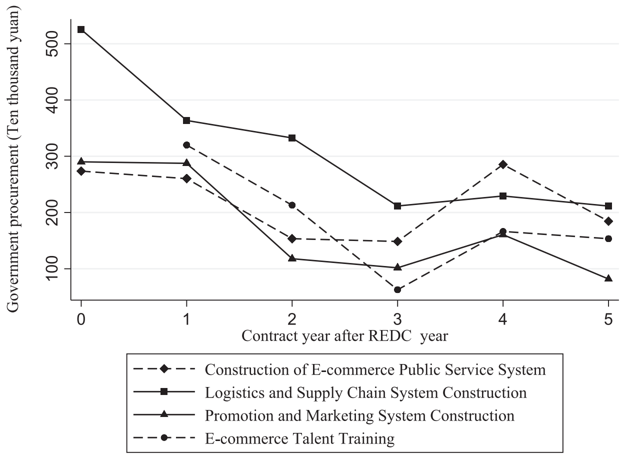


Fig. 3. Distribution of government procurement amounts of the REDC program.
Note: China Government Purchasing Service Information Platform.
See Appendix 2 for detailed information about the implementation of REDC program.

3. *E*-commerce training systems

Strengthening farmer training to enhance their knowledge and skills in e-commerce is a key prerequisite for their participation in e-commerce activities. Acquiring the necessary knowledge and capabilities to engage in e-commerce is essential for farmers to successfully operate in this field.

4. Promotion marketing systems

Actively building a promotion and marketing system for local products helps establish strong branding and prevent damage to the reputation of local industries due to quality issues. This ensures the continuous optimization of the e-commerce development environment. Such efforts include coordinating services related to quality control, branding, certification, training, and marketing.

As shown in Fig. 3, the largest portion of fiscal funds is primarily allocated to the construction of logistics and supply chain systems, with expenditures of around 3–4 million yuan. This is followed by investments in the e-commerce public service system, which amount to approximately 2–3 million yuan. The amounts allocated to e-commerce talent training and the development of the promotion and marketing system are similar, ranging from 1 to 2 million yuan. In summary, policy funds are typically disbursed 1–2 years after the contracts are signed, and the full rollout of the policy takes around two years. Therefore, the policy generally begins to show its effects 3–4 years after a county is designated as an REDC.

4. Research design

4.1. Data sources

1. China Household Finance Survey

This study uses data from the China Household Finance Survey (CHFS) from 2013 to 2021, a national sampling survey project conducted by the Survey and Research Center for China Household Finance. The CHFS aims to collect micro-level information on household finances, covering topics such as housing assets and financial wealth, debt and credit constraints, income and consumption, social security and insurance, intergenerational transfers, demographic characteristics and employment, and payment habits. The overall sampling design of the survey employs a stratified, three-stage sampling method with probability proportional to size (PPS). Since 2011, six rounds of the survey have been successfully conducted, with the sample distributed across 29 provinces, 355 counties (districts and county-level cities), and 1428 communities. The survey covers 40,011 households and 127,000 individuals, with representativeness at the national, provincial, and sub-provincial city levels. In addition to household-level data, this study also uses data from the China Urban and Rural Governance Survey, which was conducted at the community level by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics. This survey covers both urban residential communities and rural areas, collecting data on community characteristics, public services, community economy, governance structure, environmental sanitation, social security, education and culture, and grassroots legal systems. County-level socio-economic indicators were sourced from the *China County Economic Statistical Yearbook*, the *China City Statistical Yearbook*, and statistical data collected by local government statistical bureaus.[9]

2. Points of Interest (POI) data

As a form of point-based geospatial big data representing real-world geographic entities, Points of Interest (POI) are significant geographic objects within the spatial environment. POI datasets not only share the typical characteristics of big data—such as large volume, high processing speed, diversity, accuracy, and embedded value—but also contain detailed information for each entity, including name, latitude and longitude, address, type, phone number, and administrative region. These data reflect the correlation between human activities and geographic locations. The POI data used in this study are sourced from navigation electronic map platforms (Baidu/Gaode), offering rich and precise information with timely updates. The data cover the period from 2012 to 2021.[10]

4.2. Variable definition and descriptive statistics

1. Dependent variable

This study examines two dependent variables: whether a household engages in online shopping and the structure of its online and offline consumption. Household online shopping activity is determined based on the survey question regarding whether the household has any experience with online shopping. This activity serves as a proxy for consumption efficiency, as online shopping reduces transaction costs. Household online consumption is measured by the survey question asking how much the household spent on online shopping in total. Additionally, the survey includes detailed questions about various types of consumption expenditures, allowing total household consumption to be calculated by summing these expenditures.

Due to data limitations, the 2015 survey results are excluded from the analysis of online shopping and consumption because it only provides a measure of whether the household engaged in online shopping in the past month—a measure that differs from those used in other years. Furthermore, because some data on household online consumption is missing, the analysis of offline and total consumption maintains consistency by using the same sample as the one used for online consumption.

From our sample, we conclude that there is no systematic difference between the missing and non-missing data in terms of household characteristics or regional factors. However, since our data relies on self-reported information across various segmented consumer categories, misreporting may introduce bias into our results. Self-reported data tends to be more accurate when respondents clearly understand the questions and feel assured of strong anonymity, minimizing fear of potential consequences. To our knowledge, strict anonymity was maintained in the survey, which likely reduces any potential underreporting. Additionally, since this survey focuses on analyzing household economic and financial behaviors rather than evaluating the REDC program, we believe that respondents' incentive to underreport is relatively low.

[9] Source: China statistical yearbook (county-level), China city statistical yearbook.
[10] See Appendix 5 for a more concrete description of the POI data.

2. Key independent variable

The key independent variable of interest is an indicator for the REDC program, which takes the value of 1 if a county is designated as a demonstration county, and 0 otherwise.

3. Mechanism variables

In analyzing the mechanism, this study gathered detailed data on the allocation of policy funds for treatment counties, sourced from county government websites. These funds were categorized into four primary areas: (1) the construction of e-commerce public service systems, which includes county-level e-commerce public service centers as well as township and village service stations; (2) the development of logistics and supply chain systems, encompassing the three-tier logistics network covering counties, towns, and villages, along with warehousing centers, product supply chains, and traceability systems; (3) the promotion and marketing system, focusing on public branding and the promotion of agricultural products; and (4) e-commerce talent training, which involves establishing a system for training e-commerce professionals. The mechanism variables are measured by the proportion of funds allocated to each category relative to the total funds. For the control group, these values are set to zero.

4. Control variables

From a theoretical perspective, Keynes's Absolute Income Hypothesis and Duesenberry's Relative Income Hypothesis explain, from a static viewpoint, that an individual's consumption is related to both their absolute income and the relative income of others in their environment. In contrast, Friedman's Permanent Income Hypothesis and Modigliani's Life-Cycle Hypothesis consider consumption from a dynamic perspective, emphasizing the influence of an individual's lifetime permanent income. Based on consumption theory, this study controls for household income variables. Furthermore, empirical research on factors influencing household consumption behavior has primarily focused on aspects such as household age structure, dependency ratio, education level, and household assets. Additionally, drawing on the research conducted by Tang et al. (2020), this study incorporates variables related to the industrial structure and economic development levels at the community, village, and county levels. The development of the internet and digital inclusive finance has also significantly promoted household consumption. The definitions of the relevant variables can be seen in Table 1:

Table 2 presents the descriptive statistics of the variables. During the sample period, the probability of households engaging in online shopping was approximately 40.3 %, while the share of online consumption in total consumption remained relatively low, at around 4.9 %. Additionally, we found that 36.1 % of households in REDC counties engaged in online shopping, compared to 41.3 % in Non-REDC counties. Similarly, the share of online consumption in total consumption was approximately 3 % in REDC counties, compared to 5.4 % in Non-REDC counties. This suggests that households in Non-REDC counties tend to engage in online shopping more frequently and have a higher proportion of online consumption.

At the individual level, approximately 84.7 % of household heads were married, with the average age of adults being around 41 years and the average years of education being approximately 11 years. The household dependency ratio was about 63.1 %. About 33.6 % of households resided in rural areas, and the average household size was around three people. Regarding the mechanism variable, counties spent the most on logistics and the least on training. The sample exhibited an unbalanced distribution of control variables, with significant differences across most variables between the two groups. Specifically, household heads in Non-REDC counties were younger and more educated. In terms of household and community characteristics, Non-REDC counties were wealthier and have better internet infrastructure.

4.3. Empirical strategies

1. **Staggered difference-in-differences**

This paper employs the exogenous *Rural E-commerce Demonstration Counties* (REDC) policy to establish a quasi-natural experimental framework, analyzing the impact of e-commerce on household consumption behavior in terms of both online shopping behavior and consumption structure. Potential endogeneity issues are addressed as follows:

Firstly, omitted variable bias may simultaneously affect household consumption and the selection of policy intervention areas. To address this, the model includes region and time fixed effects, which helps to eliminate the influence of omitted variables that either remain constant over time or vary in the same way across all households. Additionally, controlling for individual and socio-economic baseline variables, factors that may influence whether a county is designated as a REDC, mitigates the effects of regional selectivity. As illustrated in Fig. A2, after accounting for control variables, the residuals for online shopping behavior among the untreated group average to zero, suggesting that changes in online shopping behavior within the treatment group are likely attributable to the policy intervention rather than to other concurrent factors. Finally, robustness checks using propensity score matching (PSM) further address selectivity concerns.

Secondly, the potential for reverse causality between household consumption and the REDC policy is considered. First, the differences in variable dimensions help mitigate concerns regarding reverse causality, as the key independent variable is measured at the county level, while the dependent variable is assessed at the household level. Additionally, whether a county is designated as an REDC is primarily determined by its industrial base in the early stages; later, this designation is more closely linked to poverty alleviation,

Table 1
Variable definition.

Variable	Definition
Dependent variable	
Shopping online	Did your household shop online last year? 1 for yes, otherwise 0
Per capita total consumption	Total household consumption / household population (CNY per capita)
Per capita online consumption	Household online shopping expenditure / household population (CNY per capita)
Share of online consumption	Per capita online shopping expenditure / per capita total consumption
Per capita offline consumption	Household offline consumption / household population (CNY per capita)
Share of offline consumption	Per capita offline consumption / per capita total consumption (CNY per capita)
Key independent variable	
REDC	Is the county designated as a Rural *E*-commerce Demonstration County? 1 for yes, otherwise 0
Control variable	
Individual level	
Married	Is the head of household married? 1 for yes, otherwise 0
Age	Age of the head of household
Education	Years of education of the head of household
Party member	Is the head of household a party member? 1 for yes, otherwise 0
Family level	
Dependency ratio	#Members aged 15–64 / #Total members of household
Rural	Does the household reside in a rural area? 1 for yes, otherwise 0
Household population	Number of people in the household
Household assets	Total household assets (CNY)
Household income	Total income of the household (CNY)
Community level	
Population density	Population density of the community (persons per square kilometer)
Per capita annual income	Approximate per capita disposable income of community/village residents (CNY per capita)
Internet access	Is the community/village covered by broadband? 1 for yes, otherwise 0
County level	
Number of industrial enterprises	Number of industrial enterprises above designated size
Fixed asset investment	Share of fixed asset investment in GDP
Share of agriculture	Share of agricultural value added in GDP
Share of manufacturing	Share of manufacturing value added in GDP
Per capita GDP	Per capita GDP
PIEVH[a]	Is the county a pilot for the Project of Information Entering Villages and Households, 1 for yes, otherwise 0.
City level	
BCS[b]	Is the city a pilot for the Project of Broadband China Strategy, 1 for yes, otherwise 0.
NECDC[c]	Is the city a pilot for the Project of National *E*-Commerce Demonstration City, 1 for yes, otherwise 0.
Mechanism variable	
Share of service	Funding share for e-commerce public service system development, set to zero for controls.
Share of logistics	Funding share for logistics and supply chain system development, set to zero for controls.
Share of training	Funding share for e-commerce training system establishment, set to zero for controls.
Share of marketing	Funding share for promotion and marketing system development, set to zero for controls.

[a] This project is aimed at bridging the urban-rural digital divide by providing modern information services to rural areas, improving farmers' access to agricultural information, and promoting rural informatization.
Sources: https://ap.fftc.org.tw/article/1230

[b] On August 17, 2013, the State Council of China released the Implementation Plan of the "Broadband China" Strategy, outlining the development goals and pathways for broadband over the subsequent eight years. This move signified that the "broadband strategy" had been elevated from a departmental initiative to a national strategy, with broadband being recognized as a national strategic public infrastructure for the first time.
Sources: https://baike.baidu.com/item/%E5%AE%BD%E5%B8%A6%E4%B8%AD%E5%9B%BD/1945145

[c] National *E*-commerce Demonstration Cities refer to those cities where the application of e-commerce is relatively widespread and the annual total transaction volume of e-commerce is relatively high. The purpose of designating such cities is to reduce energy consumption and develop a green economy.
Sources: https://baike.baidu.com/item/%E5%9B%BD%E5%AE%B6%E7%94%B5%E5%AD%90%E5%95%86%E5%8A%A1%E7%A4%BA%E8%8C%83%E5%9F%8E%E5%B8%82/1762285?fr=aladdin#reference-1

which has little direct relationship with household consumption.

Third, measurement error must be addressed. In the robustness checks, alternative measures of both the dependent and independent variables are employed, and the results remain robust.

The assumptions underlying the DID model are fully satisfied within our research context. Regarding potential anticipation effects, the event study analysis (see Fig. 4) confirms that the pre-trend is stable, with no significant announcement effects detected. Concerning the Stable Unit Treatment Value Assumption (SUTVA), this study assumes that the policy's impact on household consumption behavior does not produce substantial externalities.

Our model is specified as follows:

Table 2
Summary statistics for variables of interest.

Variable	Full sample			REDC		Non-REDC		Diff.
	N	Mean	SD	Mean	SD	Mean	SD	Mean
Household consumption								
Shopping online	119,603	0.403	0.490	0.361	0.003	0.413	0.002	−0.052***
Per capita total consumption	52,259	26,808.68	39,282.79	17,095.21	253.555	29,353.52	204.603	−12,258.3***
Per capita online consumption	52,577	1585.117	4988.641	597.036	22.137	1844.462	26.700	−1247.426***
Share of online consumption	52,259	0.049	0.078	0.030	0.001	0.054	0.000	−0.024***
Per capita offline consumption	52,259	25,218.62	37,508.51	16,494.62	247.309	27,504.22	195.116	−11,009.6***
Share of offline consumption	52,259	0.951	0.078	0.970	0.001	0.946	0.000	0.024***
Policy								
REDC	119,603	0.191	0.393	1.000	0.000	0.000	0.000	1.000
Household head characteristics								
Married	119,603	0.847	0.360	0.857	0.002	0.844	0.001	0.013***
Age	119,588	41.169	19.267	41.400	0.129	41.114	0.062	0.286**
Education	119,586	11.529	4.130	10.290	0.028	11.822	0.013	−1.532***
Party member	119,603	0.572	0.495	0.625	0.003	0.560	0.002	0.065***
Household characteristics								
Dependency ratio	119,603	0.631	0.735	0.705	0.005	0.614	0.002	0.091***
Rural	119,603	0.336	0.472	0.574	0.003	0.279	0.001	0.295***
Household population	119,603	3.207	1.574	3.421	0.011	3.156	0.005	0.265***
Household asset (in log)	119,600	12.676	1.745	12.182	0.010	12.793	0.006	−0.611***
Household income (in log)	119,368	10.535	1.477	10.184	0.010	10.618	0.005	−0.434***
Community characteristics								
Population density (in log)	118,951	8.253	3.201	7.475	0.023	8.437	0.010	−0.961***
Per capita annual income (in log)	119,313	9.053	1.138	8.672	0.008	9.143	0.004	−0.471***
Internet access	51,253	0.902	0.297	0.911	0.003	0.900	0.001	0.010***
County characteristics								
Number of industrial enterprises	117,744	249,391	327,197	118.999	1.397	279.023	1.104	−160.024***
Fixed asset investment	117,744	0.819	0.422	0.961	0.005	0.787	0.001	0.174***
Share of agriculture (%)	117,744	0.178	0.092	0.218	0.001	0.169	0.000	0.048***
Share of manufacturing (%)	117,744	0.469	0.107	0.444	0.001	0.474	0.000	−0.030***
Per capita GDP	117,744	10.351	0.681	9.978	0.005	10.435	0.002	−0.457***
PIEVH	119,603	0.774	0.418	1.000	0.000	0.721	0.001	0.279***
City characteristics								
BCS	119,603	0.490	0.500	0.215	0.003	0.555	0.002	−0.339***
NECDC	119,603	0.381	0.486	0.297	0.003	0.401	0.002	−0.104***
Mehcanism variable								
Share of service	119,603	0.034	0.088	0.179	0.001	0.000	0.000	0.179***
Share of logistics	119,603	0.085	0.204	0.444	0.002	0.000	0.000	0.444***
Share of training	119,603	0.018	0.044	0.096	0.000	0.000	0.000	0.096***
Share of marketing	119,603	0.035	0.095	0.185	0.001	0.000	0.000	0.185***

Note: All consumption-related variables have been deflated using the provincial consumer price index (CPI), with values based on constant 2013 prices.
Source: China Household Finance Survey, round 2013, 2017, 2019, and 2021.

$$Y_{ivct} = \beta_1 REDC_{ct} + \omega Control_{ivct} + \theta Z_{ivc} * f(t) + county_c + year_t + \delta_{pt} + \pi_{ct} \quad (1)$$

The dependent variable Y_{icvt} represents a set of outcome variables, such as whether the household engages in online shopping and various measures of household consumption, including online consumption, offline consumption, and total consumption. Here, i represents the household, v represents the community or village, c represents the county, and t represents the year. If county c is designated as a *Rural E-commerce Demonstration County* and is surveyed in year t, then $REDC_{ct}$ equals 1. $REDC_{ct}$ is equivalent to $County_c \times Post_t$. $Control_{ivct}$ includes individual and household level variables, such as whether the household head is married, age of the head of household, years of education of the head of household, is the head of household a party member, the household dependency ratio, household size, and whether the household resides in a rural area. To mitigate inconsistencies in the estimated coefficients that may result from including variables influenced by the policy post-treatment, this study additionally controls for Z_{ivc}, which includes a series of household level, community/village, county-level and city-level variables based on baseline characteristics prior to REDC implementation. These variables include total household assets and income, population density, per capita disposable income of community/village residents, county-level GDP, and industrial structure etc. Notably, we control for the baseline family and community/village income to rule out the potential mechanism that policy affects household consumption through income improving. The interaction terms between the pre-determined variables Z_{ivc} and the time trend $f(t)$ are controlled to account for potential time trend differences across households and regions. The time trend $f(t)$ is specified as a linear time trend, i.e., $f(t) = t$. $county_c$ represents county fixed effects, $year_t$ represents year fixed effects, and δ_{pt} represents provincial-year time trends. Clustering is conducted at the county level. The coefficient β_1 of $REDC_{ct}$ is the DID estimator of primary interest in this study.

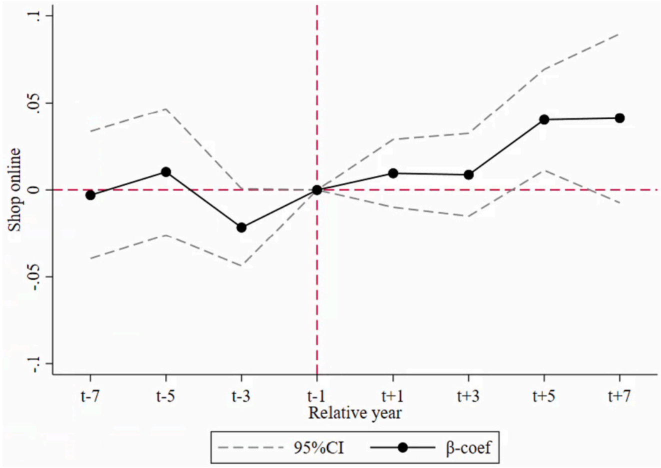


Fig. 4. The dynamic impacts of REDC on household online shopping behavior.
Note: Since the Rural *E*-commerce Demonstration Counties (REDC) policy is evaluated once per year and the China Household Finance Survey (CHFS) is conducted every two years, this paper combines 2014 and 2015 as one year, 2016 and 2017 as one year, 2018 and 2019 as one year, and 2020 and 2021 as one year in the actual analysis.

2. Dynamic DID approach

To ensure the validity of the difference-in-differences (DID) model specified in the baseline regression Eq. (1), a parallel trend test is conducted. The fundamental assumption for the unbiased estimation of β_1 in Eq. (1) is that, in the absence of the e-commerce policy intervention, the trend in the probability of online shopping should be parallel between the control group and the treatment group. This study uses a dynamic difference-in-differences approach to verify this assumption, with the regression equation presented as follows:

$$Y_{ivct} = \sum_{\substack{\tau=-7 \\ \tau\neq-1}}^{\tau=7} \delta_\tau D_{ct}^{\tau} + \omega Control_{ivct} + \theta Z_{ivc} {}^{*} f(t) + county_c + year_t + \delta_{pt} + \pi_{ct} \tag{2}$$

Where Y_{ivct} represents whether the household engages in online shopping. τ refers to the relative year, which is the difference between the actual year and the policy implementation year. The key explanatory variable is $D_{ct}^{\tau}\{t - G_c = \tau\}$, which indicates the number of periods τ between year t and the initial policy intervention in county c (denoted as G_c). It is important to note that the dummy variable for $\tau = -1$ is omitted in Eq. (2), meaning that $\tau = -1$ is treated as the baseline period, with the policy effect set to zero. This approach allows Eq. (2) to estimate the policy effects for each year after the implementation of the e-commerce policy relative to the baseline period.

The series of coefficients δ_τ estimated from Eq. (2) reflect the effects of the policy for each year before and after its implementation. When $\tau \leq -2$, δ_τ captures the differences in the probability of household online shopping between pilot counties and non-pilot counties before the policy was implemented. If the households in the pilot and non-pilot counties satisfy the parallel trend assumption, there should be no significant difference, meaning that the policy effect should equal 0 when $\tau \leq -2$. Conversely, for $\tau \geq 0$, δ_τ reflects the dynamic changes in the policy's effects as the duration of its implementation increases. The definitions of other variables remain the same as those in the baseline equation.[11]

5. Results

5.1. The impact of REDC on online shopping behavior

This section first analyzes the impact of the REDC policy on household online shopping behavior. Table 3 reports the baseline regression results for the effect of the REDC policy on household online shopping. In Column (1), only county and year fixed effects are controlled for. Columns (2) and (3) progressively add household head, household, and regional control variables based on Column (1), as well as the concurrent county and city level policy for county areas, to rule out the influence of similar policies during the same period. Specifically, in the estimation of Column (3), the coefficient of the REDC policy variable is 0.019, indicating that the policy

[11] See Appendix 3 for the primary inspection of the data.

Table 3
The impact of REDC program on household online shopping behavior.

Variable	Shopping online (1 for yes)				
	(1)	(2)	(3)	(4)	(5)
REDC	0.020**	0.022**	0.019**	0.030**	0.020**
	(0.009)	(0.009)	(0.009)	(0.014)	(0.009)
Household head control		Yes	Yes	Yes	Yes
Household control		Yes	Yes	Yes	Yes
Community control			Yes	Yes	Yes
County control			Yes	Yes	Yes
PIEVH policy			Yes	Yes	Yes
BCS policy			Yes	Yes	Yes
NECDC policy			Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes	Yes
Observation	119,603	119,603	115,860	94,794	96,816
Adjusted R^2	0.120	0.120	0.356	0.358	0.346

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses. Column 4 drops samples that joined the REDC policy between 2017 and 2021. Column 5 accounts for the impact of the COVID-19 pandemic by excluding the 2021 sample. The Project of Information Entering Villages and Households (PIEVH) is a similar policy concurrent with the REDC program, where counties listed this policy are coded as 1, and others as 0. BCS policy and NECDC policy are the programs occurred at the city level, which are "Project of Broadband China Strategy" and "Project of National *E*-Commerce Demonstration City", respectively. Due to inconsistencies in the statistical scope of the China Household Finance Survey (CHFS) data between 2015 and other years, the variable for whether households shopped online last year is missing for 2015. Therefore, only data from 2013, 2017, 2019, and 2021 are used. Unless otherwise specified, the settings in the table are similar.

intervention increased the probability of household online shopping by 1.9 %, which is significant at the 5 % level.

Furthermore, as discussed in Section 3, we found that the policy exhibits a lagged effect, with the effective implementation period lasting 3 to 4 years. By 2021, only the first three batches of counties selected between 2014 and 2016 had essentially completed the policy implementation. Including samples from counties that joined the program in 2017 or later could introduce estimation bias. Therefore, in Column 4 of the table, we exclude samples from counties that joined the policy after 2017, and the results remain significantly positive. Additionally, the outbreak of COVID-19 in 2021 may have increased the likelihood of online shopping. In Column 5, based on Column 3, we further exclude the 2021 sample, and the results remain robust.

Other control variables are generally consistent with existing literature regarding significance levels and coefficient signs. The higher the years of education of the household head and the greater the total household income, the more likely households are to engage in online shopping. Conversely, as the age household' head increases, the likelihood of online shopping decreases. Households in regions with higher levels of economic development are more likely to engage in online shopping. We also considered population density as a proxy for market size and potential, and the results indicate that in regions with higher population density, the probability of household online shopping is greater. Additionally, higher regional per capita income significantly promotes the probability of individual online shopping. Due to space limitations, the robustness analysis of the baseline staggered DID specification can be found in Appendix 7.

5.2. Parallel trend tests

Fig. 4 displays the results of the parallel trend test for household online shopping. Each point in the figure represents the estimated value of the parameter δ_τ for each period, with dashed lines indicating the 95 % confidence interval for each estimate. As shown in the figure, the coefficients for REDC in the 1st, 2nd, 3rd, and 4th periods before the policy pilot are not significantly different from zero, and the changes in the coefficient values are relatively stable. This finding suggests that there were no significant differences between the treatment and control groups prior to the implementation of the REDC policy. Based on these observations, we infer that the pre-treatment trends in the probability of household online shopping were similar between the experimental and control groups. Consequently, households in non-pilot counties during the sample period can serve as a valid control group for those in pilot counties.

Additionally, when examining the periods following the policy's implementation, no noticeable trend change is observed in the 1st and 2nd periods after the initiation of the *Rural E-commerce Demonstration Counties* policy, indicating a clear lag in the policy's effects. As illustrated in Fig. 3, this delay may be attributed to government procurement contracts in pilot counties, which were predominantly signed 1–2 years after their designation as demonstration counties. Typically, it takes two years for the policy to be fully implemented following contract signing. Consequently, if the observation period is too short, the actual effects of the policy may not be apparent.

Starting in the 3rd period, the policy gradually begins to positively impact household online shopping behavior, with the treatment group exhibiting significantly higher levels than the control group. Furthermore, the impact intensifies over time, suggesting that the policy's effects strengthen as the implementation period extends. Notably, the policy's influence on household consumption habits is long-lasting and does not diminish even after the policy ends.

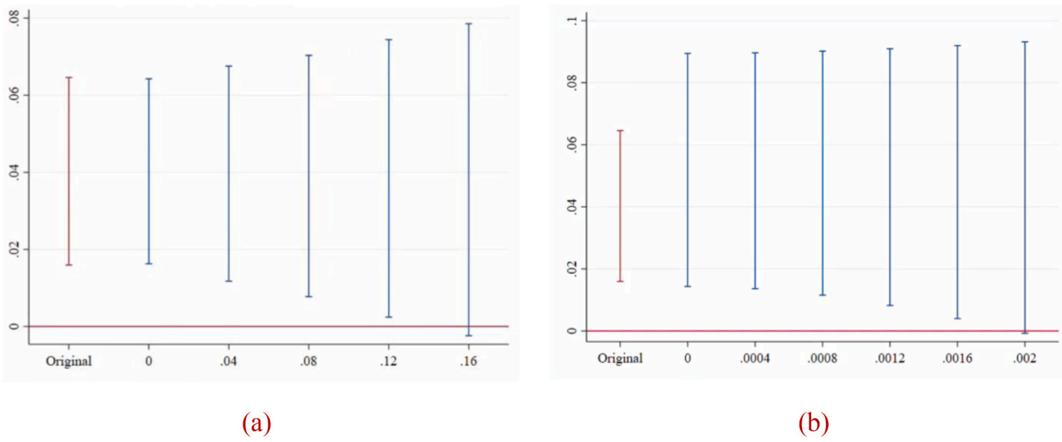


Fig. 5. Sensitivity Test.

5.3. *Parallel trends sensitivity test*

Although this paper tests the absence of pre-treatment trends using the event study method, the latest literature suggests that pre-treatment trend tests are statistically inefficient and may be biased (Roth et al., 2023). Therefore, it is necessary to conduct sensitivity analyses of parallel trends in the context of policy implementation (Rambachan & Roth, 2023). The main principle is to examine the impact of violations of parallel trends on the coefficients and confidence intervals of the policy variable, including two methods: relative deviation bounds and smoothness bounds. The specific steps are as follows: select and construct the maximum deviation from parallel trends based on the research context, and then construct the confidence interval for the post-reform policy variable corresponding to this deviation. If the estimator is significantly different from 0, it indicates that the estimated value of the policy variable is robust to deviations from parallel trends. Since the households affected by the policy experience the greatest positive impact in the third year following the policy shock, the robustness analysis for households in the third year after the policy shock is presented below. Fig. 5 (a) and Fig. 5 (b) present the results of the parallel trends sensitivity analysis under relative deviation bounds and smoothness bounds, respectively. The estimation results show that for households affected by the policy, both the estimated coefficients under the relative deviation bounds and the sensitivity analysis results under the smoothness bounds indicate a positive impact in the third period following the policy shock, thereby confirming the robustness of the benchmark regression results.[12]

In addition, this paper conducts sensitivity analyses for other periods following policy implementation, with the estimation results presented in Appendix 4 in Fig. A4. The sensitivity analysis results under both relative deviation bounds and smoothness bounds demonstrate the robustness of the benchmark regression findings in this study.

5.4. *Selection bias and spillover effects*

1. **Screen process**

The following section outlines the screening procedure for these variables. Initially, we examined the differences in various socioeconomic characteristics of the counties between the treated and control groups prior to the implementation of the policy. The results are shown in Table 4. The *t*-test findings indicate that the means of these variables (including community, county and city charateristics) are significantly different across the two groups, suggesting that they could serve as potential selection criteria for a county to be designated as an REDC.

Second, we conducted a regression analysis of these variables on *Whether this county will become a REDC county or not* in Table 5 column (1) and discovered that the coefficients of almost all these variables are statistically significant. In other words, these eleven variables play a crucial role in determining the REDC treatment status and are essential for our main specification (Wei et al., 2024). Furthermore, we created separate cross-sectional datasets for each REDC batch, and the results are displayed in Table 5 column (2)–(4). In most columns, these characteristic variables are found to be statistically significant.

We also examined the impact of controlling for these community, county and city level characteristics, since Table 6 indicates that individual and household characteristics show significant differences between the REDC and Non-REDC groups. To address potential concerns about selective pilot implementation, we assessed whether the differences between the two groups were diminished by including these specific control variables (Ma & Mu, 2020). The regression results are shown in Table 6. In columns (5), where the

[12] Since this study has controlled for contemporaneous policy variables and there were no significant shocks during 2015–2021 other than the COVID-19 pandemic, it can be reasonably determined through the research framework, policy context, and economic theory that post-treatment temporal trends will not surpass this critical threshold.

Table 4
County baseline characteristics between the treated and control group.

	Control group		Treated group		T-test
	Mean	Sd	Mean	Sd	Diff
	(1)	(2)	(3)	(4)	(5)
Population density (in log)	6.94	0.01	8.65	0.01	−1.71***
Per capita annual income (in log)	8.32	0.00	9.05	0.00	−0.73***
Internet access	0.79	0.00	0.94	0.00	−0.15***
Number of industrial enterprises	137.45	1.21	278.40	1.34	−140.95***
Fixed asset investment	0.88	0.00	0.79	0.00	0.09***
Share of agriculture (%)	0.21	0.00	0.16	0.00	0.05***
Share of manufacturing (%)	0.44	0.00	0.49	0.00	−0.04***
Per capita GDP	9.96	0.00	10.45	0.00	−0.49***
PIEVH	0.00	0.00	0.00	0.00	0.00
BCS	0.07	0.00	0.43	0.00	−0.36***
NECDC	0.00	0.00	0.00	0.00	0.00

Notes: Columns (1) and (2) report the means and standard deviation of the control group. Columns (3) and (4) report the means and standard deviation of the control group. Column (5) shows the results of the t-test between control and treated groups. The significance levels of 1 %, 5 %, and 10 % are denoted by ***, **, and *, respectively.

Table 5
County characteristics for all sample and different batches.

Variable	REDC (1 for yes)			
	All Sample	Year = 2017	Year = 2019	Year = 2021
	(1)	(2)	(3)	(4)
Population density (in log)	−0.003***	−0.019***	−0.010***	−0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Per capita annual income (in log)	−0.025***	−0.033***	−0.051***	−0.057***
	(0.001)	(0.002)	(0.002)	(0.004)
Internet access	−0.090***	−0.075***	−0.146***	−0.140***
	(0.004)	(0.006)	(0.008)	(0.012)
Number of industrial enterprises	0.000***	0.000***	0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed asset investment	0.106***	0.129***	0.135***	0.141***
	(0.003)	(0.005)	(0.006)	(0.006)
Share of agriculture (%)	0.028	0.210***	−0.036	−0.364***
	(0.020)	(0.035)	(0.044)	(0.058)
Share of manufacturing (%)	−0.008	0.080***	−0.166***	0.070*
	(0.014)	(0.023)	(0.030)	(0.039)
Per capita GDP	−0.091***	−0.181***	−0.147***	−0.015*
	(0.003)	(0.005)	(0.006)	(0.008)
PIEVH	0.313***			
	(0.003)			
BCS	−0.071***	0.022***	−0.010**	−0.120***
	(0.003)	(0.004)	(0.005)	(0.007)
NECDC	−0.160***	−0.108***	−0.242***	−0.350***
	(0.002)	(0.004)	(0.005)	(0.007)

Notes: The significance levels of 1 %, 5 %, and 10 % are denoted by ***, **, and *, respectively. Robust standard errors are reported in parentheses.

selected county characteristics are not controlled for, the coefficients for household head and household characteristics are significant. However, in column (6), after incorporating these community, county and city level characteristics, all household head and household characteristic variables except for Household population become insignificant. This suggests that the observed differences are largely due to these place-level factors rather than inherent household traits. In essence, by carefully accounting for the effects of these place-level characteristics, we effectively reduce potential endogeneity issues related to pilot selection (Liu et al., 2023; Zhao et al., 2024). Additionally, we used county characteristic variables as predictors for propensity score matching (PSM) in our robustness tests, which further enhanced the comparability between REDC and non-REDC. The results are similar to our baseline regression.

Furthermore, within the Difference-in-Differences (DID) framework, the presence of policy spillover effects would violate the Stable Unit Treatment Value Assumption (SUTVA). This violation suggests that residents in non-REDCs (non-treatment areas) could also experience policy impacts. Consequently, the control group becomes compromised, leading to biased DID estimates (Wei et al., 2024). To address this, we conducted robustness checks and empirically excluded potential spillover effects.

To put it more simply, the policy should ideally have no or very minimal spillover effects. In this study, we use two methods to examine the potential spillover effects of the REDC policy, following the methods used in earlier research (Lu et al., 2019; Wei et al., 2024). Specifically, we first create a dummy variable called REDC_spillover. This variable is assigned a value of 1 if a county borders an

Table 6
Summary statistics for variables of interest.

Variable	REDC		Non-REDC		Unconditional Diff.	Conditional Diff.
	Mean	SD	Mean	SD	Mean	Mean
	(1)	(2)	(3)	(4)	(5)	(6)
Household head characteristics						
Married	0.857	0.002	0.844	0.001	0.013***	0.004
Age	41.400	0.129	41.114	0.062	0.286**	0.535
Education	10.290	0.028	11.822	0.013	−1.532***	−0.043
Party member	0.625	0.003	0.560	0.002	0.065***	0.003
Household characteristics						
Dependency ratio	0.705	0.005	0.614	0.002	0.091***	−0.008
Rural	0.574	0.003	0.279	0.001	0.295***	−0.010
Household population	3.421	0.011	3.156	0.005	0.265***	−0.136***
Household asset (in log)	12.182	0.010	12.793	0.006	−0.611***	−0.035
Household income (in log)	10.184	0.010	10.618	0.005	−0.434***	0.005

Notes: The significance levels of 1 %, 5 %, and 10 % are denoted by ***, **, and *, respectively. Robust standard errors are reported in parentheses.

Table 7
Spillover effect.

Variable	Shopping online (1 for yes)			
	(1)	(2)	(3)	(4)
REDC_spillover	0.023	0.019		
	(0.018)	(0.019)		
REDC			0.032***	0.025**
			(0.011)	(0.012)
Household head control	Yes	Yes	Yes	Yes
Household control	Yes	Yes	Yes	Yes
Community control		Yes		Yes
County control		Yes		Yes
PIEVH policy		Yes		Yes
BCS policy		Yes		Yes
NECDC policy		Yes		Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes
Observation	83,597	82,230	92,411	91,652
Adjusted R^2	0.331	0.332	0.333	0.334

Notes: The significance levels of 1 %, 5 %, and 10 % are denoted by ***, **, and *, respectively. Robust standard errors are reported in parentheses.

REDC county, and 0 if it does not. The results indicate that the coefficient on REDC_spillover is not statistically significant in Table 7 column (2), implying that the REDC policy did not seem to have notable spillover effects on adjacent counties. Additionally, to assess the potential spillover effects of the policy, we exclude neighboring counties from the analysis and re-estimate the treatment impact. By doing so, we aim to isolate the direct effects of the policy on the treated units, thereby providing a more accurate estimation of the treatment effect in the absence of spillovers. The results obtained in column (4) show similar effects of the baseline regression, indicating that the policy has minimal spillover effects.

5.5. Heterogeneous impacts of REDC on online shopping behavior

The REDC policy, as a county-level intervention, necessitates rigorous examination of its heterogeneous impacts across geographic and socioeconomic dimensions. To assess potential distributional effects, we specifically investigate whether the policy's outcomes vary systematically between urban and rural area, and also between impoverished and non-impoverished counties. Building upon the baseline difference-in-differences framework established in Eq. (1), we employ triple-difference (DDD) specifications with policy and area interaction terms. As presented in Table 8 (Columns 2), the urban-rural interaction coefficient ($\beta = 0.009$, SE $= 0.011$) fails to attain statistical significance, indicating no measurable disparity in policy effectiveness between urban and rural area. Similarly, Columns 3–4 reveal an insignificant poverty-status interaction effect, suggesting comparable policy impacts across impoverished and non-impoverished counties. This result suggests that the REDC policy has not exacerbated pre-existing spatial inequalities—a critical concern in the era of rapid digital transformation. This policy impact across heterogeneous regions implies that the REDC's implementation mechanisms may have successfully bridged infrastructure and capacity disparities between urban/rural and impoverished/non-impoverished counties.

Considering the heterogeneity of the policy's impact on household online shopping behavior across different household types, we further analyzes the heterogeneous effects of the REDC policy on household consumption behavior based on age structure, education

Table 8
Heterogeneous impacts of REDC on household online shopping behavior across region types.

Variable	Shopping online (1 for yes)			
	(1)	(2)	(3)	(4)
REDC	0.017*	0.013	0.024*	0.020
	(0.010)	(0.011)	(0.013)	(0.014)
REDC × Rural	0.010	0.009		
	(0.011)	(0.011)		
Rural	−0.140***	−0.128***		
	(0.007)	(0.007)		
REDC × Impoverished County			−0.003	−0.004
			(0.016)	(0.017)
Household head control	Yes	Yes	Yes	Yes
Household control	Yes	Yes	Yes	Yes
Community control		Yes		Yes
County control		Yes		Yes
PIEVH policy		Yes		Yes
BCS policy		Yes		Yes
NECDC policy		Yes		Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes
Observation	118,496	115,825	118,496	115,825
Adjusted R^2	0.326	0.327	0.326	0.327

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses.

level, and income.

Huang et al. (2022) found that intergenerational support from the children of household heads plays a significant role. Specifically, younger and more educated children in the household often help other family members learn how to shop online. Therefore, in this section, household age and education are measured at the household level rather than based solely on the household head. Additionally, Wang (2020) pointed out that the key heterogeneous factors influencing whether a household shops online are the minimum age of adults and the years of education in the household. Online shopping requires households to be familiar with the process, and age and education are critical factors affecting online shopping behavior. In this section, we use whether the minimum age of adults in the household is greater than 60 years to measure household age structure and find that the policy significantly increases the probability of elderly households (with adults over 60) to shop online to 2.9 % (−5.1 % + 8.0 %). Furthermore, we measure the household education structure using whether the minimum years of education in the household is below the 9-year compulsory education threshold. The results show that the policy significantly improves the probability of households with less than 9 years of education to shop online to 0.1 % (3.4 % - 3.3 %). Overall, Columns 1 and 2 of Table 9 reveal that the policy reduces the transaction barriers faced by individuals, promoting online shopping among older and less-educated households. In addition to human capital, this paper also uses initial household income to measure household physical capital and finds that the policy benefits relatively more poor households, increasing their probability of shopping online by 2.2 %. In summary, the policy promotes inclusive growth by reducing the barriers to online shopping faced by households with lower human and physical capital. This is likely because the policy provides e-commerce training, enabling vulnerable groups such as the elderly, women, and poor households to acquire online skills. This will be further explained in the mechanism analysis later in the paper.

5.6. *Mechanism analysis for the impact of the REDC program*

The previous section analyzed the heterogeneous impacts of the policy from the perspective of residents. The next question is through what mechanisms the policy operates to bring about these heterogeneous effects for different groups. Specifically, the actual impact of the policy is closely related to how the funds are used, the rollout process, and the implementation cycle. Given that the policy requires a coordination mechanism led by the county's top government officials to develop local plans or implementation schemes for rural e-commerce development, this paper further collects information on the specific allocation of policy funds from the websites of county governments in the treatment group. The specific URLs are provided in Appendix 6. This helps explore how the use of funds influences household online shopping behavior.

The model used in this section to estimate the relationship between policy fund allocation and household consumption behavior is specified as follows:

$$Y_{icvt} = \beta_1 Usage\_share_{ct} + \omega Control_{icvt} + \theta Z_{ivc} * f(t) + county_c + year_t + \delta_{pt} + \pi_{ct} \tag{3}$$

This paper categorizes the specific use of funds into four categories (see Fig. 3). The variable $Usage\_share_{ct}$ measures the proportion of total policy funds allocated to each category, including the share of funds for the service system, logistics system, training system, and promotion and marketing system. The definitions of other variables remain the same as in Eq. (1). Table 10 reports the results of Eq. (3).

Table 9
Heterogeneous impacts of REDC on household online shopping behavior across household types.

Variable	Shopping online (1 for yes)		
	(1)	(2)	(3)
REDC	0.004	0.001	0.006
	(0.010)	(0.010)	(0.010)
REDC × Elderly	0.080***		
	(0.014)		
Elderly	−0.051***		
	(0.007)		
REDC × Low education		0.034***	
		(0.008)	
Low education		−0.033***	
		(0.005)	
REDC × Low income			0.022***
			(0.008)
Low income			−0.052***
			(0.004)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes
Observation	115,825	115,825	115,825
Adjusted R^2	0.328	0.328	0.328

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses. "Elderly" in Column 1 is a dummy variable indicating whether the minimum age of adults in the household in 2013 baseline year was greater than 60 years. "Low education" in Column 2 is a dummy indicating whether the minimum years of education of adults in the household in 2013 was less than 9 years. "Low income" in Column 3 is a dummy indicating whether the household's total income in 2013 was below the median household income level.

Table 10
Mechanism analysis for the impact of REDC program on online shopping.

Variable	Shopping online (1 for yes)				
	(1)	(2)	(3)	(4)	(5)
Share of service	0.052				0.095
	(0.041)				(0.087)
Share of logistics		0.043**			0.058**
		(0.017)			(0.028)
Share of training			0.131**		−0.111
			(0.051)		(0.189)
Share of marketing				0.002	−0.084
				(0.035)	(0.059)
Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes	Yes
Observation	115,825	115,825	115,825	115,825	115,825
Adjusted R^2	0.327	0.327	0.327	0.327	0.327

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses.

From Column 2 of Table 10, it is evident that the policy primarily influences household online shopping behavior by improving logistics. For every 1 % increase in the share of funds allocated to logistics, the probability of household online shopping increases by 0.043 %. The annual notices issued by the Ministry of Finance and the Ministry of Commerce regarding the REDC emphasize that central government support is concentrated on establishing and enhancing a three-tier logistics distribution system for counties, towns, and villages. The implementation of the policy has further strengthened the logistics and supply chain system, reducing obstacles to the circulation of daily consumer goods and facilitating smoother distribution of goods. As a result, residents can receive deliveries from closer locations, thereby expanding their online shopping options.

Furthermore, the results in Column 3 indicate that for every 1 % increase in the proportion of total policy funds allocated to training, the probability of household online shopping increases by 0.131 %. This finding highlights an important intermediary mechanism. Specifically, another goal of the policy is to strengthen e-commerce talent development, particularly targeting local registered impoverished households, farmers, veterans, individuals with disabilities, and women for rural e-commerce education and skills training. This initiative enables relatively disadvantaged groups—such as the elderly, women, and low-income households—to understand the e-commerce development system, complete online shopping independently, and utilize e-commerce platforms effectively. This also further supports the findings from the heterogeneous analysis presented in Table 9.

Lastly, we could see from column (5) that, when controlled for all these four mechanisms, the positive effect is more pronounced for the logistics mechanism. It indicates that for every 1 % increase in the proportion of total policy funds allocated to logistics, the probability of household online shopping increases by 0.058 %, which is statistically significant at the 5 % level as indicated by the two asterisks. This suggests that the logistics mechanism plays a more substantial role in facilitating online shopping among households compared to the training mechanism, whose effect is not statistically significant in this model. Furthermore, the coefficients for the service and marketing mechanisms are also not statistically significant, implying that these factors may not have a direct or strong influence on the likelihood of households engaging in online shopping.

Logistics barriers are the primary issue the policy aims to address, with logistics receiving the largest share of funds among the four impact channels. However, Table 10 shows that the impact of logistics remains limited. In this section, we plan to use logistics POI data from navigation platforms (Baidu/Gaode) to analyze the actual impact of the policy on logistics. The original data covers 2837 counties nationwide, spanning the years from 2012 to 2021, and is nationally representative.[13]

Fig. 6 presents the parallel trend test results for the overall county level as well as subdistricts, towns, and township levels. As shown in the figure, for the four periods prior to the policy, the coefficients for REDC are not significantly different from zero, and the coefficient values remain relatively stable, indicating no significant differences between the treatment and control groups before the REDC policy. Additionally, when examining the years following the policy implementation, there is no noticeable trend change in the 1st and 2nd periods after the pilot policy implementation, showing a clear lag in the policy's effects. This may be due to the time lag in signing government procurement contracts and rolling out the policy. Starting from the 3rd year, the policy gradually begins to have a positive impact on the number of logistics points at the town level, with the treatment group significantly outperforming the control group. This impact grows over time, with the policy effects strengthening as the implementation duration extends. However, there is no significant impact on the subdistricts and township level logistics points. For the data restriction, we cannot calculate the effect on the village level. The construction of the three-tier logistics system (county-town-village) mainly affects the township level, with limited effects at the town level. Effectively addressing the "last mile" issue in the downward distribution of consumer goods could significantly enhance the policy's impact on household online shopping.

In addition to analyzing the policy mechanisms through the lens of government design and fiscal allocation, this study extends the investigation to the micro-level by exploring how behavioral adjustments among individuals, driven by the policy, ultimately influence household consumption patterns. As demonstrated in Table 11, our data shows that the policy increased the average weekly working hours of individuals by 0.84 h, though it exhibits no discernible effect on overall employment rates. This rise in labor supply may translate into higher household income, creating a potential channel for elevated consumption expenditures. Two plausible mechanisms underpin the observed increase in working hours. First, the expansion of e-commerce—spurred by localized investments in logistics infrastructure (see Table 10)—likely amplifies labor demand within affected regions. Second, as evidenced in Appendix Table A9, the REDC policy correlates strongly with the digitization of industrial and commercial operations, which may necessitate extended working hours to accommodate online business activities.[14]

6. Further discussions

Fostering new forms of online consumption is an important measure to comprehensively boost domestic consumption and mitigate urban-rural development inequality. The promotion and penetration of e-commerce have reshaped consumer habits and consumption structures, meeting the demand for a more diverse range of goods and services. This section further explores whether the policy, by promoting online shopping, also influences the consumption structure and choices of residents. Table 11 divides household consumption into online and offline categories based on the shopping channels, and further investigates whether the policy, in addition to encouraging online shopping behavior, has also led to an increase in online spending.

As shown in Table 12, while the REDC policy expanded consumption channels for residents, it did not crowd out offline consumption. The policy has no significant impact on total consumption. Since total consumption reflects various factors such as price and quantity, although the policy increased the probability of online shopping, online goods are generally priced lower, which aligns with findings by Couture et al. (2021). At the same time, the policy significantly promotes household per capita income, likely due to e-commerce facilitating the upward flow of products, thereby increasing household sales income.[15]

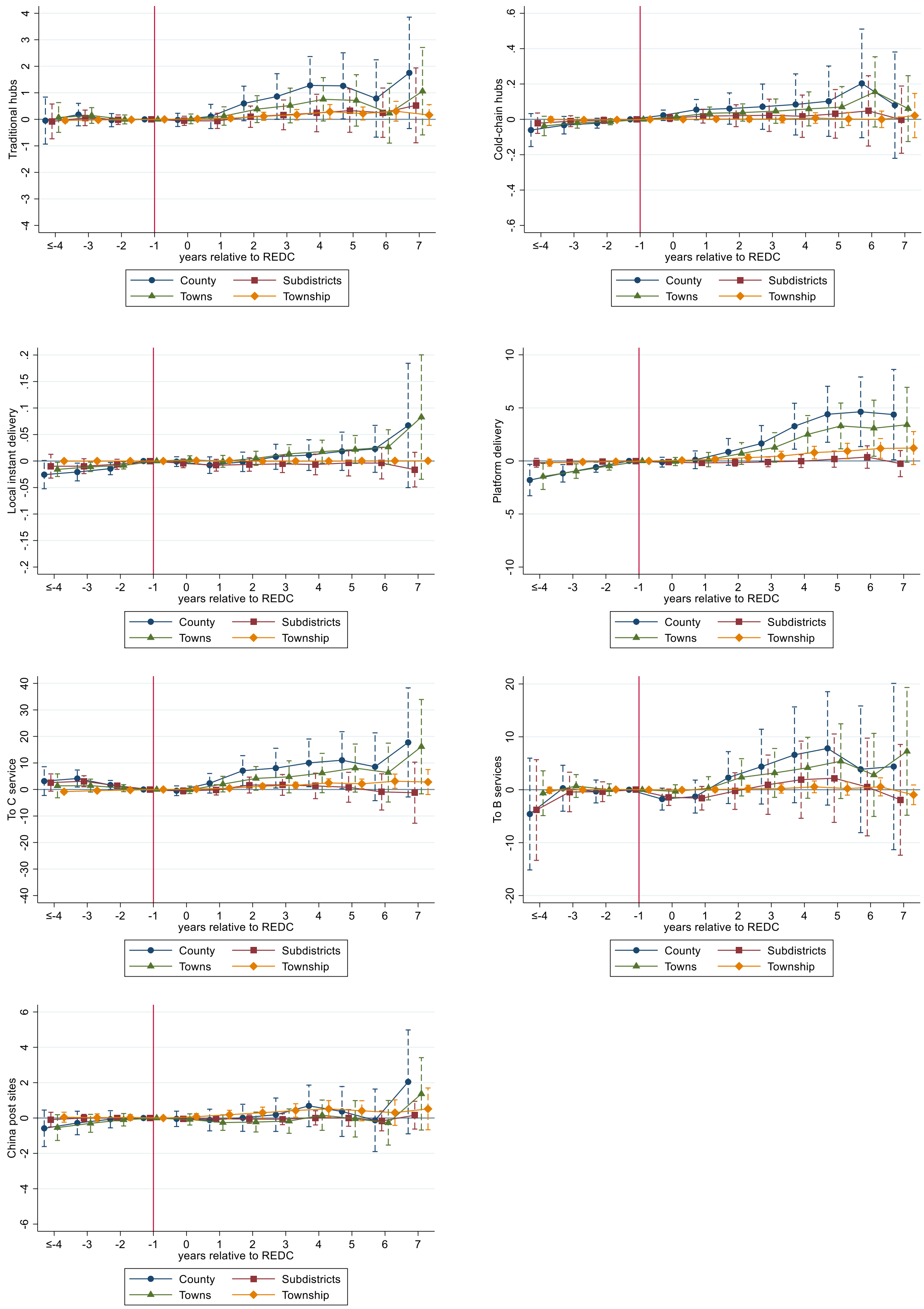
Fig. 7 presents the parallel trend test results for household online, offline, and average total consumption and income. As shown in the figure, for the 1st, 2nd, 3rd, and 4th periods prior to the policy pilot, the coefficients for REDC are not significantly different from zero, and the coefficient values remain relatively stable. This indicates that before the *Rural E-commerce Demonstration Counties* policy was piloted, there were no significant differences between the treatment and control groups. Additionally, when examining the years following the policy implementation, no significant trend changes are observed, suggesting that the policy has no noticeable effect on household consumption and income.

To examine potential heterogeneity across regions, we further divide the sample into urban and rural households. As shown in

[13] See Appendix 5 for detailed data description.

[14] While the observed labor supply increase aligns with localized demand shocks, we cannot rule out complementary mechanisms such as time savings from reduced offline shopping. Future studies with granular time-use data could further disentangle these channels.

[15] The underlying reasons behind the increase of household income is demonstrated in appendix 8.



(caption on next page)

Fig. 6. The dynamic impacts of REDC on logistics POIs.
Notes: *Traditional hubs* refers to number of logistics infrastructures, such as logistics centers, warehouses, processing centers, distribution centers, transfer points, unloading points. *Cold-chain hubs* refers to logistics infrastructures only applicable to cold-chain delivery. *Local instant delivery* refers to instant delivery sites, and mainly used for fresh and takeout food in local area, such as Ele.me, Meituan and Freshippo. *Platform delivery*: Offline sites operated by e-commerce platforms such as Taobao, JD and Suning; *To C service* refers to convenient delivery sites, such as SF, Yuantong and Shentong Express, and delivery pick-up points (convenience service stations and EMS operated by China Post are included. *To B service* refers to freight delivery, typically used for bulk goods and primarily operated by businesses. *China Post sites* refers to traditional post offices and postal stations operated by state-owned China Post. The final sample retains a balanced county-level panel dataset from 2012 to 2021, covering a total of 1362 counties. Additionally, the 2021 treatment group sample is used as the control group, as it shares similarities with previously enrolled samples, allowing for better comparison.

Table 11
The impact of REDC program on labor supply.

Variable	Having a job (1 for yes)		Average weekly working hours	
	(1)	(2)	(3)	(4)
REDC	0.002	0.003	1.496***	0.841**
	(0.006)	(0.006)	(0.386)	(0.367)
Controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes
Observation	362,504	349,744	383,514	369,866
Adjusted R^2	0.041	0.094	0.042	0.082

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses.

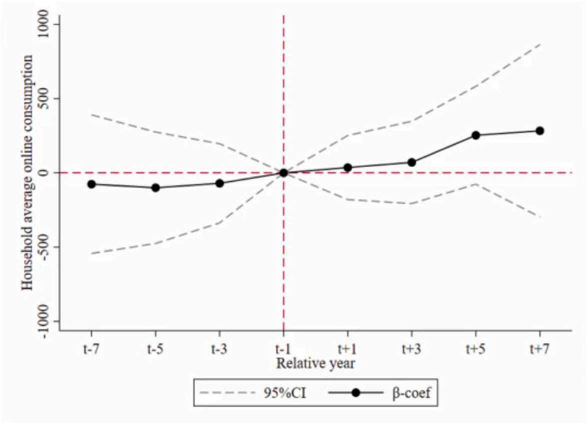
Table 12
The impact of REDC on consumption expenditures (online, offline and total).

Variable	Per capita online consumption	Share of online consumption	Per capita offline consumption	Share of offline consumption	Per capita total Consumption	Income per capita
	(1)	(2)	(3)	(4)	(5)	(6)
REDC	77.855	−0.002	−910.437	0.002	−833.938	5492.464*
	(76.659)	(0.002)	(1047.423)	(0.002)	(1068.186)	(3051.635)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes	Yes	Yes
Observation	50,868	50,566	50,566	50,566	50,566	50,808
Adjusted R^2	0.113	0.121	0.131	0.121	0.149	0.361

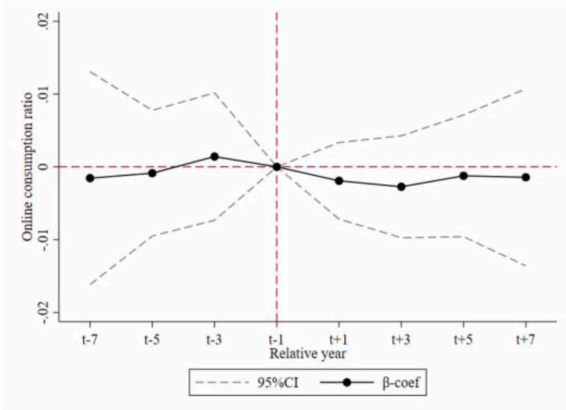
Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses. All variables related to consumption are deflated by CPI. Only samples with non-missing online consumption expenditure are included in the analysis.

Tables 13, the estimated coefficients of REDC on consumption behavior are statistically insignificant, suggesting no significant differences in REDC's overall impact across the two groups. Similar to the results we obtained from Table 8, the findings indicate that the policy has not exacerbated existing spatial inequalities in consumption expenditure. This implies that the digital divide at the regional level has not widened as a result of REDC, addressing a critical concern in the context of rapid digital transformation.

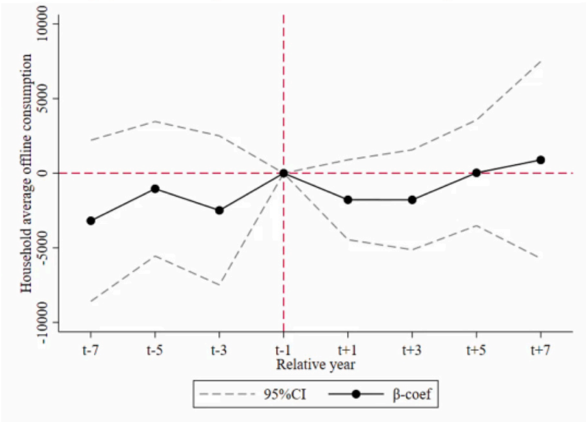
To further assess the robustness of our findings, we conduct additional analyses excluding the pandemic-affected year of 2021 (Table 14). The exclusion of 2021 data yields result consistent with the full-sample estimates: the coefficients of REDC on total consumption remain statistically insignificant across both specifications. Additionally, in columns 7 and 8 of the table, since total consumption and total income are not influenced by online consumption, regression analyses using the full sample reveal that the REDC policy still exhibits no significant impact on these variables. This further corroborates the conclusions of this study. Combined with the urban-rural heterogeneity analysis in Tables 13 and 14, the evidence collectively highlights the limited role of REDC in shaping consumption patterns, regardless of regional or temporal sample restrictions.



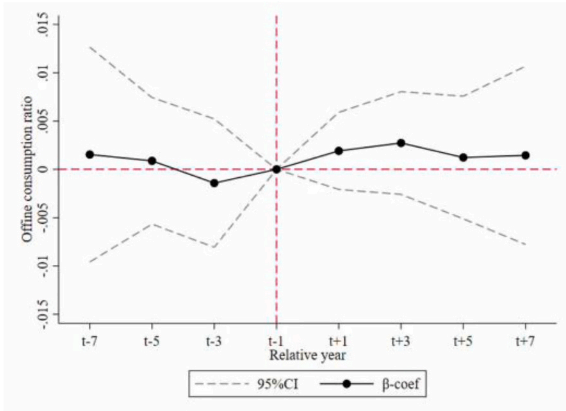
(a) Per capita online consumption



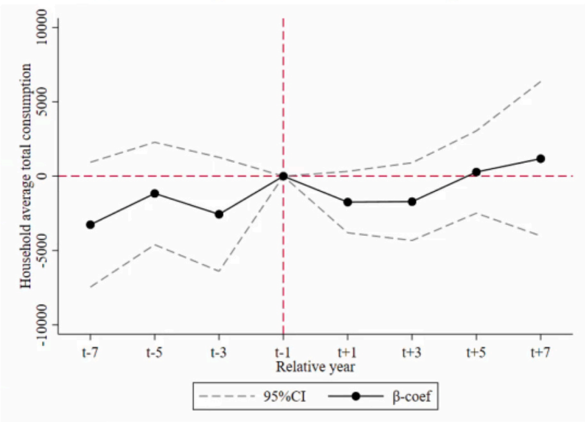
(b) Share of online consumption



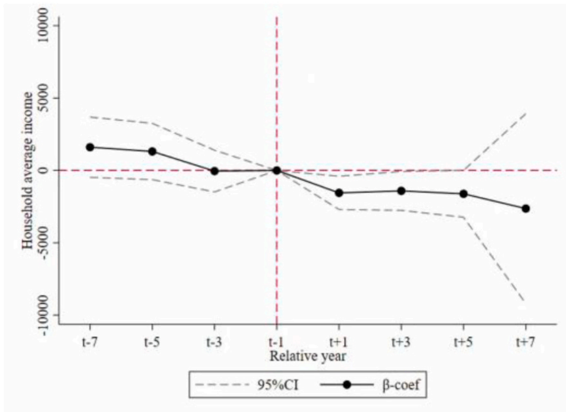
(c) Per capita offline consumption



(d) Share of offline consumption



(e) Per capita total Consumption



(f) Income per capita

Fig. 7. Dynamic impacts of REDC program on household consumption expenditure and income.

Table 13
The impact of REDC on rural and urban consumption expenditures (online, offline and total).

Variable	Per capita online consumption	Share of online consumption	Per capita offline consumption	Share of offline consumption	Per capita total consumption	Income per capita
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Rural Area						
REDC	−31.128	−0.002	676.645	0.002	652.831	116.925
	(54.205)	(0.003)	(1037.804)	(0.003)	(1048.127)	(4043.646)
Observation	11,222	11,222	11,222	11,222	11,222	11,222
Adjusted R^2	0.104	0.089	0.071	0.089	0.076	0.293
Panel B: Urban Area						
REDC	17.577	−0.002	−1100.901	0.002	−1082.003	6869.107*
	(116.339)	(0.002)	(1598.629)	(0.002)	(1632.140)	(3655.272)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes	Yes	Yes
Observation	39,646	39,344	39,344	39,344	39,344	39,586
Adjusted R^2	0.104	0.098	0.116	0.098	0.133	0.356

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses. All variables related to consumption are deflated by CPI. Only samples with non-missing online consumption expenditure are included in the analysis.

Table 14
The robustness check of REDC on consumption expenditures (online, offline and total).

Variable	Per capita online consumption	Share of online consumption	Per capita offline consumption	Share of offline consumption	Per capita total consumption	Income per capita	Per capita total consumption	Income per capita
	Excluding sample of year 2021						Full sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REDC	−117.928	−0.002	−2234.314	0.002	−2350.344	3180.159	−193.366	−1308.626
	(109.713)	(0.003)	(1456.213)	(0.003)	(1480.519)	(3821.623)	(351.413)	(1338.741)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	33,440	33,440	33,440	33,440	33,440	33,440	115,264	115,264
Adjusted R^2	0.105	0.083	0.128	0.083	0.145	0.369	0.165	0.370

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses. All variables related to consumption are deflated by CPI. Columns 1–6 exclude samples from 2019, while columns 7 and 8 retains the full sample.

Table 15
Impacts of REDC on various types of consumption.

Variable	Food	Clothing	Housing	Daily use	Transportation	Communication	Education and entertainment	Healthcare
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REDC	−202.533	144.205**	349.720	22.044	−655.778	−17.786	−20.433	−74.335
	(308.320)	(63.852)	(349.814)	(82.676)	(836.693)	(49.233)	(146.364)	(95.244)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	50,821	50,599	50,864	50,860	50,861	50,861	50,865	50,866
Adjusted R^2	0.150	0.091	0.032	0.042	0.039	0.063	0.086	0.054

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses.

Apart from analyzing the structure of online and offline consumption, this paper further disaggregates total consumption into eight distinct categories to investigate the policy's impact on various types of consumption. The results presented in Table 15 indicate that the policy intervention promotes an increase in the share of survival-oriented consumption, particularly in clothing expenditures. This finding is consistent with Startz's (2016) trade theory, which posits that e-commerce fosters growth in high-turnover consumption categories, such as cosmetics and clothing. Furthermore, our data show that in 2019, approximately 66.7 % of households purchased clothing, footwear, and hats online, making these items the most frequently purchased within online consumption.

7. Conclusion

This paper investigates the extent to which the Rural *E*-commerce Demonstration Counties (REDC) policy promotes household online consumption and, consequently, influences household consumption patterns. The findings suggest that, overall, e-commerce enhances consumption expenditure primarily from the supply side by increasing the availability of logistics and training. Baseline results indicate that the REDC policy increases the likelihood of household online shopping by 1.9 %, and this effect remains robust across a series of robustness checks. In addition, the policy's impact demonstrates a lagged effect, with an effective implementation period of 3 to 4 years, after which the policy effect strengthens with prolonged intervention. The influence of the policy on household consumption habits is enduring and does not diminish after the policy concludes.

Mechanism analysis reveals that the intervention of e-commerce platforms has a tangible effect on the real economy within counties. The policy facilitates household online shopping by developing consumption infrastructure, such as constructing logistics networks and providing training. However, the construction of the three-tier logistics system (county-town-village) still requires further development, and the “last mile” challenge in delivering consumer goods to rural areas remains unresolved. Additionally, the observed rise in households' average weekly working hours further substantiates the hypothesis that online shopping expansion generates additional employment opportunities. These opportunities, in turn, elevate household income levels, creating a plausible pathway for subsequent increases in household consumption. This aligns with the broader narrative that digital commerce not only reshapes labor markets through localized demand (e.g., logistics investments) but also amplifies income-consumption linkages within affected communities.

Given that policy impact often varies across different demographic groups, this paper also analyzes the heterogeneous effects of the REDC policy. Regional-level heterogeneity suggests no significant difference of the policy's impact between urban and rural areas, as well as between impoverished and non-impoverished counties. Meanwhile, individual-level heterogeneity indicates that the policy reduces barriers to online shopping for households with lower levels of human and physical capital. Furthermore, this study explores whether the REDC policy has altered traditional household consumption habits. The results show that the policy did not displace offline consumption nor negatively impact traditional offline industries.

Based on these findings, this paper proposes several policy recommendations. First, to further stimulate household consumption in China, it is crucial to improve the “last mile” of rural logistics. Strengthening the three-tier logistics system—which encompasses counties, towns, and villages—can effectively increase online shopping among residents in remote areas. Second, the government and relevant institutions should expand digital skills training to enhance digital literacy, particularly within rural communities. These initiatives would not only reduce transaction barriers but also equip residents with the necessary skills to identify and process information, thereby boosting their competitiveness in the digital economy. Finally, differentiated policy support should be implemented by the government to promote balanced development between urban and rural areas. In policy design, it is advisable to consider the urban-rural divide and to provide more targeted support for rural households, such as through tax reductions and subsidies, to unlock the online consumption potential of rural families. Regular evaluations of program implementation should be conducted, with policies adjusted flexibly based on the specific conditions of different regions. Such an approach will enhance both the precision and effectiveness of these initiatives.

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4. Humanities and Social Science Research Youth Fund of the Ministry of Education of China, “Market Access and the Development of Service Industry Enterprises - Theoretical and Empirical Evidence under the Impact of Labor Cost Shock” (Grant No. 24C10651088)

Appendix 1. Covers of government procurement contracts

景泰县电子商务进农村综合示范
建设项目合同

合同编号：BGZJ-ZC17181(001)HT

项目名称：景泰县电子商务进农村综合示范建设项目

（第一包）景泰县电子商务进农村县级服务中心建设项目

采购人（甲方）：景泰县工业和信息化局

供应商（乙方）：南京点石电子商务有限公司

采购代理机构：甘肃中金国际招标有限公司

景泰县电子商务进农村综合示范
建设项目合同

合同编号：BGZJ-ZC17181(002)HT

项目名称：景泰县电子商务进农村综合示范建设项目

（第二包）景泰县乡（镇）、村电子商务服务站点建设项目

采购人（甲方）：景泰县工业和信息化局

供应商（乙方）：景泰县丝路荟电子商务有限公司

采购代理机构：甘肃中金国际招标有限公司

景泰县电子商务进农村综合示范
建设项目合同

合同编号：BGZJ-ZC17181(003)HT

项目名称：景泰县电子商务进农村综合示范建设项目

（第三包）景泰县电子商务进农村人才培训体系建设项目

采购人（甲方）：景泰县工业和信息化局

供应商（乙方）：甘肃淘一郎电子商务有限公司

采购代理机构：甘肃中金国际招标有限公司

景泰县电子商务进农村综合示范
建设项目合同

合同编号：BGZJ-ZC17181(004)HT

项目名称：景泰县电子商务进农村综合示范建设项目

（第四包）景泰县农产品供应链管理体系建设项目

采购人（甲方）：景泰县工业和信息化局

供应商（乙方）：甘肃厨联天下网络科技股份有限公司

采购代理机构：甘肃中金国际招标有限公司

Fig. A1. Sample of County Government Procurement Contract.

Appendix 2. Detailed policy background of the REDC program

1. The development goals and key support areas of the REDC policy

In July 2014, the Ministry of Finance and the Ministry of Commerce jointly issued the “Notice on Carrying Out the Rural E-commerce Demonstration County Program”, initiating the first batch of demonstration projects in 56 counties across 8 provinces. Since then, program coverage has continuously expanded, and its influence has strengthened (As shown in Table A1). In November 2016, the State Council's Office of Poverty Alleviation, along with 16 other departments, issued the “Guiding Opinions on Promoting E-commerce for Targeted Poverty Alleviation”, recommending the acceleration of e-commerce initiatives for poverty alleviation. This marked the integration of rural e-commerce development with the national strategy for targeted poverty alleviation. The REDC program, implemented by the Chinese government, provides an appropriate quasi-experimental framework for this study.

Table A1
The development goals and key support areas of the REDC policy.

Year	Development goal	Key support area
2014	(1) Expand the coverage of rural e-commerce, improve the rural commercial circulation system, promote rural consumption, and cultivate a group of demonstration counties with distinctive characteristics and replicable, scalable experiences.	(1) Support cooperatives, postal services, and leading e-commerce enterprises in building and upgrading rural e-commerce distribution and service networks; (2) Support rural e-commerce training programs.
2015	(2) In demonstration areas, logistics costs have significantly decreased, and the annual growth rate of rural online retail sales and agricultural product online retail sales exceeds the national average. The flow of agricultural products to urban areas and industrial goods to rural areas has become more efficient, helping farmers increase their income and achieve prosperity.	(1) Support the establishment and improvement of a county-township-village logistics distribution system; (2) Support the construction and upgrading of county-level e-commerce service centers and village-level e-commerce service stations; (3) Support rural e-commerce training programs.
2016		(1) Support the establishment and improvement of a county-township-village logistics distribution system; (2) Support the construction and upgrading of county-level e-commerce service centers and village-level e-commerce service stations; (3) Support rural e-commerce training programs； (4) Make full use of social resources, avoiding unnecessary construction of e-commerce parks, duplication, and resource waste.
2017		(1) Focus on the upward flow of rural products; (2) Support the construction and renovation of county-level e-commerce public service centers and rural e-commerce service sites; (3) Support rural e-commerce training programs; (4) The demonstration county should fully utilize the existing various types of industrial parks, idle factories, and commercial e-commerce platforms within its jurisdiction to maximize the use of social resources.
2018		(1) Focus on the upward flow of rural products; (2) Improve the rural public service system; (3) Support rural e-commerce training programs.
2019		(1) Improve the rural circulation infrastructure (2) Improve the rural public service system; (3) Support rural e-commerce training programs.
2020		(1) Support the improvement of a county-township-village logistics distribution system; (2) Improve the rural e-commerce public service system; (3) Establish rural modern circulation service system; (4) Support rural e-commerce training programs.
2021		(1) Improve the rural e-commerce public service system; (2) Support the improvement of a county-township-village logistics distribution system; (3) Promote the transformation and upgrading of rural commercial circulation enterprises; (4) Cultivate rural e-commerce entrepreneurs.

Although the specific development goals and areas of support for this program vary slightly from year to year, they can generally be summarized into two development goals, two fundamental purposes, and four key areas of support. The two development goals are increasing "county-level online retail" and "product online sales", which aim to boost both household online consumption and product sales through e-commerce platforms. The fundamental purposes are to promote household consumption and support income growth for residents. The four key areas of support are as follows: the construction of an e-commerce public service system (e.g., county-level e-commerce service centers, village-level service stations, and the integration of postal services, supply and marketing cooperatives, courier services, financial services, and government resources); the development of a three-tier logistics distribution and supply chain system spanning counties, towns, and villages; the establishment of a rural e-commerce talent training system; and the creation of a promotion and marketing system, which coordinates services such as quality control, branding, certification, training, and marketing.

2. The detailed implementation of REDC program

The *Rural E-commerce Demonstration Counties* (REDC) program designates the county governments of demonstration counties as the primary responsible entities. Nationwide, provincial departments of finance, commerce, and poverty alleviation select demonstration counties through a competitive process, focusing on those with relatively favorable economic conditions, infrastructure, and e-commerce development capacity. These counties are then tasked with organizing and implementing the projects. In the later stages of the program, additional support is directed toward underdeveloped areas and impoverished counties. The demonstration counties are required to establish a coordination mechanism led by the county's top officials and to formulate a local development plan or implementation scheme to advance rural e-commerce.

Logistics barriers are a key issue that the program aims to address. In the evaluation system, full marks are awarded only if packages are delivered from the county warehouse to the village center within three days. Central government funds cannot be used for acquiring online store traffic or constructing e-commerce industrial parks, which may limit the program's impact on online sales. As the coverage of REDC counties expands, the focus has increasingly shifted toward the central and western regions.

Appendix 3. Primary inspection of the data

1. Correlation between REDC and household online shopping

First of all, this section analyzes the heterogeneous impacts for samples that entered the policy in different years.

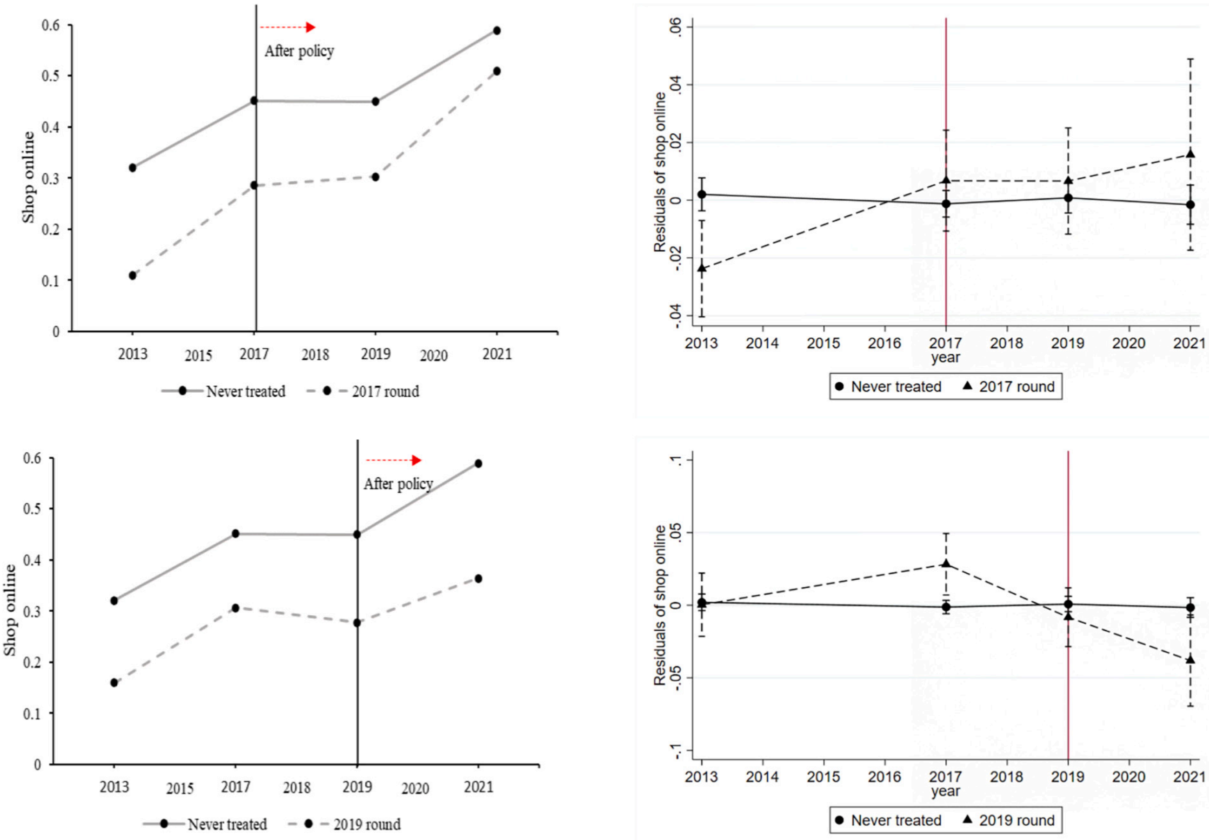


Fig. A2. Changes in Online Shopping Probability for Samples Entering the Policy in 2017 and 2019.
Note: Since the 2015 CHFS questionnaire measures online shopping with the question “Did your household shop online last month?”—which differs from the definition used in other years, “Did your household shop online last year?”—the 2015 sample was excluded from the actual regression analysis.

From the left side of Fig. A2, it can be observed that households in areas not covered by the policy exhibit better online shopping behavior compared to those in areas that are part of the policy, as the policy tends to target relatively underdeveloped and impoverished regions. For the samples that entered the policy in 2017, changes in consumption behavior gradually became evident three to four years later, with a convergence trend between the groups participating in the policy and those not participating. However, for the group that entered the policy in 2019, the observable window is relatively short, and no clear trend has emerged.

Secondly, given that counties entered the *Rural E-commerce Demonstration Counties* policy at different times and were thereby subject to various economic and social influences, we further analyze the right side of Fig. A2 to isolate the policy's specific effects from these confounding factors. After adjusting for concurrent confounding variables, any remaining variation in household consumption can reasonably be attributed to the policy's exogenous shocks, with changes in the residuals reflecting the policy's true impact. As shown, after removing the influence of concurrent economic and social factors, the residuals for the counties not covered by the policy form a straight line with a mean of zero, exhibiting no significant fluctuations over time. Consequently, changes in the mean residuals of counties covered by the policy in different years can be approximately ascribed to the policy intervention.

For counties that adopted the policy in 2017, the intervention did not immediately lead to an increase in household online shopping behavior. Rather, the probability of online shopping rose gradually over the subsequent three to four years and eventually stabilized. For those counties that joined the policy in 2019, however, no clear trend was observed. In summary, the effect on counties entering the policy in different years follows a consistent trend over time. Therefore, in the subsequent analysis, we consolidate the samples from various entry years into a single treatment group to assess the overall impact of the policy.

2. REDC and the distribution of household online shopping

The previous section explored the impact of the policy on the average household online shopping behavior. In the following section, this paper further analyzes the impact of the policy on the distribution of household online shopping.

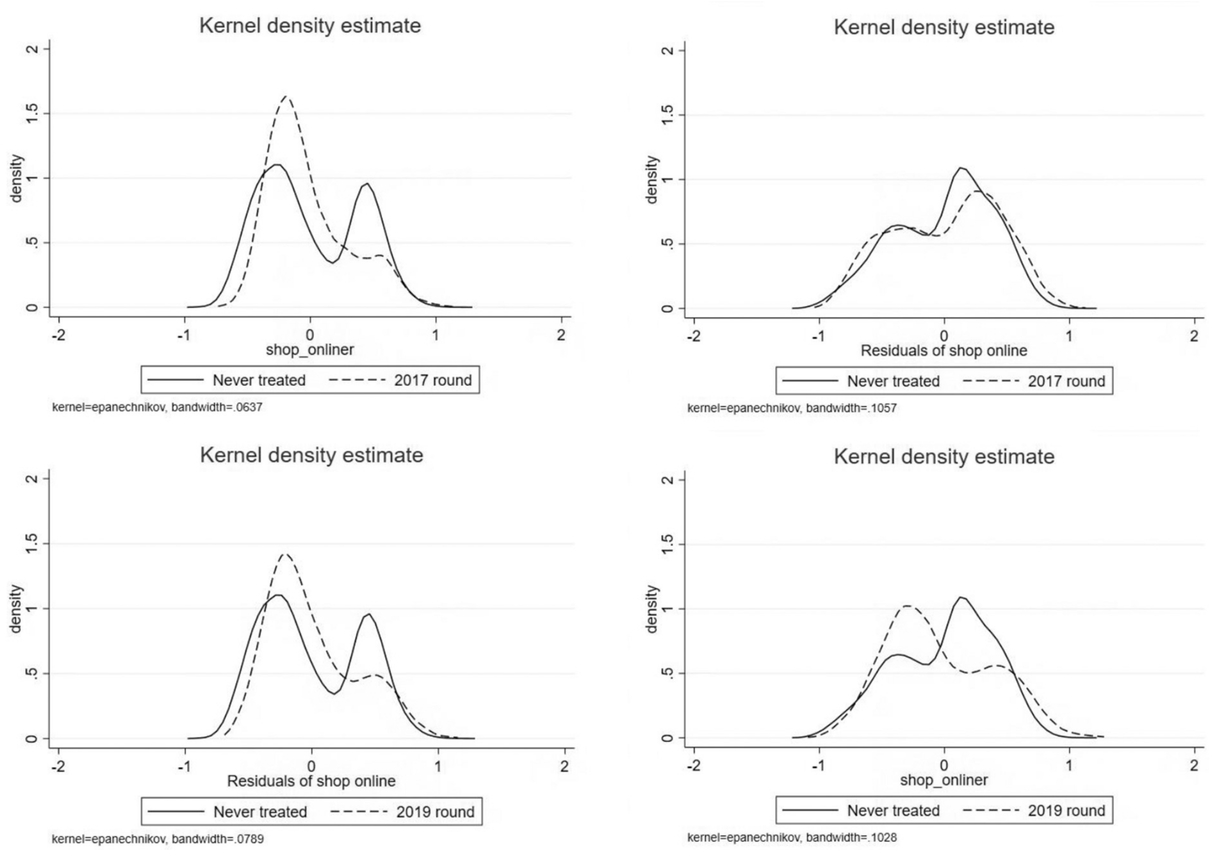


Fig. A3. Distribution of Household Online Shopping for Samples Entering the Policy in 2017 and 2019.
Note: The left side shows the distribution of the dependent variable for the 2013 sample, while the right side shows the distribution for the 2021 sample.

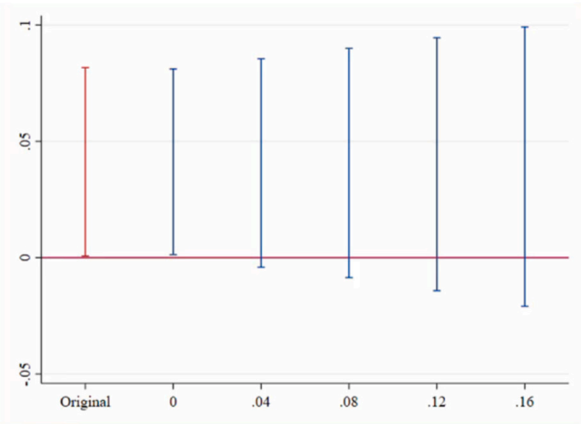
This section employs kernel density plots to visually represent the residual distribution of household online shopping behavior for samples that entered the policy at different times, comparing distributions from 2013 and 2021. Since policy implementation began in 2014, the plot on the left (2013) illustrates the residual distribution before any group experienced policy intervention. It can be observed that the groups poised to enter the policy display a leftward skew, with a higher concentration around −1, relative to the group that would remain outside the policy.

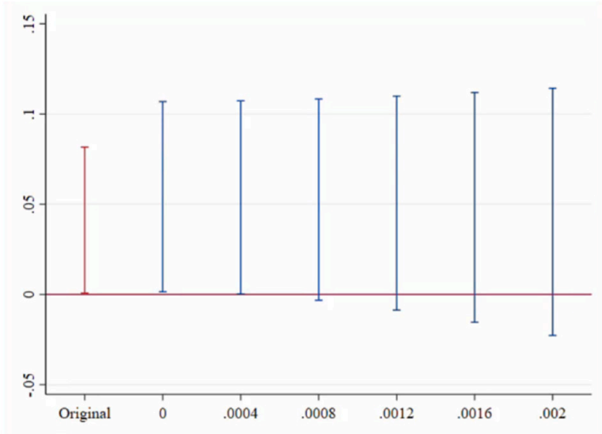
In contrast, the 2021 plot shows samples from the 2017 and 2019 groups, which had already been influenced by the policy. The distribution for the group that entered the policy in 2017 has shifted to the right, now concentrated around a value of 1, indicating increased household engagement in online shopping. Meanwhile, the group unaffected by the policy displays no notable change in distribution. For the 2019 entry group, however, the shorter duration of policy intervention results in no significant difference between the kernel density distributions in 2013 and 2021.

Based on the above analysis, this paper employs both the progressive difference-in-differences (DID) and dynamic difference-in-differences methods to estimate how the REDC policy impacts household consumption behavior. We match the annual list of REDC counties from 2014 onwards with the China Household Finance Survey (CHFS) data from 2013 to 2021, identifying which counties belong to the treatment group and which to the control group. The matching results show that by 2017, there were 78 counties in the treatment group, with an additional 39 counties in 2019 and 28 more counties added in 2021. A total of 268 counties remained untreated. By 2021, a total of 145 counties could be matched. The DID analysis provides Intent To Treat (ITT) results.

Appendix 4. Robustness test

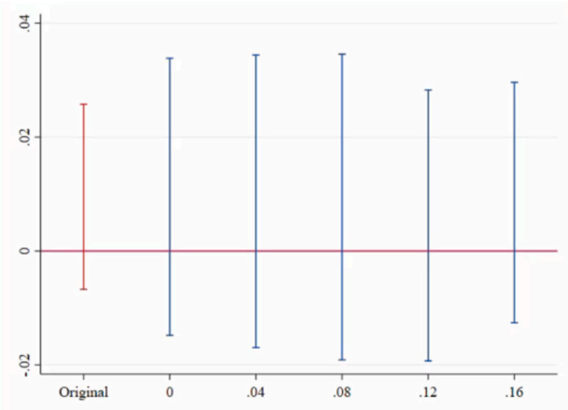
Robustness test

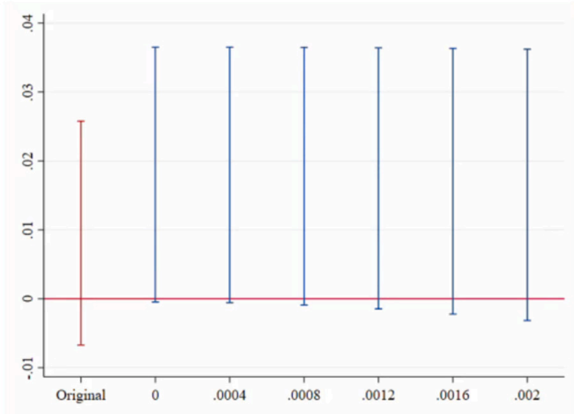




(a) (b)

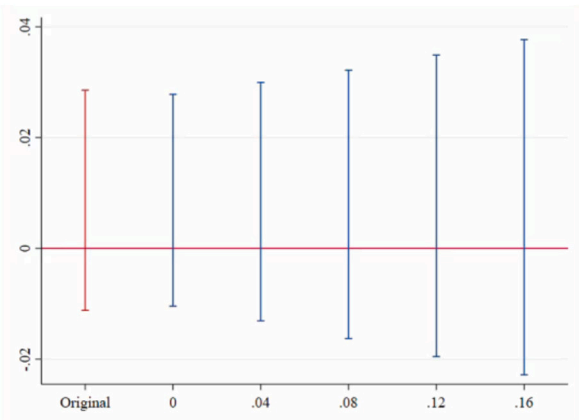
The fourth period

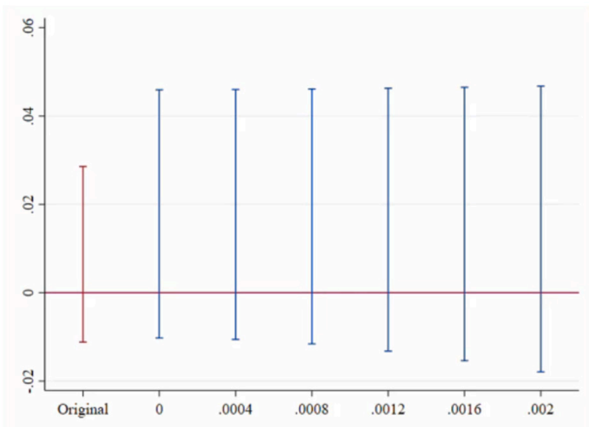




(a) (b)

The first period





(a) (b)

The second period

(caption on next page)

Fig. A4. Sensitivity Test.
Note: For the left side represent the relative deviation bounds, the right side represent the smoothness bounds.

Appendix 5. Description of the POI data

This paper compiles logistics data for 31 provinces, 366 cities, and 2837 counties. The total number of business outlets reported by the National Bureau of Statistics in 2021 was 412,522, slightly lower than the sum of the three types of data in this paper, as their statistics only include business transactions handled by postal enterprises above a certain scale.

Table A2
Aggregate counts of logistics points by year and category.

	Hubs		Delivery				China post
Year	Traditional	Cold chain	Local instant	Platform	To C	To B	China post
2012	5362	22	0	14	6942	21,894	55,396
2013	5862	36	0	61	12,818	27,846	55,701
2014	11,055	104	0	83	14,225	59,233	53,371
2015	9999	159	11	3537	220,987	72,544	52,264
2016	18,935	497	56	6357	259,651	194,122	43,276
2017	22,239	582	79	8614	305,927	226,821	51,916
2018	22,584	847	273	26,372	275,433	229,901	50,706
2019	25,680	1056	349	31,252	314,286	240,412	53,353
2020	21,442	986	263	33,135	283,038	173,708	60,103
2021	28,575	1721	371	41,953	382,505	210,568	58,983

The regression uses data aggregated at the county level, summing the number of logistics points belonging to townships. The balanced county panel data spans 10 years (from 2012 to 2021). A detailed description of the data is provided below.

Table A3
Average counts of logistics points at the county level by year and category.

	Traditional	Cold chain	Local instant	Platform	To C	To B	China post
2012	1.69	0.01	0	0	1.58	6.47	19.36
2013	1.84	0.01	0	0.01	3.35	8.04	19.47
2014	3.53	0.03	0	0.02	4.04	18.95	19.3
2015	3.18	0.05	0	1.26	71.58	21.83	18.59
2016	6.19	0.16	0.02	2.29	83.82	63.13	15.39
2017	7.29	0.19	0.03	3.09	98.94	73.87	18.39
2018	7.44	0.27	0.09	9.62	90.72	74.32	17.87
2019	8.47	0.34	0.11	11.33	104.12	77.93	18.86
2020	6.99	0.32	0.08	11.89	92.69	55.83	21.12
2021	9.45	0.57	0.12	15.1	125.48	68.31	20.65

Table A4
Average counts of logistics points at the subdistrict level by year and category.

	Traditional	Cold chain	Local instant	Platform	To C	To B	China post
2012	1.13	0	0	0	1.06	4.45	6.63
2013	1.25	0.01	0	0.01	2.45	5.67	6.67
2014	2.2	0.01	0	0.01	2.7	12.97	4.83
2015	1.8	0.03	0	0.41	44.32	13.15	5.08
2016	3.49	0.09	0.01	0.73	51.18	38.1	4.72
2017	4.11	0.11	0.02	0.96	59.9	44.73	5.78
2018	3.99	0.15	0.07	2.46	48.99	42.04	5.63
2019	4.51	0.18	0.08	2.98	55.77	43.26	5.29
2020	3.7	0.16	0.06	3.35	47.44	29.7	5.9
2021	4.51	0.27	0.09	3.83	59.54	32.9	5.59

Table A5
Average counts of logistics points at the town level by year and category.

	Traditional	Cold chain	Local instant	Platform	To C	To B	China post
2012	0.53	0	0	0	0.46	1.92	10.92
2013	0.55	0	0	0	0.84	2.25	10.95
2014	1.23	0.02	0	0.01	1.18	5.57	11.73
2015	1.24	0.02	0	0.75	25.19	7.95	10.76
2016	2.42	0.06	0	1.39	30.17	23.11	8.79
2017	2.86	0.07	0.01	1.88	36.04	26.94	10.3
2018	3.09	0.12	0.02	6.12	37.95	29.77	10.01
2019	3.53	0.15	0.03	7.15	43.29	31.84	10.49
2020	2.94	0.14	0.02	7.29	39.2	24.06	11.71
2021	4.35	0.27	0.03	9.47	56.82	32.23	11.63

Table A6
Average counts of logistics points at the township level by year and category.

	Traditional	Cold chain	Local instant	Platform	To C	To B	China post
2012	0.03	0	0	0	0.06	0.1	1.81
2013	0.04	0	0	0	0.06	0.12	1.85
2014	0.1	0	0	0	0.15	0.41	2.75
2015	0.14	0	0	0.09	2.07	0.73	2.75
2016	0.28	0.01	0	0.17	2.48	1.92	1.88
2017	0.32	0.01	0	0.24	3	2.19	2.31
2018	0.36	0.01	0	1.05	3.78	2.51	2.22
2019	0.43	0.02	0	1.21	5.06	2.83	3.09
2020	0.34	0.02	0	1.25	6.05	2.07	3.51
2021	0.59	0.03	0	1.79	9.12	3.19	3.43

Appendix 6. The websites used for the mechanism tests

Santai County (三台县)
http://www.santai.gov.cn/xxgk/tzgg/17632121.html
Renshou County (仁寿县)
http://www.rs.gov.cn/info/3580/33282.htm
Xichong County (西充县)
https://www.xichong.gov.cn/xwdt/tzgg/201608/t20160805_1224085.html
Yongsheng County (永胜县)
http://www.ynljys.gov.cn/xljsysx/c102701/201711/50850ffa154a4af5a557a7cf1e174164.shtml
Yanji City (延吉市)
http://www.yanjinews.com/html/news/gonggao/2015/1210/77804.html
Tongyu County (通榆县)
http://swt.jl.gov.cn/dzswjnczhsfxgzzl1/201704/t20170425_2925561.html
Raoping County (饶平县)
http://www.raoping.gov.cn/gkmlzl/content/post_3781849.html
Tunchang County (屯昌县)
http://tunchang.hainan.gov.cn/tunchang/xxgkzl/zfxxgkml/201812/t20181229_2047496.html
Zigui County (秭归县)
http://www.hbzg.gov.cn/zfxxgk/show.html?aid=12&id=39493
Wafangdian City (瓦房店市)
http://www.dlwfd.gov.cn/2015/1014/3223.html
Huangzhong County (湟中县)
https://www.huangzhong.gov.cn/html/4221/308972.html
Shangdou County (商都县)
http://www.shangdu.gov.cn/Search/Details/12667.html
Aohan Banner (敖汉旗)
http://www.ahq.gov.cn/dzgk/zfxxgk/fdzdgknr/gfxwj/202202/t20220214_1659921.html
Guang'an District (广安区)
http://www.guanganqu.gov.cn/gaqrmzf/c100204/2022-10/09/content_f086adf84981483dbe89d85df3b125c2.shtml
Junlian County (筠连县)
http://swt.sc.gov.cn/sccom/zcdx/2018/3/2/919faaad359943888128f5fb7848e0c7.shtml
Pujiang County (蒲江县)
http://www.pujiang.gov.cn/pjxzf/c113685/2019-07/15/content_6ba8844569484ff8a3416e58616aee75.shtml
Leibo County (雷波县)

http://www.lbx.gov.cn/xxgk/zdxxzz/gjjdzswjnczhsfxxm/201802/t20180205_113604.html
Helan County (贺兰县)
http://www.nxhl.gov.cn/xxgk_7799/zfbmzsjgxxgkml/hlxzfb/xxgkml/zfbwj/202112/t20211210_3215323.html
Longde County (隆德县)
http://www.nxld.gov.cn/xxgk/zcjd/201803/t20180322_720004.html
Huoqiu County (霍邱县)
https://www.huoqiu.gov.cn/public/6596251/34285167.html
Yingshang County (颍上县)
https://www.ahys.gov.cn/xxgk/detail/5ac42ce37f8b9ace1430edbc.html
Wanrong County (万荣县)
http://www.wanrong.gov.cn/doc/2021/01/25/10151746.shtml
Lingshan County (灵山县)
http://www.gxls.gov.cn/zfxxgk/zcwj/zfwj/lzbf/t14386897.shtml
Wenchang City (文昌市)
http://wenchang.hainan.gov.cn/wenchang/zdpzfw/201705/0213dadd270d41aba3fb03cc9012486d.shtml
Zhenyuan County (镇原县)
http://www.gszy.gov.cn/xxgk/zcwj/xzfwj/zzbf4zyxrmzf/content_3468
Korqin Right Front Banner (科右前旗)
http://www.kyqq.gov.cn/kyqq/zwgk3/xxgkml88/zfxxgkml92/3424824/index.html
Lingbi County (灵璧县)
https://www.lingbi.gov.cn/public/6628011/144141571.html
Xiushui County (修水县)
http://www.xiushui.gov.cn/sjb/sjbzwzx/sjbztbd/014/dszc/202109/t20210901_5231370.html
Daming County (大名县)
http://www.daming.gov.cn/xwzx/gggs/201712/t20171220_733806.html
Ningling County (宁陵县)
https://www.ningling.gov.cn/ztzl/dzswjnczl/content_109508
Minquan County (民权县)
http://www.hngp.gov.cn/shangqiu/content?infoId=1530612453454301
Yangxin County (阳新县)
http://www.yx.gov.cn/zmhd/myzj/201801/t20180117_96363.html
Pingjiang County (平江县)
https://www.pingjiang.gov.cn/34930/55973/content_1495418.html
Xinshao County (新邵县)
https://www.xinshao.gov.cn//xinshao/zhengcwjb/201912/80a32123887c434faef4a7ad6f65bffc.shtml
Huayuan County (花垣县)
http://www.huayuan.gov.cn/zwgk_23240/xzfxxgkml_23243/tzgg_23248/201812/t20181211_1005933.html
Gangu County (甘谷县)
http://iic21.com/iic-zxbtz/index.php?m=Home&c=Articles&a=showart&artid=146679
Pinghe County (平和县)
http://www.pinghe.gov.cn/cms/siteresource/article.shtml?id=60456730997750004&siteId=60426747780620000
Fenggang County (凤冈县)
http://www.gzfenggang.gov.cn/ztzl/dzswjnc/gswj/201903/t20190328_64914707.html
Huize County (会泽县)
http://www.huize.gov.cn/article/description/12007.html
Wuding County (武定县)
http://www.ynwd.gov.cn/info/egovinfo/1007/overt_centent/11532329015178442p-/2019-0523001.htm
Mouding County (牟定县)
Hunyuan County (浑源县)
http://www.hunyuan.gov.cn/hyxrmzf/dssfgzzl/202201/d9e9ff6d48474ac2a5ea14275ba29f75.shtml
Quyang County (曲阳县
https://www.quyang.gov.cn/content-1464-56202.html
Wangdu County (望都县)
https://www.wangdu.gov.cn/col/1618903800825/2021/04/21/1618994826981.html
Xincai County (新蔡县)
https://www.xincai.gov.cn/web/front/news/detail.php?newsid=9829
Luxi County (泸溪县)
http://www.lxx.gov.cn/zwgk/qzfxxgkml/tzgg/202003/t20200327_1653649.html
Kongtong District (崆峒区)
http://www.kongtong.gov.cn/ztzl/ktqdzswjnczhsfxmzl/art/2022/art_05bad2811fc846119956b298a8d27f4c.html
Maiji District (麦积区)

http://www.maiji.gov.cn/html/news/xxgk/zfxxgkml/hcz/zfwg/2019-04/14656.html
Zhenyuan County (镇远县)
http://www.zygov.gov.cn/ztzl/zyxdzswjnc_5882943/gsgg_5882944/202202/t20220228_72779969.html
Pucheng County (蒲城县)
http://www.pucheng.gov.cn/ztzl/2019nzt/gjjdzswjnczgqf/100226.htm
Longjiang County (龙江县)
http://www.ljxrmzfw.gov.cn/zwxxgkzl/fdzdgknr/cdlyxxgk/yhyshj/sqzc/sqzcsx/2021/06/49693.html
Shiping County (石屏县)
http://www.hhsp.gov.cn/ztzl/dzswjnc/202205/t20220518_584791.html
Jieshou City (界首市)
https://www.ahjs.gov.cn/content/detail/5eeae0847f8b9ad6528b4571.html
Gaoyou City (高邮市)
http://gaoyou.yangzhou.gov.cn/
XiXia County (西峡县)
http://www.xixia.gov.cn/sitesources/xxxrmzf/page_pc/ztbd/xxxdzswjnczhsfgzzl/articlec8adbe1da87f4a3bb4d0176507eb7346.html
Yongkang City (永康市)
Chunan County (淳安县)
http://www.qdh.gov.cn/art/2022/3/11/art_1229561282_58993586.html
Ledong Li Autonomous County (乐东黎族自治县)
http://ledong.hainan.gov.cn/ldxswzsj/gzdt/202112/b9cb8db7e26d4128bc886d34a77856af.shtml
Baisha County (白沙县)
http://baisha.hainan.gov.cn/baisha/zfxxgkzl/xgbmzfxxgk/bsxzfb/0202/201910/t20191015_2684413.html
Jianli County (监利县)
http://www.jianli.gov.cn/ztzl_30/dzswjnc/gsgg/202011/t20201118_542601.shtml
Qidong County (祁东县)
http://www.qdx.gov.cn/xxgk/xxgkml/xzfgzbmxxgkml/xswlsj/fgwj/20200909/i2140917.html
Linxia County (临夏县)
https://www.linxiaxian.gov.cn/lxx/ztzl/GJDZSWJNC/art/2022/art_ab0b2c8536cb4bb093c1865fffd60ff0.html
Pingnan County (屏南县)
http://www.pingnan.gov.cn/zwgk/zfxxgkzl/zfxxgkml/fggzhgf_28894/gfxwj/202108/t20210826_1514687.htm
Dehua County (德化县)
http://www.dehua.gov.cn/ztzl/dzswjnczhsf/gsgg/202301/t20230104_2833745.htm
Nong'an County (农安县)
http://zwgk.changchun.gov.cn/na/naxrmzf/zfxxgkml/202210/t20221008_3070714.html
Lianjiang City (廉江市)
http://www.lianjiang.gov.cn/ztym/dsnc/fawj/content/post_1666863.html
Hejian City (河间市)
http://hejian.gov.cn/hejian/dzswjnc/202204/ab982a7649744b66a736126b967eb243.shtml
Qi County (杞县)
http://www.zgqx.gov.cn/2020/1124/30856.html
Changjiang Li Autonomous County (昌江黎族自治县)
http://changjiang.hainan.gov.cn/changjiang/05032/202110/1dbf366b102d45099f0e69f938f947a6/files/40f5857f02d448e28fca7b1193b17caa.pdf
Kuandian Manchu Autonomous County (宽甸满族自治县)
https://www.lnkd.gov.cn/html/KDXZF/202104/0163904092929041.html
Cangwu County (苍梧县)
http://www.cangwu.gov.cn/ztzl/dzswjnczhsfxm/xmgs/t13235308.shtml
Jianhu County (建湖县)
http://www.jianhu.gov.cn/art/2023/2/27/art_12512_3968784.html
Funing County (阜宁县)
https://www.cgwenjian.com/view/file/202211030000311834

Appendix 7. Robustness test

1. PSM-DID approach

Although the event study analysis suggests that the treatment and control groups exhibit similar time trends before the policy implementation, there may still be a self-selection issue within the policy treatment group. For example, when the Ministry of Finance and the Ministry of Commerce finalize the list of demonstration counties, they consider factors such as the counties' economic development levels, e-commerce foundations, and regional balance, selecting the most suitable regions for piloting, which could lead to bias in the final regression coefficients. Therefore, this section further employs the PSM-DID (Propensity Score Matching - Difference in Differences) method for estimation to obtain more accurate results. First, a Logit model is used for estimation, as shown in the following equation:

$$\text{Logit}\left(Treatment_{ct}=1\right)=\alpha_c+\gamma_t+X_{ct}^{\prime}\beta+\varepsilon_{ct} \tag{A1}$$

The definition of $Treatment_{ct}$ is whether the county is a policy treatment county. $X_{ct}^{\prime}$ includes county-level variables that may influence whether a county is selected for treatment, such as regional per capita GDP, population density, the number of industrial enterprises, and the regional industrial structure, reflecting the county's e-commerce foundation and economic development status. Before conducting further regression using the PSM-DID method, this paper performs “balance tests” and “common support tests” for three different PSM matching approaches. The results show that, after matching, the bias between the control and treatment groups is significantly reduced, satisfying the common support assumption. After excluding samples that do not meet the common support assumption, the difference-in-differences method is used to further estimate the policy's impact on consumption.

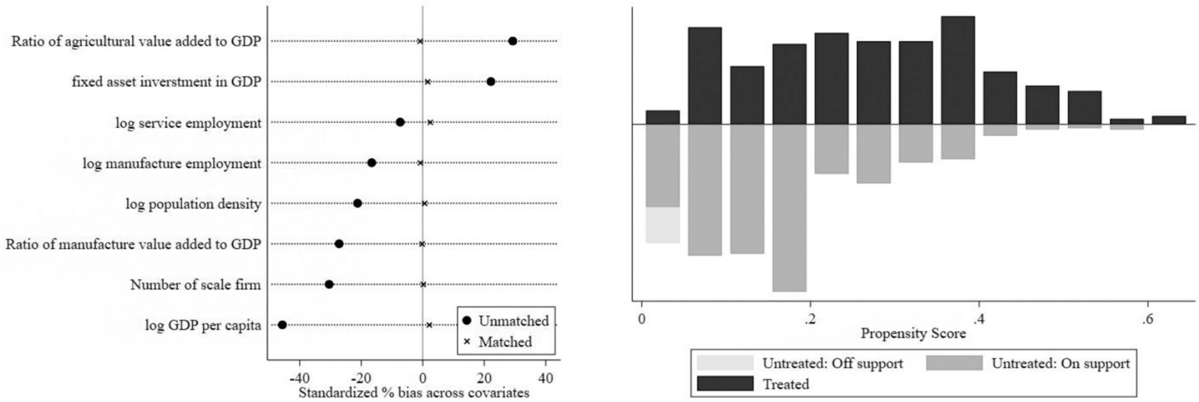


Fig. A5. Matching performance of PSM.

Table A7
Impacts of REDC program on online shopping (PSM-DID).

	Shopping online (1 for yes)		
	Nearest Neighbor	Caliper	Kernel
	(1)	(2)	(3)
REDC	0.019**	0.019**	0.020**
	(0.009)	(0.009)	(0.009)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-year trend	Yes	Yes	Yes
Observation	94,239	94,239	92,649
Adjusted R^2	0.312	0.312	0.312

Note: ***, ** and * represent significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors clustered at the county level are shown in parentheses.

As shown in the table above, columns (1)–(3) present regressions using the matched sample, with treatment effect values remaining robust. The implementation of the REDC policy increased the probability of household online shopping by 0.19 %, significant at the 5 % level. Results obtained using different matching methods are similar.

2. Robust estimator

The distribution of counties entering the policy across different years, indicating that counties entered the policy at various times. In standard difference-in-differences (DID) analysis, all treatment groups are assumed to be exposed to the intervention at the same point in time. However, in practice, many policies are not implemented all at once but are instead piloted in certain regions before being gradually rolled out in stages, resulting in varying policy initiation times. Numerous studies (Callaway & Sant'Anna, 2021a, 2021b; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021) have shown that, if policy effects vary across time or are heterogeneous, the two-way fixed effects model can introduce bias, as its estimates represent a weighted average of multiple standard DID treatment effects, which may lead to issues with negative weights. Therefore, following De Chaisemartin and d'Haultfoeuille (2020), this paper conducts a diagnostic analysis of the model specification to examine the potential bias introduced by the two-way fixed effects model. The results show that, when the dependent variable is whether households engage in online shopping, out of all 811 weights, 657 are positive, while 154 are negative. This suggests that, under heterogeneous treatment effects, the standard DID estimates may lack robustness.

Table A8
Impacts of REDC program on online shopping (robustness staggered DID).

Variable	Shopping online (1 for yes)		
	DID MULTIPLEGT	DID IMPUTATION	DID2s
	(1)	(2)	(3)
REDC	0.028** (0.011)	0.026* (0.007)	0.038*** (0.010)
Control	Yes	Yes	Yes
County characteristics	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Province-year FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The model in column 1 is proposed by De Chaisemartin and d'Haultfoeuille (2020), with a theoretical basis that calculates a weighted average of the effects in both positive (from untreated to treated) and negative (from treated to untreated) directions. The model in column 2 is proposed by Borusyak et al. (2021), based on interpolation estimation theory. The model in column 3 is proposed by Gardner (2022), grounded in an alternative two-stage GMM estimation framework.

Drawing on the study by De Chaisemartin and d'Haultfœuille (2020), the model used in column (1) of Table A8 is theoretically based on calculating a weighted average of treatment effects in both directions—positive ("untreated to treated") and negative ("treated to untreated"). This command has broad applicability, and the results show that the policy increased the probability of online shopping by 2.8 %. Following Borusyak et al. (2021), the model in column (2) of Table A8 employs an "imputation" estimation method to address the above issues. Specifically, it first estimates the model coefficients using untreated observations and then applies these coefficients to treated samples, producing counterfactual values as if the treated samples had not been exposed to the policy. The difference between actual values and these counterfactuals represents the estimated treatment effect. This approach relaxes the parallel trend assumption and allows for the inclusion of some control variables. The results, similar to those from the original regression in this study, indicate that the policy increased the probability of online shopping by 2.6 %. Column (3) follows Gardner (2022) and constructs an alternative two-stage GMM estimation framework. In this framework, the first stage identifies group and time effects; after removing these, the second stage compares the differences between the treatment and control groups to estimate the average treatment effect. This two-stage method is robust to staggered treatment timing and heterogeneous treatment effects. According to the regression results, the outcome in column (3) is also similar to that of the original regression, with the policy increasing the probability of online shopping by 3.8 %.

3. Placebo tests

Although we control for individual, household, and community-level characteristics, the final model results may still be affected by unobserved variables. Following the study by Wang et al. (2022), this paper employs a randomly generated "Rural E-commerce Demonstration Counties" policy as a placebo test. The specific results are shown below:

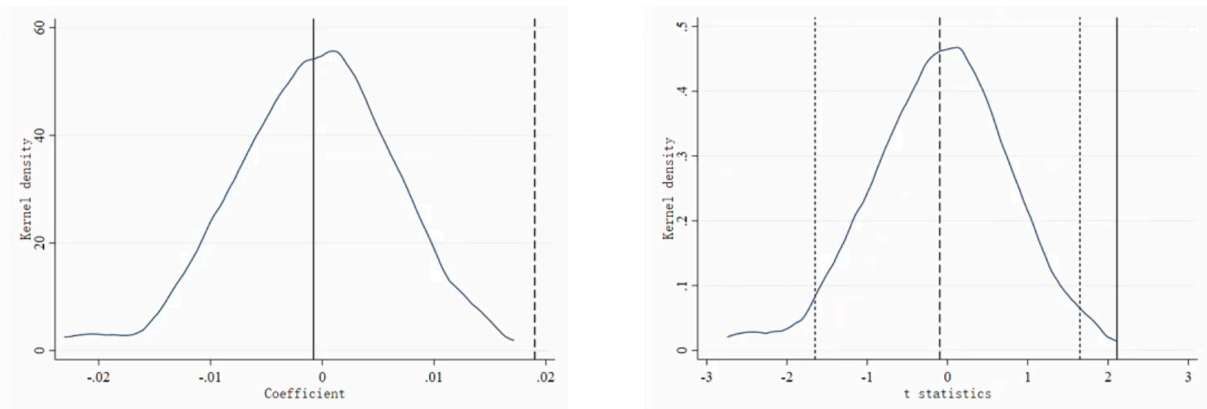


Fig. A6. Placebo tests.
Note: To ensure that the placebo policy aligns with the actual phased implementation of the policy, we randomly selected the same number of counties as those that entered each year in the original regression, repeating this random process 100 times. Specifically, 78 counties entered before 2017, 39 counties entered in 2019, and 28 counties entered in 2021.

The left panel of Fig. A6 shows that the mean estimated value for the randomly generated REDC policy is close to 0 (solid line), which is far from the estimated coefficient of the baseline model under the actual policy impact (dashed line). This indicates that the baseline regression results are minimally affected by omitted variables, confirming the robustness of our estimates. The right panel of

Fig. A6 reports the distribution of the t-statistics for the estimated values of the randomly generated REDC policy, with a mean of approximately −0.09 (dashed line), which is far from the t-statistic of 2.44 under the actual e-commerce policy intervention and falls outside the 90 % significance level (dashed line). The vertical solid line represents a t-statistic value of 2.44.

Appendix 8

We further investigate the underlying reasons behind the increase of household income. The table below demonstrates that the proportion of households who sell agricultural products online accounts only a minor proportion of the whole sample, increasing from 0.09 % in year 2015 to 0.26 % in year 2019 (see column 3). Apart from the agricultural sector, the ratio of people who operate industrial and commercial businesses online demonstrate a similar but higher statistic, ranging from 0.94 % to 1.47 % from year 2015 to 2019 (see column 6). Compared to households who shop online which accounts for 40.3 % of the whole sample, households who sale online is relatively a minor portion. From the intensive margin, column (8) reveal that sales revenue generated by industrial and commercial businesses through the internet increases from 1803.565 yuan in year 2015 to 4587.21 yuan in year 2019, while the proportion of internet sales in the total sales of agricultural products is still low at 1.03 % in year 2019. So we can infer that the income increase of the REDC policy can be largely attributed to the online operation of industrial and commercial businesses.

Table A9
The changes in online sales of agricultural products and online business operations over time.

Variable	Online sales of agricultural products (1 = yes)			Online operation of industrial and commercial businesses (1 = yes)			Sales revenue generated by industrial and commercial businesses through the internet		The proportion of internet sales in the total sales of agricultural products	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year	Total Sample	Number of online agri sales	Ratio	Total Sample	Number of online business	Ratio	Total Sample	Average Sales Business Income	Total Sample	Average Ratio
2015	37,289	34	0.0009	37,289	351	0.0094	37,261	1803.565	36,938	0
2017	40,011	129	0.0032	40,011	677	0.0169	39,728	4114.758	39,396	0.0073
2019	34,643	91	0.0026	34,643	510	0.0147	34,527	4587.21	34,145	0.0103

Data availability

The data that has been used is confidential.

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