E-Commerce as a Driver of Gender Equity: Labor Supply and Household Outcomes in Rural China*

Zengdong Cao Wei Huang Hantao Wu

Abstract

We examine the gendered impacts of e-commerce expansion on labor supply, intra-household bargaining, and child outcomes in rural China, using the staggered rollout of the Rural E-Commerce Comprehensive Demonstration Project (RECD). E-commerce boosts women's labor force participation and working hours, without affecting male labor supply. It also enhances women's bargaining power, increasing their control over finances, reducing time spent on household chores, and improving satisfaction with task-sharing. E-commerce improves girls' educational and health outcomes, with no significant effects on boys. These findings suggest digital transformation can reduce gender disparities and improve socioeconomic outcomes for women and girls in rural areas.

Keywords**:** E-commerce, Labor Supply, Intra-household Bargaining Power, Child Outcomes

JEL classifications**:** O22, H54, J21, D13

* Cao: Business School, Beijing Normal University, email: caozengdong@foxmail.com. Huang: China Center for Economic Research (CCER), National School of Development (NSD), Peking University, email: huangwei@pku.edu.cn. Wu: Office of Population Research, Princeton University, email: hantao.wu@princeton.edu.

1. Introduction

The rapid expansion of e-commerce has reshaped global labor markets, creating new opportunities for flexible, remote, and self-employment, especially for women (OECD, 1999; Bauer & Fernández, 2023). From 2014 to 2023, global e-commerce sales rose dramatically from USD 1.34 trillion to USD 5.80 trillion, with China emerging as the world's largest business-to-consumer (B2C) e-commerce market, reaching USD 1.9 trillion in sales—30% of the country's retail transactions. Unlike traditional employment sectors such as agriculture, which are typically male-dominated and physically demanding, e-commerce provides women with job opportunities that are less dependent on physical labor (Luo & Niu, 2019; UNCTAD, 2023). For women in developing economies, e-commerce enables engagement in income-generating activities beyond traditional sectors, allowing for a more effective balance between market work and household responsibilities (Goldin & Katz, 2016; Olivetti & Petrongolo, 2016). This shift has the potential to reduce gender disparities in employment, earnings, and decision-making within households (Blau & Kahn, 2017).

Despite the transformative potential of e-commerce, there is limited empirical evidence on its gender-specific impacts, particularly in rural areas where entrenched gender norms and unequal access to digital technologies persist (Duflo, 2012; Greenwood et al., 2017). While previous research has largely concentrated on e-commerce's broader economic effects, such as its impact on consumer welfare, living costs, spatial consumption inequality, and retail employment (Couture et al., 2021; Dolfen et al., 2023; Fan et al., 2018; Chun et al., 2023),[1] few studies have explored its specific influence on gender disparities in labor market outcomes. Understanding how e-commerce affects women's participation in the labor market and their bargaining power within households is crucial, particularly in developing regions where gender inequalities are more pronounced. This paper addresses this gap by leveraging the staggered rollout of the Rural E-Commerce

[1] E-commerce enhances consumer welfare by providing broader access to goods and services, often at competitive prices, benefiting those in remote or underserved areas with limited retail options (Dolfen et al., 2023; Couture et al., 2021). However, spatial consumption inequality can increase, as urban and wealthier consumers generally gain more from digital platforms than those in rural or low-income regions (Fan et al., 2018). While e-commerce creates new roles in digital services and logistics, it also contributes to job displacement within traditional retail (Chun et al., 2023).

Comprehensive Demonstration (RECD) Project to estimate its effects on labor supply, household bargaining power, and child outcomes in rural China, focusing on the differential impacts on men and women.

In China, the government has positioned e-commerce as a central tool for tackling both economic and social challenges, with a particular focus on rural areas. Launched in 2014, the Rural E-Commerce Comprehensive Demonstration (RECD) Project aligns with broader national strategies aimed at poverty alleviation and rural revitalization. This initiative leverages digital platforms to economically empower women by offering opportunities that enhance work flexibility, allowing them to balance market employment with household responsibilities (Luo & Niu, 2019; UNCTAD, 2023). The phased rollout of the RECD Project provides a quasi-experimental setting, enabling us to estimate the impacts of e-commerce expansion on gender-specific labor outcomes. Utilizing nationally representative panel data from the China Family Panel Studies (CFPS) covering 2012 to 2020, we employ a difference-in-differences (DID) strategy and event study methodology to assess the RECD Project's effects on labor supply, intra-household bargaining power, and child outcomes. Our analysis centers on the differential impacts of e-commerce expansion on men and women, examining how digital platforms transform labor market behavior, household dynamics, and children's well-being.

In traditional two-way fixed effects (TWFE) models, treatment effects are often estimated as weighted averages across different treatment periods. This can introduce bias, especially when earlier-treated groups serve as controls for later-treated groups and treatment effects vary over time (Goodman-Bacon, 2021; De Chaisemartin & d'Haultfoeuille, 2020). To address these potential biases, we supplement the traditional staggered DID estimation with an event study approach and the CSDID estimator proposed by Callaway and Sant'Anna (2021). This combined approach allows us to assess the dynamic effects of e-commerce expansion through the RECD project on labor market outcomes, household bargaining, and child welfare.

Our main findings indicate that e-commerce significantly reshapes rural labor market dynamics, with particularly strong effects for women. Exposure to the RECD project is associated with an approximately 3.0 percentage point (pp) increase in female labor force participation (LFP),

representing a 4% rise from the mean, along with a 2.5-hour increase in weekly working hours, equivalent to an 8% increase. Beyond basic labor supply, the project also fosters women's involvement in new forms of market engagement, with an increase of around 2.8 pp in e-commerce activities and an increase of around 2.2 pp in entrepreneurship. In contrast, no significant changes are observed in men's labor market outcomes across these dimensions. These gender-differentiated impacts suggest that e-commerce development can effectively narrow labor market disparities by creating opportunities aligned with women's specific needs and capabilities.

The shifts in women's economic participation further translate into broader household and child outcomes. At the household level, we observe substantial increases in total household income, primarily driven by growth in business revenues from both agricultural and non-agricultural sources. Patterns of household expenditure also change, with increases of around 0.1 pp in cosmetics spending, around 0.7 pp in education spending, around 1.5 pp in healthcare spending, and around 2.0 pp in housing spending. Correspondingly, women's roles in household decision-making strengthen, as indicated by an increase of around 5.1 pp in the likelihood of women being designated as household heads. There is also a notable shift in time allocation, with women gaining 0.2 hours of daily leisure while reducing time spent on household chores by 0.5 hours per day. Furthermore, we observe an increase of around 4.7 pp in satisfaction with spousal contributions to household tasks, collectively suggesting that e-commerce expansion enhances women's bargaining power within households.

Finally, we examine the gendered impacts of e-commerce on children, finding an increase of 3.0 pp in girls' school enrollment rates and an increase of around 7.5 pp in their self-assessed health scores, with no significant effects observed for boys. These findings imply that e-commerce expansion not only transforms household economic dynamics but also contributes to reducing long-standing gender disparities in human capital investment, particularly benefiting girls.

The RECD project's impact on gendered labor and household dynamics is robustly supported by our findings, validated through an event study and CSDID estimators, alongside extensive robustness checks. Our event study confirms parallel pre-treatment trends and reveals steady post-implementation increases in women's labor force participation, bargaining power, and girls'

outcomes, reinforcing the causal interpretation of RECD's benefits. Additional robustness checks address potential confounders by controlling for concurrent policies and regional developments, including China's investments in education, public health, and internet infrastructure, and incorporating various fixed effects to account for unobserved heterogeneity. Moreover, our balance tests show that after adjusting for selection criteria, the economic characteristics of treated and control counties become statistically indistinguishable, enhancing the credibility of our comparative analysis. Tests for population composition changes due to migration show no significant effects, and sample attrition analyses reveal minimal impacts. Finally, a placebo test with randomized treatment assignments produces no significant effects, further confirming the reliability of our identification strategy. Collectively, these results demonstrate that e-commerce expansion through the RECD program meaningfully enhances gender-specific labor and household outcomes.

Our study makes significant contributions to several key areas of research. First, we extend the literature on the gendered impacts of technological change in labor markets. Previous studies, such as those by Goldin (1990, 2014, 2021), Blau et al. (2014), and Greenwood et al. (2017), have shown that technological advancements, including electrification (Dinkelman, 2011) and IT innovations (Beaudry & Lewis, 2014; Black & Spitz-Oener, 2010), have increased women's labor market participation and earnings by enhancing the value of non-manual skills (Olivetti & Petrongolo, 2016). Our research focuses on e-commerce as a rapid form of technological adoption, demonstrating how it boosts women's labor supply through engagement in online commerce and entrepreneurship. Moreover, we show that e-commerce enhances access to higher-paying jobs for women while also improving girls' educational and health outcomes. These findings provide valuable insights into how digital transformation can influence gender disparities in labor markets.

Second, our research contributes to the literature on women's empowerment through technology adoption and digital inclusion in developing countries (Duflo, 2012). While existing studies often examine targeted interventions, such as healthcare (Lee & Finlay, 2017; Cesur et al., 2023), trade liberalization (Ouyang et al., 2022), and vocational training (Bandiera et al., 2020), fewer explore the broader impacts of technology. Our study highlights the transformative potential of e-commerce in improving women's labor market outcomes, household decision-making, and

girls' welfare. Furthermore, these results align with the digital inclusion literature, which underscores how access to digital technologies can help reduce socio-economic disparities and empower marginalized populations, particularly rural women (Cook et al., 2021; Wagg et al., 2019). Our findings suggest that large-scale technological adoption, even when not explicitly aimed at women, can have significant positive effects on their economic and social well-being.

Lastly, we contribute to the literature by demonstrating how technological interventions, specifically e-commerce, can have substantial impacts on children's outcomes. While much of the existing research has focused on the direct effects of women's labor market participation and empowerment (Duflo, 2012; Goldin, 2014; Heath & Jayachandran, 2017), our findings reveal that improvements in women's economic status through e-commerce also lead to enhanced educational and health outcomes for their children, particularly girls (Aizer, 2010). Girls in households benefiting from e-commerce expansion experience higher school enrollment and better health, consistent with evidence that empowering women leads to greater investments in children's well-being (Qian, 2008). This underscores the broader, intergenerational benefits of digital technologies and highlights the critical role of women's economic participation in shaping future opportunities for children (Wagg et al., 2019).

The remainder of this paper is organized as follows. Section 2 provides background on the RECD project and its role in promoting rural e-commerce in China. Section 3 presents a conceptual framework predicting RECD's effects on labor market participation, household dynamics, and child outcomes. Section 4 describes the data sources and key variables. Section 5 outlines our empirical strategies. Section 6 presents results on labor market dynamics, while Section 7 presents results on household and child outcomes. Section 8 conducts robustness checks. Finally, Section 9 concludes with implications for rural development and gender equity policy.

2. Background: The Rural E-commerce Comprehensive Demonstration Project

2.1 Motivation and Context of the RECD Project

China's rural regions, despite representing a significant share of the country's population, have long struggled with economic underdevelopment. These areas are characterized by limited access to

markets, poor infrastructure, and a scarcity of modern employment opportunities (Glauben et al., 2012). Historically, rural economies have relied heavily on agriculture, but challenges such as low productivity, fragmented supply chains, and constrained market access have resulted in stagnant incomes and persistent poverty (Adamopoulos et al., 2022). In contrast, China's urban areas have undergone rapid modernization, fueled by technological innovation and industrialization, which has only widened the economic and digital divide between urban and rural populations (Hao et al., 2020). This disparity has left rural communities isolated from the opportunities generated by the country's broader economic growth.

Recognizing both the vast untapped potential of rural markets and the urgency of promoting inclusive economic development, the Chinese government launched the Rural E-Commerce Comprehensive Demonstration (RECD) Project in 2014. Jointly initiated by the Ministry of Finance and the Ministry of Commerce, this ambitious project aimed to bring rural areas into the fold of the burgeoning digital economy.

The core objective was to leverage e-commerce as a transformative tool for poverty alleviation and rural revitalization, directly addressing the structural barriers that had long hindered rural economic progress (Couture et al., 2021). By facilitating access to e-commerce platforms, the initiative sought to empower rural producers, particularly small-scale farmers and artisans, to reach wider markets, thereby improving income opportunities and spurring local entrepreneurship. In doing so, the RECD project also sought to create new employment avenues, not only in production but also in related services such as logistics and digital marketing, helping to modernize the rural economy and close the urban-rural economic divide. The project's broader vision aligns with China's national strategy for poverty reduction and balanced regional development, positioning e-commerce as a critical driver of inclusive growth.

2.2. Timing of the RECD Project Implementation

The RECD project, which initially launched in 2014 with 56 demonstration counties, quickly expanded nationwide due to its early success in fostering rural e-commerce development. Between 2015 and 2020, the number of demonstration counties grew steadily, with more than 200 new counties added each year (see Appendix Figure A1). By 2020, the Chinese government had

invested a total of CNY 25 billion into the program, establishing 1,466 demonstration counties across the country (Appendix Figures A1 and A2). This rapid scaling reflects the government's commitment to integrating rural areas into the digital economy, emphasizing e-commerce as a crucial driver of rural revitalization and poverty alleviation.

Figure 1 provides a clear depiction of the phased rollout of the RECD project across counties from 2014 to 2020, illustrating the steady year-over-year expansion. The staggered implementation is evident, beginning with a modest group of 56 counties in 2014 and gradually reaching over 1,466 counties by 2020. This incremental rollout offers a quasi-natural experimental setting, which is instrumental for evaluating the causal impact of e-commerce expansion on various socioeconomic outcomes. By providing variation in treatment timing across different counties, the phased implementation allows us to examine how the timing and intensity of e-commerce adoption affect labor market participation, household income, and other key variables over time.

[Insert Figure 1 Here]

Crucially, the selection of demonstration counties was not random. According to the central government's guideline, the project explicitly prioritized counties with high levels of poverty and underinvestment, making e-commerce a key component of the government's broader poverty alleviation and rural development strategy.[2] This targeted approach enhances the policy's focus on disadvantaged areas but also introduces potential selection bias. To mitigate this concern in our empirical analysis, we account for county-level characteristics such as poverty status and fixed asset investment, ensuring that our evaluation of the RECD project's effects reflects its true

[2] For example, the Notice on Carrying Out the 2017 Rural E-commerce Comprehensive Demonstration Work issued by the General Offices of the Ministry of Finance, the Ministry of Commerce, and the Comprehensive Department of the State Council Leading Group Office of Poverty Alleviation and Development states that the demonstration work will continue to prioritize poor areas with insufficient public investments. The Notice on Carrying Out the 2020 Rural E-commerce Demonstration Comprehensive Work issued by the General Offices of the Ministry of Finance, the Ministry of Commerce, and the Comprehensive Department of the State Council Leading Group Office of Poverty Alleviation and Development points out that, in provinces with poverty alleviation tasks, the number of poor counties applying should, in principle, account for no less than one-third of the total counties applying in the region. It encourages poor counties and underdeveloped counties in old revolutionary base areas to apply, and gives priority support to poor counties with significant achievements in e-commerce poverty alleviation (Official website of The Ministry of Commerce of the People's Republic of China).

socioeconomic impacts rather than pre-existing conditions in the selected regions.

2.3. Investment Areas and Economic Impact of the RECD Project

Each demonstration county received approximately CNY 20 million in financial support, which was strategically allocated across four key areas. First, the development of logistics distribution systems aimed to integrate online sales with physical distribution, enhance payment services, and upgrade logistics information platforms to streamline operations. Second, the project funded the construction and renovation of e-commerce service sites, primarily through agricultural cooperatives, postal services, and leading enterprises, to bolster local infrastructure and better facilitate rural e-commerce development. Third, comprehensive e-commerce training programs were launched to equip local governments, agricultural enterprises, cooperatives, and farmers with essential digital skills, enabling them to participate more effectively in the expanding online marketplace. Lastly, efforts were concentrated on promoting the sale of agricultural products by improving certification standards, developing regional brands, refining marketing strategies, and strengthening quality assurance systems to help rural specialty products penetrate urban markets.

The RECD project empowered rural residents—particularly women—by enabling them to establish online stores on platforms such as Taobao, where they could sell their products remotely. This flexibility was especially beneficial for women, allowing them to balance work with household responsibilities by operating from home or nearby workshops. Many rural women also leveraged livestreaming technologies provided by e-commerce platforms to market their agricultural products, benefiting from the freedom to control their own broadcasting schedules. Furthermore, the project facilitated the establishment of rural express logistics points, creating flexible employment opportunities for women in roles such as delivery personnel, which offered the convenience of working close to home.

During this period, rural online retail sales experienced exponential growth, soaring from CNY 0.11 trillion in 2013 to CNY 2.17 trillion by 2022. Notably, the growth rate of rural online retail sales consistently outpaced that of national online retail sales from 2014 to 2022, highlighting the transformative impact of e-commerce on rural economies (Appendix Figure A3).

2.4 Comparison with Similar Projects in Other Countries

While China's RECD project is unique in its size and scope, other countries have implemented similar e-commerce and digital inclusion initiatives, particularly in rural areas. For instance, India's Digital India program, launched in 2015, similarly aims to bridge the digital divide by increasing access to digital services in rural regions, though it focuses more broadly on public service delivery and less directly on e-commerce. The primary difference between China's RECD and India's Digital India initiative lies in the explicit focus of RECD on e-commerce as a vehicle for economic development and poverty alleviation, whereas Digital India encompasses a wider range of digital governance and service access efforts.

In Latin America, the Brazilian government's "*Programa Nacional de Acesso ao Mundo Digital*" (National Access to the Digital World Program) also aims to connect rural and underserved communities with digital platforms. However, like India's approach, the focus is not as tightly tied to economic outcomes through e-commerce but rather to social inclusion via internet access.

In contrast to these broader initiatives, China's RECD project targets economic outcomes through structured, market-driven e-commerce channels. It incorporates training for entrepreneurs, logistical improvements, and infrastructure development to help rural businesses thrive in online marketplaces. This market-oriented approach has allowed China's project to accelerate income generation and entrepreneurship, especially for women, in ways that are distinct from other national efforts.

3. Conceptual Framework

Our conceptual framework integrates economic theories of household decision-making and labor supply to understand how e-commerce expansion influences labor market participation and household dynamics in rural China. Drawing on the collective household framework (Chiappori, 1992), we model household resource allocation as an outcome of members' relative economic contributions and resulting bargaining positions. The framework suggests that if e-commerce creates opportunities better suited to women's comparative advantages, we should observe increased female labor force participation and enhanced bargaining power within households.

Several features of e-commerce make it potentially transformative for women's economic

participation. E-commerce activities often emphasize skills such as communication, customer service, and attention to detail - competencies that studies have found to be particularly strong among women (Galor and Weil, 1996; Ge and Zhou, 2020). Additionally, the flexible working arrangements enabled by digital platforms can help overcome the time constraints imposed by household responsibilities that have traditionally limited women's participation in formal labor markets. If these characteristics of e-commerce indeed reduce the opportunity cost of market work for women relative to traditional sectors dominated by physical labor, we would expect to see greater female engagement in e-commerce activities and entrepreneurship.

3.1 Model Setup

Consider a household consisting of two adults—a female (*f*) and a male (*m*)—and one child. Each adult allocates time between leisure, home production, and market labor. Following the standard labor supply model, each individual's time allocation is constrained by a total time endowment normalized to one:

$$l_i + t_i + h_i = 1, \;\; i \in \{f, m\} \tag{1}$$

where l_i denotes leisure time, t_i is time spent on home production (e.g., childcare, household chores), and h_i is time allocated to market labor.

Labor Market. Each adult can work in either the traditional sector or the e-commerce sector. The e-commerce sector is characterized by greater flexibility and lower physical demands, which we assume makes it more attractive to women, particularly in rural settings. The development of e-commerce is represented by the parameter E, which affects wages differentially for women and men. Women's wages rise more with e-commerce development due to a comparative advantage in e-commerce-related tasks. Wage rates are defined as:

$$w_f = w_0 + \alpha_f E, \;\; w_m = w_0 + \alpha_m E, \text{ with } \alpha_f > \alpha_m \geqslant 0 \tag{2}$$

where $w_0 > 0$ is the base wage in the traditional sector, and α_f and α_m capture the differential impact of e-commerce development on women's and men's wages.

Home Production. Total time required for home production, T, must be shared between the two adults. The traditional gender norms in rural China suggest that women bear a disproportionate share of home production responsibilities: $t_f + t_m = T$, with $t_f > t_m$.

Household Utility Function and Budget Constraint. We adopt the collective household model (Chiappori, 1992), where the household maximizes a Pareto-weighted sum of the individuals' utilities. Each individual derives utility from consumption (C), and leisure (l_i), and, for the female, from the well-being of her child, which depends on parental investments I in child human capital:

$$\max_{C,I,l_f,l_m,t_f,t_m,h_f,h_m} \lambda U_f + (1-\lambda)U_m \tag{3}$$

$$U_f = u(C) + v(l_f) + w(H),\ U_m = u(C) + v(l_m)$$

Here, $\lambda \in [0, 1]$ is the female's bargaining power, which is endogenously determined by her relative contribution to household income. The child's human capital H depends on parental investment I:

$$H = H(I), \text{ with } H'(I) > 0 \text{ and } H''(I) < 0 \tag{4}$$

The household's budget constraint is given by: $C + I = w_f\, h_f + w_m\, h_m$, where C is household consumption, h_f and h_m refer to the time women and men allocate to the labor market, respectively.

Intra-Household Bargaining Power. The female's bargaining power λ depends on her share of household earnings:

$$\lambda = \lambda(s_f), s_f = \frac{w_f h_f}{w_f h_f + w_m h_m} \tag{5}$$

with $\lambda'(s_f) > 0$.

This means that as women's participation in the e-commerce sector increases their earnings, their bargaining power within the household improves, allowing them more influence over decisions such as consumption and time allocation.

3.2 Model Predictions and Implications

From this framework, we derive three key predictions about the impact of e-commerce expansion on household outcomes. Our detailed model derivation is provided in Appendix A.

Female Labor Supply: An increase in e-commerce development raises women's wages more than men's, incentivizing women to shift time from home production to market labor. This is consistent with the standard labor supply model, where higher wages reduce the opportunity cost of market work.

Proposition 1: An increase in e-commerce development E leads to a larger increase in women's labor supply h_f relative to men's h_m, thereby reducing the gender gap in labor supply.

Intra-Household Bargaining Power: As women's earnings increase due to e-commerce participation, their share of household income rises, strengthening their bargaining power. Greater bargaining power allows women to allocate less time to home production and more to leisure or market work, and it gives them more control over household spending.

Proposition 2: An increase in women's labor supply and earnings due to e-commerce development (*E*) enhances their bargaining power within the household.

Child Outcomes: Women are more likely to invest in child well-being, particularly daughters, when their bargaining power increases. This is in line with existing evidence that women tend to prioritize investments in children's health and education (Qian, 2008; Duflo, 2012).

Proposition 3: Enhanced female bargaining power results in greater investment in children's human capital *I*, with potentially larger benefits for daughters if mothers exhibit a preference for investing in girls.

This conceptual framework illustrates how e-commerce can reshape labor market behavior and household dynamics by offering women more flexible and higher-paying work opportunities. The expansion of e-commerce increases female labor force participation, strengthens intra-household bargaining power, and improves child outcomes, particularly for girls. These theoretical predictions guide our empirical analysis, where we exploit the staggered rollout of the RECD project to identify the causal effects of e-commerce expansion in rural China.

4. Data and Summary Statistics

4.1 China Family Panel Studies (CFPS) and Supplement Data

China Family Panel Studies (CFPS). This study uses data from the China Family Panel Studies (CFPS), a longitudinal and nationally representative survey that provides detailed information on Chinese individuals, families, and communities. The CFPS is well-suited to our analysis, as it captures essential socioeconomic variables—including employment, household structure, education, health, and intra-household decision-making dynamics—that are crucial for evaluating the gendered effects of e-commerce expansion in rural China. Its longitudinal design allows us to observe temporal changes in these variables, making it especially appropriate for a

difference-in-differences (DID) approach that leverages the staggered rollout of the RECD project.

The CFPS survey employs a multistage, implicit stratification, and probability proportional to size (PPS) sampling strategy. This ensures that the dataset covers 162 counties across 25 provinces, representing approximately 95% of China's population. Our analysis draws on five waves of CFPS data from 2012 to 2020, excluding the 2010 wave due to inconsistencies in employment status reporting.[3] We focus on the rural population aged 20–60, the prime working-age group, yielding a longitudinal sample of 51,750 individual-year observations from 127 counties, including 64 RECD counties. For each individual, we examine labor market outcomes through multiple dimensions. The extensive and intensive margins of labor supply are measured through labor force participation (LFP, a binary indicator) and weekly working hours, respectively. We also capture forms of market participation through indicators for e-commerce engagement (defined as engaging in online commercial activities at least once a month) and entrepreneurship (being a sole proprietor or owner of private firms).

For household economic outcomes, we examine both income and expenditure patterns. On the income side, we focus on total household income and its main components, particularly business income, which includes revenues from agricultural product sales and non-agricultural business operations. The CFPS data also provide detailed information on household expenditures across various categories, such as cosmetics (services like haircuts and beauty treatments), cultural and entertainment (books, newspapers, movies, plays), tourism (transportation, accommodation, meals, tickets), education (tuition, fees, extracurricular classes), healthcare (medical equipment, pharmaceuticals, services), housing (rent and utilities), and food (both at home and dining out). Recent studies suggest that these expenditure patterns reflect household priorities and resource

[3] In the 2010 survey, CFPS used a simple subjective method to assess employment status, directly asking respondents if they currently have a job and letting them determine their own employment status (employed, unemployed, or out of the labor force market). Starting from 2012, CFPS switched to an objective method by asking a series of objective questions to determine the respondents' employment status. CFPS referenced the International Labour Organization's standards for the definition of employment, integrated the design ideas from surveys such as CPS (Current Population Survey), CULS (China Urban Labor Survey), HRS (Health and Retirement Survey), CHARLS (China Health and Retirement Longitudinal Study). Source: http://www.isss.pku.edu.cn/cfps/cjwt/zy/1356888.htm

allocation (Booysen & Guvuriro, 2021; Bobonis, 2009; Porter, 2016; Doepke & Tertilt, 2019; Gu et al., 2022).[4]

To measure intra-household bargaining power, we adopt a multifaceted approach inspired by the collective household model (Chiappori, 1992; Browning et al., 1994). Our primary measure is household headship, with the head typically overseeing financial decisions. We also examine time allocation, specifically time spent on leisure (e.g., watching TV or movies) and household chores. A rise in leisure time alongside a reduction in time spent on chores can signify a shift in bargaining power. Additionally, we measure women's satisfaction with their spouse's contribution to household chores, creating a binary variable (1 = satisfied, 0 = dissatisfied). For child outcomes, we focus on education and health. Educational outcomes are measured through school enrollment status and whether parents are saving for their child's future education, indicating parental investment. Health outcomes are self-reported on a 5-point scale, ranging from "very poor" to "very good." We create a binary health indicator (1 = good or very good health, 0 = otherwise).

To analyze the impact of e-commerce expansion through the RECD project, we merge CFPS data with data on the rollout of e-commerce infrastructure across counties. Each individual or household in the CFPS dataset is assigned to a county of residence, and we use this information to map their exposure to e-commerce based on the year of RECD implementation in their county. This allows us to exploit the staggered rollout of the RECD project across counties, generating variation in treatment timing that is essential for our identification. The RECD project data includes detailed records on the timing of the project introduction, which is crucial for determining the "pre" and "post" periods for each county. Specifically, we construct a binary treatment variable indicating whether a county is exposed to the RECD project in a given year.

Supplement Data. In addition to the CFPS and RECD rollout data, we incorporate several

[4] This choice of goods is informed by recent empirical evidence: Booysen and Guvuriro (2021) suggest that women tend to prioritize investments in communal family assets more than men, such as food and children's education; Bobonis (2009), Porter (2016), and Doepke and Tertilt (2019) identify spending on housing, education and healthcare as indicators of women's bargaining power; Gu et al. (2022) find that women's influence over family finances is reflected in spending on beauty products and clothing, while Mauri and Wolf (2021) document systematic differences in preferences for cultural and entertainment activities across households.

other key data sources to enhance our analysis and control for potential confounding factors. By integrating regional economic indicators, poverty status, and concurrent infrastructure initiatives, we isolate the effects of e-commerce expansion on gender disparities and household outcomes more accurately.

China County Statistical Yearbook (2013): This source provides county-level data on per capita fixed asset investment and other economic indicators, helping to control for pre-existing differences in economic development across counties. These controls ensure that we can distinguish the effects of the RECD project from other regional economic trends.

China Poverty Alleviation Office: We use the list of impoverished counties to control for baseline poverty levels, as the RECD project primarily targeted economically disadvantaged areas. This helps avoid bias in our results due to systematic differences between poor and non-poor counties.

Broadband Expansion and Smart City Policies: We manually collect data on the timing of implementation for China's Broadband Expansion and Smart City policies to account for concurrent digital infrastructure initiatives that could influence e-commerce or labor outcomes. These additional controls help ensure our estimates specifically capture the impact of the RECD project, rather than other overlapping policy interventions.

4.2 Summary Statistics

Table 1 presents summary statistics for key variables, focusing on the rural population aged 20–60. The data reveal notable gender disparities across several dimensions, highlighting the structural inequalities that persist in rural China. These disparities provide essential context for our analysis of the RECD project's impact on gendered labor market outcomes, household dynamics, and child welfare.

Labor force participation (LFP) is significantly lower for women, with 81.7% of women participating in the labor market compared to 88.7% of men. This gender gap in LFP underscores the barriers that rural women face in accessing economic opportunities, which may stem from traditional gender roles, limited access to flexible employment, and disproportionate household responsibilities.

In terms of weekly working hours, women work an average of 31 hours per week, considerably less than the 42 hours worked by men. This disparity in working hours may reflect the dual burden women often carry, balancing market work with unpaid household labor. The data on household responsibilities reinforce this: women spend more time on housework, averaging 2.9 hours per day, while men spend 1.6 hours. This uneven distribution of domestic duties can limit women's ability to engage in full-time employment and pursue higher-paying opportunities.

The data also reveal stark differences in household decision-making power. Only 30% of women are designated as household heads, compared to 53% of men. Given that household headship often confers greater control over financial decisions and resource allocation, this disparity is indicative of broader imbalances in intra-household bargaining power. Furthermore, women report lower satisfaction with their spouse's contributions to household chores, with only 87% expressing satisfaction compared to 97% of men. This gap in satisfaction further reflects gender imbalances within households, particularly in the division of labor and shared responsibilities.

[Insert Table 1 here]

These summary statistics underscore the deeply entrenched gender inequalities in labor supply, household responsibilities, and decision-making power in rural areas. They provide crucial baseline evidence for assessing the impact of e-commerce expansion through the RECD project. By addressing these disparities, the RECD project holds potential to reshape rural gender dynamics, increase women's labor market participation, and enhance their bargaining power within households.

5. Identification Strategy: Difference-in-Differences and Event Study

5.1 Main Identification Strategies

Staggered DID. To estimate the causal impact of the RECD project on labor supply, intra-household bargaining, and child outcomes, we employ a DID strategy. The staggered rollout of the RECD project across counties provides a quasi-experimental setting, allowing us to compare changes in treated counties (those exposed to RECD) with changes in control counties (those not yet exposed) before and after the project's implementation. This identification strategy relies on the

assumption that, in the absence of the RECD project, treated and control counties would have followed parallel trends in the key outcomes of interest.

Our primary empirical specification is a standard DID model, expressed as follows:

$$Y_{ict} = \alpha + \beta RECD_{ct} + X_{ict}^{'}\phi + \lambda_c + \delta_t + T_c + Select_c \times \delta_t + \varepsilon_{ict} \quad (6)$$

where *i*,*c*,*t* denotes individual, county, and year. Each individual (*i*) responds to the RECD during a survey wave (*t*) and reports their counties of residence (*c*). The dependent variable is the outcomes of interest: labor supply, intra-household bargaining power and child outcomes. $RECD_{ct}$ indicates whether county *c* is an RECD county in year *t*. X'_{ict} contains a vector of individual characteristics, including age, education years, and hukou dummies.[5]

The inclusion of county fixed effects λ_c controls for unobserved heterogeneity across counties, while year fixed effects δ_t account for macroeconomic shocks and national policies that could affect all counties simultaneously. Additionally, we include the county-specific linear year trends (T_c), to capture differential linear trends across counties over year, which allows each county to follow its own unique linear trajectory, rather than assuming all counties change similarly over year.[6]

Moreover, we account for non-random site selection by controlling for observable county characteristics that likely influenced the timing of RECD implementation. Following the methodology of Lu and Yu (2015), we introduce a flexible functional form by interacting year-fixed effects with these baseline characteristics including county-level poverty status and per capita fixed asset investment ($Select_c \times \delta_t$). This allows us to capture differential trends across counties based on their initial economic conditions, thereby mitigating concerns about omitted variable bias and strengthening the credibility of our empirical approach. ε_{ict} is the error term. All standard errors are clustered at the county level to account for arbitrary correlation within counties over time, following Bertrand et al.'s (2004) recommended approach.

Appendix Table A1 shows that province-year and city-year fixed effects account for less than 40% and approximately 50% of the RECD policy implementation across counties, respectively,

[5] Hukou is the household registration system in China, which officially identifies a person as a permanent resident of an area and defines one's eligibility for local welfare benefits.

[6] Dube et al. (2010) similarly used state-specific linear trends to control for differential trends in employment across states when identifying the effect of minimum wage changes on earnings and employment.

indicating that most variations stem from differences between counties rather than provinces. In Section 5.2, a balance test (Appendix Table A2) further validates this by demonstrating that adjusting for selection criteria eliminates initial disparities between RECD and non-RECD counties, ensuring that observed effects are attributable to the RECD project and supporting the inclusion of $Select_c \times \delta_t$ in the model.

The estimated coefficient β represents the intent-to-treat (ITT) effects of the RECD project on outcomes. We do not estimate the treatment of the treated effects, because it is not possible to define whether an individual participates in the RECD project. Even if it can be defined, the RECD project also indirectly affects the behaviors of individuals who do not participate in the project within the same counties. The treatment of the treated effects estimated at the individual level could be misleading if the potential spillover effect exists.

Nonparametric Event Study. To complement our DID approach and conduct a more thorough analysis of our identification strategy, we estimate both nonparametric and parametric event study models. This nonparametric event study serves two critical functions in our analysis. First, it allows us to dissect the dynamic effects of the RECD project over time, providing nuanced insights into the temporal pattern of impacts that may be obscured in the average treatment effects estimated by our main DID specification. Second, it enables a formal statistical test of the parallel trends assumption, which is crucial for the validity of our identification strategy. Specifically, we estimate the following equation:

$$Y_{ict} = \alpha + \sum_{k=-3, k\neq -1}^{2+} \beta_k * I(t - t_{c0} = k) + X_{ict}^{'}\phi + \lambda_c + \delta_t + T_c + Select_c \times \delta_t + \varepsilon_{ict} \quad (7)$$

where *i*,*c*, and *t* index individuals, counties, and years, respectively. The regression equation also incorporates the same covariates as in Equation (6). The key parameters of interest are the β_k coefficients associated with the indicator variables $I(t - t_{c0} = k)$, which measure the time relative to the implementation year t_{c0} of the RECD project in each county. This specification offers several advantages. First, it allows us to test the parallel trends assumption underlying our DID strategy by examining the pattern of β_k coefficients for $k < -1$. Statistical insignificance of these coefficients would provide strong support for the validity of our identification strategy. Moreover, it enables us to trace out the dynamic effects of the policy, revealing whether the impact of RECD is immediate,

gradual, or potentially non-monotonic over time.

Parametric Event Study. To quantify the magnitude of estimated effects and their statistical significance from the nonparametric event study, we employ a parametric event study approach. Our choice of functional form is guided by the patterns observed in the nonparametric event study. The parametric event study takes the form:

$$Y_{ict} = \alpha + \sum_{k=0}^{2+} \mu_k^{'} + X_{ict}^{'}\phi + \lambda_c + \delta_t + T_c + Select_c \times \delta_t + \varepsilon_{ict} \quad (8)$$

The key coefficients of interest, the μ'_k, represent the change in outcome following the RECD program relative to all periods before the the implementation of this project. We present our results by estimating the average treatment effects of μ'_k in all regressions, in addition to TWFE and CSDID estimators.

5.2 Validity of the Identification Strategies

Validating Parallel Trends and Selection Bias Adjustment. For the Difference-in-Differences (DID) approach to produce unbiased and credible estimates, the parallel trends assumption must hold. This assumption stipulates that in the absence of the RECD project, treated and control counties would have experienced similar trends in the outcomes of interest. However, the non-random selection of RECD counties presents a potential challenge to the validity of this assumption. To address this, we employ a two-pronged approach that combines rigorous testing of pre-treatment trends with adjustments for observable selection criteria.

First, we conduct an event study analysis to evaluate whether treated and control counties displayed parallel trends in key outcomes before the implementation of the RECD project. By examining the dynamic effects over time, we assess whether differences in outcomes emerged prior to treatment. The results show no statistically significant differences between treated and control counties in the pre-treatment period, providing strong evidence to support the validity of the parallel trends assumption. This analysis is crucial in establishing a solid foundation for our identification strategy.

Second, in our main analysis, we incorporate a flexible functional form by interacting year-fixed effects with baseline characteristics, such as county-level poverty status and per capita fixed asset investment, to address potential biases arising from non-random selection. To validate

the robustness of these adjustments, we conduct a balance test comparing RECD and non-RECD counties. The results, presented in Appendix Table A2, show that RECD counties were initially disadvantaged, with lower GDP, smaller populations, higher shares of agricultural value added, and greater distances from prefecture-level cities—reflecting the project's targeted design. However, after accounting for the selection criteria in our model, the economic characteristics of treated and control counties become statistically indistinguishable. This balance confirms that our adjustments effectively mitigate baseline disparities, enabling a more equitable comparison for the analysis.

In sum, by combining an event study framework with rigorous controls for selection bias, our approach not only ensures the validity of the parallel trends assumption but also highlights the importance of addressing non-random site selection in policy evaluations.

Controlling for Concurrent Policies. One potential threat to the validity of our estimates is the possibility that concurrent policies or regional developments may confound the effects of the RECD project. For instance, policies such as the Broadband Expansion and Smart City Initiatives could have influenced e-commerce participation and labor market outcomes in treated counties. To address this concern, we include controls for these concurrent policies, incorporating data on their implementation timing and coverage at the county level. This ensures that our estimates reflect the specific impact of RECD, rather than other overlapping policy interventions.

Accounting for Heterogeneous Treatment Effects. Recent literature has highlighted the potential biases introduced by traditional two-way fixed effects (TWFE) models when treatment effects vary across groups and over time (Goodman-Bacon, 2021). In our setting, treatment effects may differ depending on the year a county was exposed to RECD and the characteristics of the county. Moreover, event study can also suffer from contamination problems, particularly in settings with staggered treatment adoption.

To address this, we employ the Callaway and Sant'Anna (2021) DID estimator (CSDID) for stagger DID and event study estimation. This approach allows us to estimate group-time average treatment effects while accounting for heterogeneous treatment effects across different treatment

groups and time periods.[7] The CSDID method provides more robust and unbiased estimates of RECD's dynamic effects on labor supply, intra-household bargaining power, and child outcomes, thereby complementing and validating the results obtained from the TWFE model.

Other Concerns. We also conduct several robustness checks to ensure the validity of our findings. First, we perform placebo tests by randomly assigning treatment status to counties and re-estimating our models to check for spurious effects. If the treatment is truly driving the results, we should find no significant effects in the placebo specifications. Next, we address the possibility of migration-related composition change by examining whether RECD implementation affects migration behavior. We create a variable indicating whether individuals have returned from urban areas or migrated to other counties, and we find no significant effects of RECD on migration patterns. This analysis rules out the possibility that migration is driving our results. Finally, we test for sample attrition, as differential dropout rates between treated and control counties could bias our estimates. We find that RECD implementation has no statistically significant effect on attrition, ensuring that our results are not driven by changes in the sample composition over time.

6. Impact of the RECD on Labor Market Dynamics

6.1 Effects on Labor Market Outcomes

Table 2 presents our primary findings on the impact of the RECD project on labor market outcomes, estimated using the DID specification described earlier. The results highlight a notable gender disparity in the project's effects across various labor market dimensions. Columns 1 and 2 indicate that traditional TWFE, CSDID estimators, and parametric event study all show statistically significant positive effects for women. RECD exposure is associated with a 3 pp increase in female LFP, representing a 4% increase from the mean. Additionally, women experience an increase of approximately 2.5 hours in weekly working hours, which equates to an 8% rise from the mean. In contrast, the effects on male labor supply are smaller and statistically insignificant, underscoring

[7] CSDID estimators only use observations with pair balance, so the observations of CSDID estimators is smaller than that of TWFE estimators.

the differential impact of the RECD program across genders.

[Insert Table 2 here]

The robustness of these findings is confirmed by further analyses. Appendix Table A3 shows that the results remain consistent when we use a more parsimonious set of controls, including only county and year fixed effects and county-specific linear year trends. This consistency across various specifications supports the reliability of the main results. An additional layer of analysis reveals heterogeneity in the effects of RECD, particularly by age and education levels. Younger and more educated women—who are typically more familiar with internet and e-commerce platforms—appear to benefit more from the RECD project. Appendix Table A4 shows a more pronounced positive effect on LFP for younger women compared to their older counterparts, and for more educated women than their less educated counterparts.

To contextualize the magnitude of these estimated effects, we compare them with other public interventions aimed at increasing female labor force participation. The impacts of RECD on female labor supply are comparable to those reported in seminal studies such as Dinkelman et al. (2011), which found that South Africa's rural electrification program led to a 9 to 9.5 pp increase in female employment over a 5-year period. Similarly, our results align with Anelli et al. (2021), who documented a 1.8 pp increase in female LFP for each standard deviation increase in robot exposure, with negligible effects on male participation.

To address potential concerns about pre-existing trends and to further explore the dynamic effects of the RECD program, we employ an event study approach based on the event study specification. Figure 2 presents the estimated coefficients of β_k and their corresponding 90% confidence intervals. The results suggest that prior to RECD implementation, treated and control counties followed parallel trends in labor supply, supporting the validity of the parallel trends assumption underlying the DID strategy.

[Insert Figure 2 here]

Post-implementation, we only observe a clear and sustained increase in female labor force participation and working hours. Specifically, RECD implementation leads to an immediate 1.5 percentage point (2% of the mean) increase in LFP, growing to 2.5 percentage points (3% of the

mean) in the first year and further expanding to 4.2 percentage points (5% of the mean) from the second year onward. Similarly, working hours for women show an approximate 3-hour (10% of the mean) increase in the implementation year, with this effect persisting in subsequent periods except for a slightly smaller effect of 1.2 hours (4% of the mean) in the first year.

6.2 Effects on E-commerce-related Activities

To further explore the mechanisms through which the RECD project affects women's labor market participation, we examine its impact on e-commerce adoption and entrepreneurship. These outcomes are particularly important as they represent direct measures of program take-up and potential pathways for economic empowerment.

The results in Columns 3-4 of Table 2 reveal substantial gender differences in project utilization. For women, RECD implementation increases e-commerce participation by 1.6 to 4.1 pp, representing a 10% to 24% rise from the mean. The program also boosts female entrepreneurship significantly, with the probability of being a sole proprietor or business owner increasing by 2.1 to 2.3 pp (31% to 34% from the mean). In contrast, we observe no significant changes in either e-commerce participation or entrepreneurship rates among men.

One limitation of our survey data is that it does not distinguish between buying and selling activities online. To address this concern and better understand the nature of e-commerce engagement, we conduct a subgroup analysis based on the presence of agricultural specialty products in each county. We hypothesize that if e-commerce expansion primarily facilitates the sale of agricultural products, counties specializing in high-value agricultural goods would experience larger gains in e-commerce engagement, particularly among women. The results in Table A5 support this hypothesis. Women in counties with agricultural specialty products exhibit significantly higher engagement in e-commerce activities post-RECD compared to women in counties without such products. In contrast, we observe no significant differential impact on e-commerce participation among men.

Taken together, these findings suggest that e-commerce expansion through RECD has been particularly effective in promoting women's economic participation through multiple channels. The project not only increases women's basic labor supply but also facilitates their engagement in

entrepreneurial activities and e-commerce operations. The gender-specific nature of these effects highlights how digital platforms can help overcome traditional barriers to female employment in rural areas.

7. Impact of RECD on Household and Children Outcomes

7.1 Effects on Household Income and Expenditures

Table 3 presents our findings on the impact of RECD implementation on household economic outcomes, focusing on total household income and, in particular, income from entrepreneurial activities and self-employment. The results indicate that RECD implementation is associated with a significant increase in total household income, estimated to be around 4,000 to 5,900 CNY, depending on the estimation method. The TWFE estimator suggests an increase of roughly 4,000 CNY, while the CSDID and parametric event study estimates show larger effects, around 5,900 CNY and 5,100 CNY, respectively. These increases represent approximately 10–14% of the mean household income, highlighting the project's positive economic impact on rural households.[8]

[Insert Table 3 here]

Notably, business income, which includes revenues from entrepreneurial activities and self-employment, rises by approximately 1,700 to 2,300 CNY (representing 27–36% of the mean). This substantial increase accounts for about 40% of the total household income gain, suggesting that entrepreneurship and self-employment are key channels through which RECD enhances household welfare. The consistency of these effects across various estimation methods reinforces the robustness of our findings. Total household expenditure also sees a significant increase of 2,900 to 4,400 CNY (6–10% of the mean), indicating that the income gains from RECD are translating into higher consumption levels.

In addition to the aggregate effects, we examine how RECD influences household expenditure patterns across various categories. Table 4 reveals significant shifts in spending allocation

[8] Couture et al. (2021), using a randomized controlled trial, highlight that the effect of e-commerce expansion on income gains of rural households is limited. However, as the sample in this study only covers three provinces in China, it is difficult for the findings to be nationally representative.

following RECD implementation, with increases in several key expenditure categories as a share of total household spending. Specifically, RECD is associated with a rise of about 0.1 percentage points (pp) in spending on cosmetics, which includes personal care products and services. Education expenditures increase by approximately 0.5–1.1 pp, medical expenditures by 1.3–1.8 pp, and housing-related expenses by 1.9–2.7 pp. These shifts remain robust even after controlling for total household income (see Appendix Table A6). In contrast, there are no significant changes in the shares allocated to cultural and entertainment, tourism, or food expenditures, suggesting that RECD primarily influences spending on essential and investment-oriented categories.

[Insert Table 4 here]

The event study analysis in Figure 3 provides insights into the evolving impact of RECD on household expenditure patterns. Following RECD implementation, the share of expenditures allocated to education, medical needs, and housing generally increases, though the magnitude varies by category. Education expenditures have a mild upward trend, reflecting an increase in focus or allocation toward educational spending, while medical expenditures show a more pronounced increase, suggesting greater attention to health. Housing expenditures grow steadily, indicating investments in home quality. These shifts highlight how RECD influences spending priorities, with households directing more resources toward well-being and quality of life.

[Insert Figure 3 here]

These shifts in expenditure patterns could reflect several underlying changes in household dynamics and priorities. The increased spending shares on categories like education, healthcare, and housing suggests a reallocation toward investment-oriented expenditures that could benefit long-term household welfare. The rise in cosmetic expenditures, while small in absolute terms, represents a substantial 13% increase relative to the mean share and might reflect changes in consumption preferences. While these expenditure patterns align with what we might expect to see with increased female influence over household spending decisions, establishing whether they truly reflect changes in women's bargaining power requires examining more direct measures of intra-household decision-making. Therefore, in the next section, we investigate how RECD affects various indicators of women's bargaining power within households.

7.2 Effects on Intra-household Bargaining Power

Theories of intra-household bargaining suggest that increasing women's labor market participation can enhance their bargaining power, potentially leading to more equitable decision-making and promoting gender equality within households (Luke & Munshi, 2011; Majlesi, 2016; Getahun & Villanger, 2018). In this section, we examine the impact of the RECD project on three key dimensions of intra-household bargaining: (1) the likelihood of women being designated as household heads, (2) time allocation between housework and leisure activities, and (3) satisfaction with spousal contributions to household tasks.

Table 5 suggest that exposure to RECD significantly increases the probability of women being designated as the household head by 4.1 to 6.1 pp, representing a 14% to 21% increase from the baseline. This suggests that the program improves women's control over household resources. Concurrently, RECD reduces women's daily housework time by approximately 0.5 hours, which translates to a 17% reduction relative to the mean. This decrease in housework is coupled with an increase in women's leisure time, ranging from 0.138 to 0.227 hours per day, suggesting a reallocation of responsibilities that frees up time for market work or personal development.

[Insert Table 5 here]

Moreover, the RECD project appears to foster more equitable domestic arrangements, as evidenced by a 3.5 to 6.0 pp increase in women's satisfaction with their spouse's contributions to household chores. Collectively, these results indicate that RECD may be catalyzing a shift towards more egalitarian household dynamics. Importantly, these effects are largely gender-specific, as no statistically significant changes are observed for men in household head status, time allocation, or satisfaction with spousal contributions. This asymmetry highlights the potential of e-commerce to empower women within the household by increasing their economic contributions and enhancing their influence over domestic decision-making.

Event study estimates provided in Figure 4 further support and extend these findings. Panel (a) shows a gradual increase in the likelihood of women being designated as household heads following RECD implementation, with the effects becoming more pronounced over time. Panel (b) demonstrates a substantial reduction in women's housework hours post-RECD, while men's

housework hours remain stable. Panel (c) suggests an increase in women's leisure time. Although men's leisure time also sees a slight increase, it is only significant in the first period. These dynamic effects confirm the gender-specific impact of RECD on intra-household bargaining power and suggest that the changes in household dynamics are persistent rather than temporary.

[Insert Figure 4 here]

To address concerns that our findings might be driven by changes in marriage market composition rather than empowerment of existing wives, we examine RECD's effects on marriage market outcomes. Results in Appendix Table A7 show negligible effects on marriage decision, alleviating this concern and supporting the validity of our main results.

These findings on intra-household bargaining power help interpret our earlier results on expenditure patterns. The increased spending on categories like education, healthcare, and housing, along with the rise in cosmetic expenditures, appears to be accompanied by genuine changes in women's decision-making authority within households. This alignment between expenditure patterns and direct measures of bargaining power suggests that RECD is indeed transforming household dynamics in ways that enhance women's status and influence.

7.2 Effects on Child Outcomes

A growing body of literature suggests that women in developing economies tend to prioritize family-oriented investments, particularly those benefiting children (Duflo, 2012). Furthermore, evidence indicates that women often show a preference for investing in female children relative to male children. For instance, Qian (2008) demonstrates that an increase in women's relative income is associated with improved survival rates for girls and a reduction in gender disparities in educational attainment. Building on these insights, we examine whether the growth of e-commerce, which disproportionately benefits women, results in increased investments in children's human capital, with a particular focus on daughters' outcomes.

To test this hypothesis, we estimate the impact of the RECD project on child outcomes. Table 6 presents estimates separately for girls and boys under 15 years of age. Our findings provide clear evidence of gender-differentiated effects of RECD exposure on educational outcomes. Specifically, RECD implementation is associated with an increase in school enrollment rates for girls aged 6-15

by 2.9 to 4.0 pp, representing a 3.1-4.2% increase relative to the mean. In contrast, boys' enrollment rates have also risen, but this increase is not statistically significant. This finding aligns with the hypothesis that mothers tend to invest more in daughters when their bargaining power increases.

[Insert Table 6 here]

In terms of health outcomes, we observe improvements exclusively among girls, with an increase in self-assessed health status by 5.2-9.7 pp. These effects suggest that mothers, empowered by the RECD project, are more likely to allocate resources towards improving their daughters' health and education. We also find suggestive evidence that RECD induces parents to allocate more savings toward their daughters' future education, further confirming the gender-specific benefits of e-commerce expansion.

To further explore the dynamics of RECD's impact on child outcomes, we conduct an event study analysis. Figure A4 presents the results for school enrollment and self-assessed health. The analysis reveals an upward trend in both outcomes for girls following the implementation of the RECD project, while no clear trend is observed for boys. This reinforces the idea that the RECD program disproportionately benefits female children by improving their educational attainment and health outcomes.

These findings suggest that e-commerce development has positive spillover effects on children's human capital accumulation, with particularly pronounced benefits for girls. By empowering women economically, the RECD project not only helps narrow the gender gap in adult labor market outcomes but also influences investments in the next generation, particularly daughters. This dynamic plays a crucial role in the broader context of women's empowerment and gender equality in rural China.

8. Robustness Checks

In this section, we perform a series of robustness checks to validate the reliability of our findings. These checks aim to address potential confounding factors, assess whether the treatment group composition remains consistent, and test the robustness of our results across various

alternative specifications. The results for labor market, intra-household bargaining power, and child outcomes are presented in Figure A5 and Figure A6. We also examine any potential changes in group composition and sample attrition to ensure the accuracy of our results, which are presented in Table A8. Overall, our results are consistent with the baseline findings.

8.1 Confounding Factors

Our estimates may be influenced by concurrent policies or other factors, such as China's investments in education, healthcare, and digital infrastructure, which overlap with the RECD implementation period. To address these concerns, we incorporate controls for these factors, including data on China's Broadband Expansion and Smart City Development policies, which aim to improve internet infrastructure and promote local economic growth. Additionally, we include community-level controls—such as the number of schools and healthcare facilities, and distance to the county seat—to capture local infrastructure changes that may impact our outcome variables.

Figure A5 illustrates how the inclusion of these additional controls affects the estimates. In Panel A, we present the baseline results by gender, controlling only for county and year fixed effects. In Panel B, we add controls for the Broadband and Smart City policies. In Panel C, we further introduce interaction terms between community-level characteristics (e.g., number of schools, hospitals) and year fixed effects to capture any local trends. Panel D includes province-by-year fixed effects to account for regional shocks. Finally, Panel E incorporates individual fixed effects to control for time-invariant individual heterogeneity. In all these alternative specifications, the estimated impacts of the RECD project remain robust, suggesting that our results are not driven by these other factors.

8.2 Possible Composition Changes

One possible concern is that the RECD project may have induced changes in the composition of the treatment and control groups. For instance, the program might have encouraged rural-urban migrants to return to their hometowns or attracted migrants from non-RECD counties. If these migrating individuals have higher levels of human capital, this could lead to upward bias in our estimates of labor supply and household outcomes.

To test for this possibility, we create two dummy variables: one indicating whether an

individual's current place of residence matches their household registration location (hukou) and another indicating whether the individual has returned from an urban area. We then estimate the effect of RECD on these variables using our baseline specification. The results, presented in Table A8, show no statistically significant effects of RECD on migration patterns, indicating that changes in population composition are unlikely to be driving our findings.

8.3 Sample Attrition and Other Placebo Tests

Sample attrition could also bias our results if individuals in RECD counties are more or less likely to drop out of the survey over time. To address this, we estimate the impact of RECD on the likelihood of attrition using a balanced panel dataset of individuals who were interviewed in the first wave of the CFPS and re-interviewed in subsequent waves. The results, shown in columns (3) and (6) of Table A8, indicate that RECD has no significant effect on attrition rates, suggesting that attrition is not a concern for our analysis.

The validity of our identification strategy relies on the assumption that in the absence of the RECD, the trend in outcomes would have been similar across counties adopting the RECD project at different times. Although the results of the event study support our identification assumption, we provide further evidence by performing a placebo test. We randomly assign 64 treatment groups to different counties and re-estimate our baseline specification (6) for 500 times. If there are no differential trends in family outcomes, the estimated coefficients of RECD should follow an approximate normal distribution centered around zero. The results, shown in Figure A6, consistently indicate no evidence of an effect in the placebo projects, further strengthening the credibility of our identification assumption.

9. Conclusion and Discussion

This study investigates the effects of the Rural E-Commerce Comprehensive Demonstration (RECD) Project on labor supply, intra-household bargaining, and child outcomes in rural China. We find that the RECD project significantly boosts women's labor force participation by 3 pp and increases their weekly working hours by 2.5 hours, without affecting male labor supply. These results indicate that e-commerce expansion is particularly beneficial for women, helping narrow the

gender gap in rural labor markets. Furthermore, RECD empowers women within households: women in treated counties report greater decision-making authority, a reduction in time spent on household chores, and improved satisfaction with their spouse's domestic contributions. Importantly, RECD also improves educational and health outcomes for girls, signaling a positive intergenerational effect. As women gain economic power, they are more likely to invest in their daughters' education and health, promoting gender equity across generations.

Our study makes several key contributions to the literature. First, it provides robust evidence of how e-commerce can reduce gender disparities in rural labor markets, demonstrating that women's increased economic participation leads to more equitable household dynamics and greater financial decision-making power. Second, we document important intergenerational benefits, showing that women's empowerment through digital platforms translates into increased investments in children, particularly daughters, thereby promoting gender equality across generations. From a theoretical perspective, this study extends existing models of household bargaining and labor supply by illustrating how e-commerce, as a flexible labor market innovation, reshapes labor dynamics, enhances women's bargaining power, and fosters more equitable resource allocation within households. Our work also highlights the critical role of accessible labor market opportunities in enabling women to balance market work with household responsibilities, a challenge that is particularly pronounced in developing economies.

The findings of this study highlight the importance of targeted policies to maximize the benefits of e-commerce expansion for women. Policymakers should focus on investing in digital infrastructure and delivering gender-sensitive e-commerce training programs that cater to the specific needs of rural women. Moreover, addressing structural barriers to women's participation in the labor market, such as unequal access to financial resources and the disproportionate burden of household responsibilities, will be crucial to fostering inclusive growth. Integrating social protection measures, such as flexible pension schemes and health insurance for informal workers, can further enhance the sustainability of the economic gains derived from e-commerce.

While our results provide clear evidence of the short-term impacts of e-commerce on women's labor market participation and household dynamics, future research should explore the long-term

sustainability of these effects as digital platforms evolve. Additionally, our study focuses on rural China, limiting the generalizability of the findings. Future research should examine how e-commerce affects gender equity across diverse cultural and policy contexts, particularly in other developing countries. There is also scope for further exploration of complementary policies, such as childcare support and digital financial inclusion, which could further enhance the role of e-commerce in promoting women's economic empowerment and broader development outcomes.

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Figures

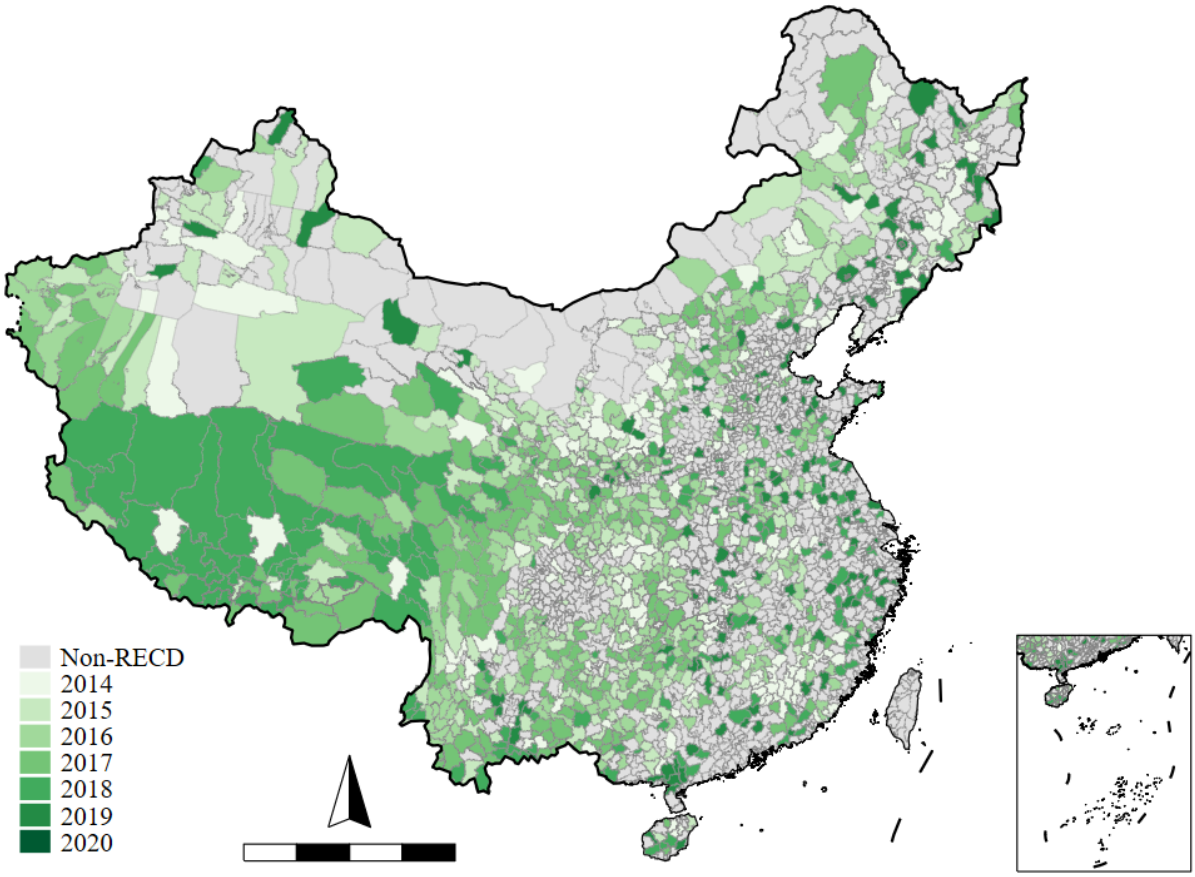
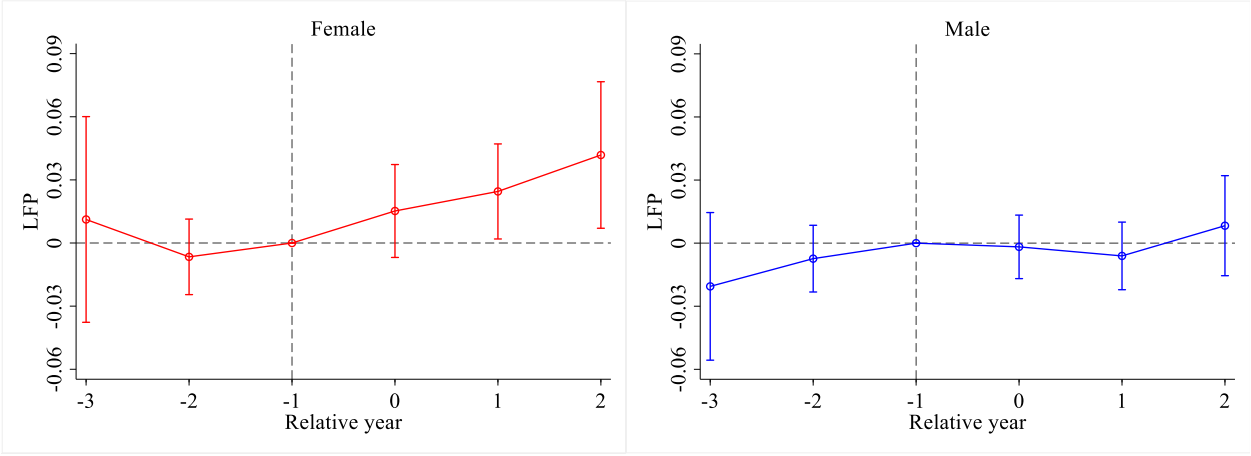


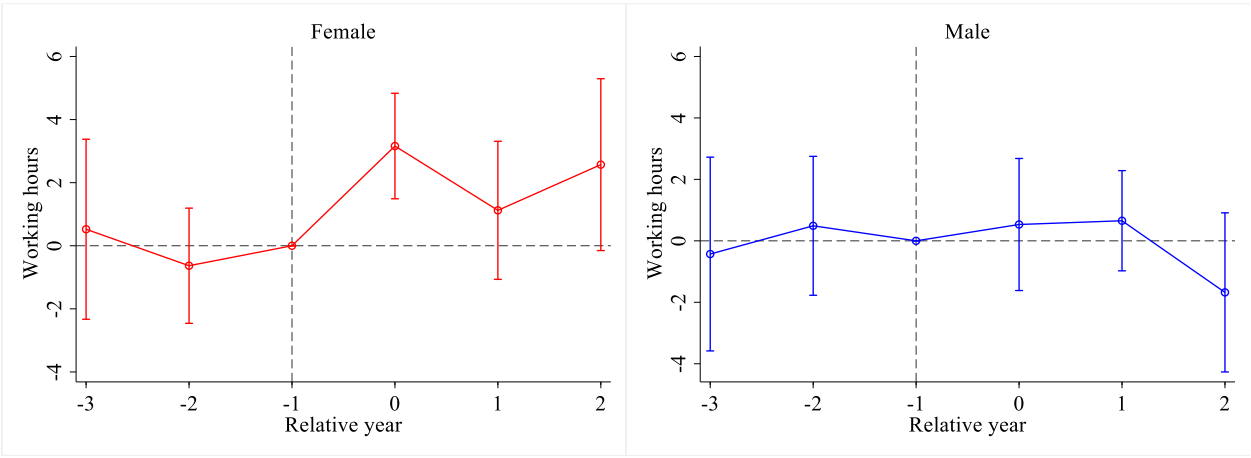
Figure 1: Staggered Implementation of the RECD Project

Notes: This map illustrates the staggered rollout of the Rural E-Commerce Comprehensive Demonstration (RECD) Project across counties in China from 2014 to 2020. This variation in rollout timing allows for difference-in-differences and event study analyses to identify the effects of RECD on labor market, household, and child outcomes.

Source: The list of RECD counties (2014-2020) released by the Ministry of Commerce.



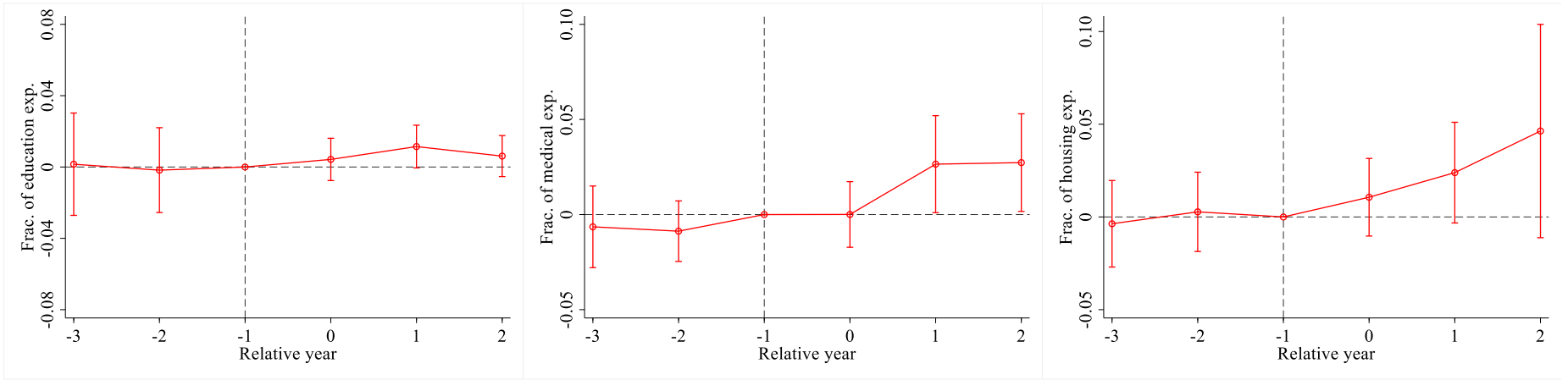
(a) LFP



(b) Working hours

Figure 2: Event-Study Estimates: Impacts of the RECD on LFP and Working Hours

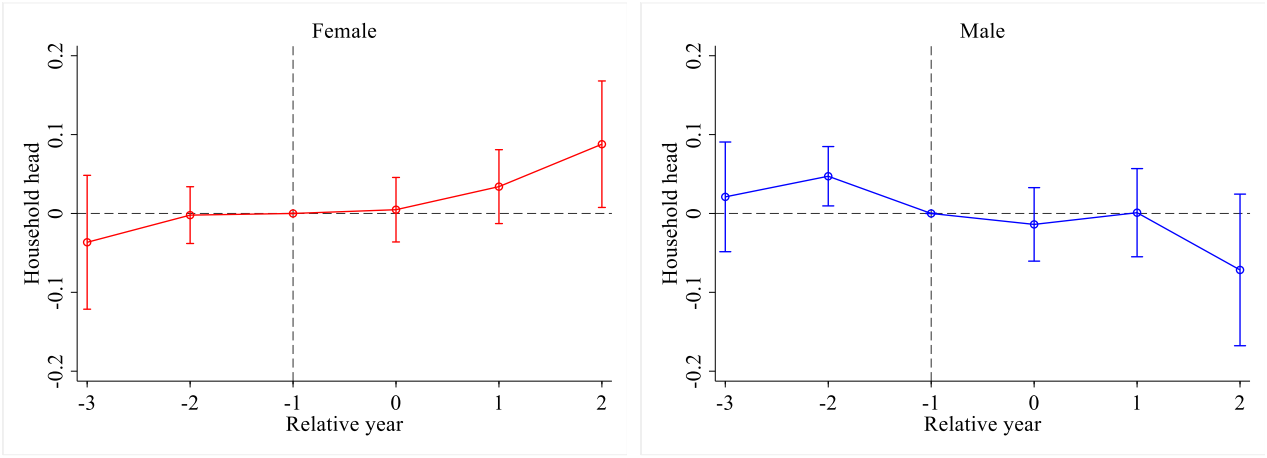
Notes: The figure shows the dynamic effects of the RECD project on labor force participation (LFP) and weekly working hours by gender, using the estimators proposed by Callaway and Sant'Anna (2021). The sample draws on the China Family Panel Studies (CFPS) 2012–2020, including rural residents aged 20–60. The figure comprises two panels: (a) LFP and (b) Working hours. Each panel presents point estimates with corresponding 90% confidence intervals. The x-axis represents years relative to the RECD implementation (with -1 as the reference year), while the y-axis displays the magnitude of the estimated effects.



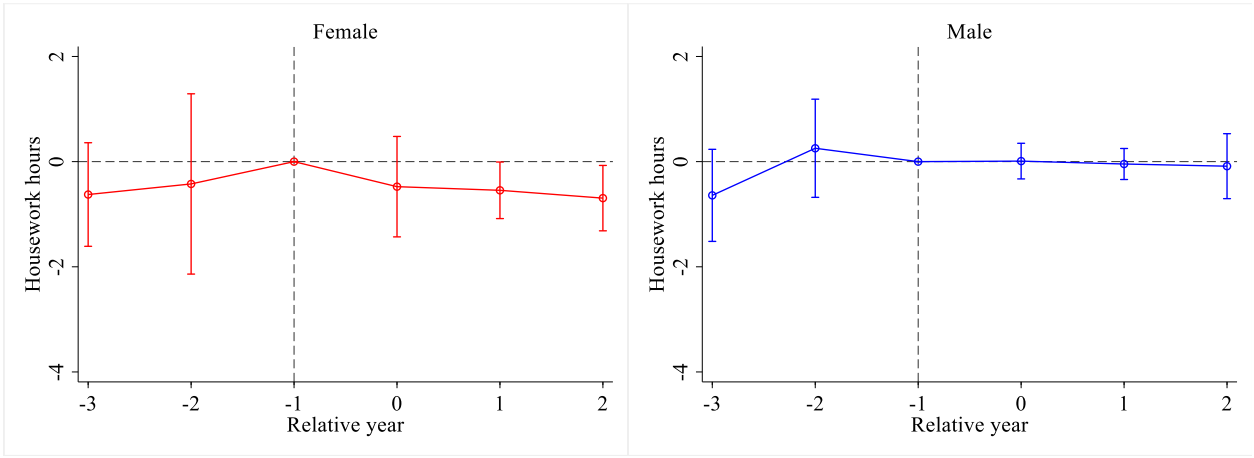
(a) Frac. of education exp. (b) Frac. of medical exp. (c) Frac. of housing exp.

Figure 3: Event-Study Estimates: Impacts of RECD on Household Expenditures Patterns

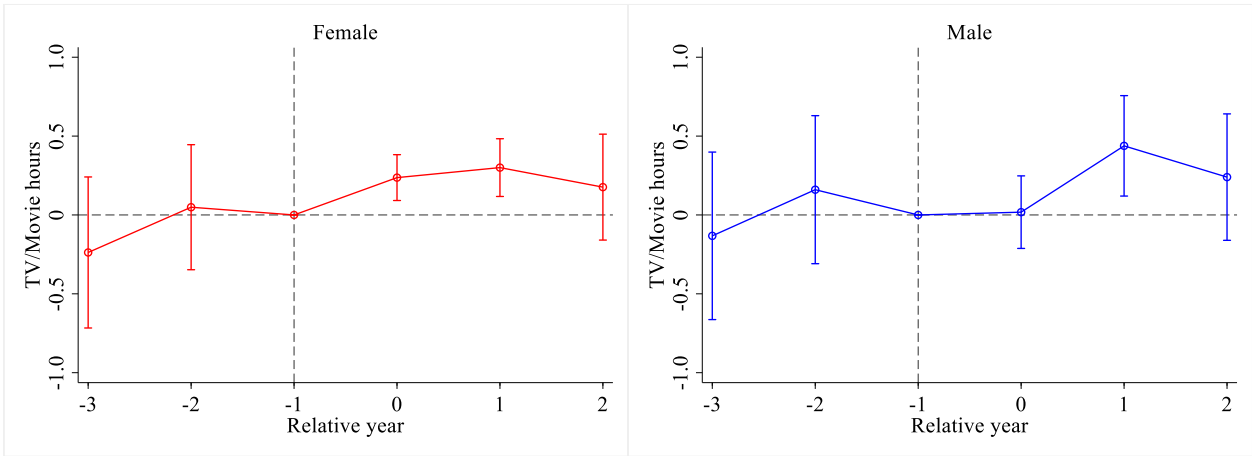
Notes: The figure shows the dynamic effects of the RECD project on household expenditures patterns, using the estimators proposed by Callaway and Sant'Anna (2021). The sample draws on a household-year panel from the China Family Panel Studies (CFPS) 2012–2020. The figure comprises three panels: (a) Frac. of education expenditures, (b) Frac. of medical expenditures, and (c) Frac. of housing expenditures. Each panel presents point estimates with corresponding 90% confidence intervals. The x-axis represents years relative to the RECD implementation (with -1 as the reference year), while the y-axis displays the magnitude of the estimated effects.



(a) Household head



(b) Housework hours



(c) TV/Movie hours

Figure 4: Event-Study Estimates: Impacts of RECD on Household Head and Time Use

Notes: The figure shows the dynamic effects of the RECD project on household head and time use by gender, using the estimators proposed by Callaway and Sant'Anna (2021). The figure comprises three panels: (a) Household head, (b) Housework hours, (c) TV/Movie hours. Sample for Panel (a) come from CPFS 2012–2020, while sample for Panel (b) and (c) come from CFPS 2014–2020, including married rural residents aged 20–60. Each panel presents point estimates with corresponding 90% confidence intervals. The x-axis represents years relative to the RECD implementation (with -1 as the reference year), while the y-axis displays the magnitude of the estimated effects.

Tables

Table 1: Descriptive statistics

	Female Sample			Male Sample		
Variable	Obs.	Mean	Std.dev	Obs.	Mean	Std.dev
Panel A. Labor Supply (Samples for people aged 20-60)						
Labor force participation (LFP) (Yes=1)	25,953	0.817	0.387	25,797	0.887	0.317
Working hours weekly	25,953	30.685	23.951	25,797	42.105	24.605
Dependent variable						
RECD exposure	25,953	0.215	0.411	25,797	0.210	0.407
Covariates						
Education years	25,953	6.208	4.705	25,797	7.909	3.983
Agricultural hukou (Yes=1)	25,953	0.935	0.247	25,797	0.907	0.291
Age	25,953	41.287	11.746	25,797	41.404	11.636
Panel B. Intra-household Bargaining Power (Samples for married people aged 20-60)						
Household head (Yes = 1)	22,918	0.296	0.456	20,887	0.530	0.499
Housework hours	16,368	2.863	1.752	14,535	1.585	1.765
TV/Movie hours	16,509	1.383	1.329	14,658	1.487	1.270
Satisfaction with spouse's housework	11,757	0.866	0.341	10,578	0.965	0.183
Panel C. Children outcomes						
School enrollment (Yes=1)	6,406	0.943	0.231	7,335	0.945	0.229
Self-assessed health (Yes=1)	3,222	0.653	0.476	3,685	0.665	0.472
Saving for children's education (Yes=1)	6,364	0.135	0.342	7,288	0.145	0.352
Panel D. Household Income and Consumption						
Total income (1000 yuan)	26,375	41.363	40.376			
Business income (1000 yuan)	26,418	6.408	10.760			
Total expenditures (1000 yuan)	26,070	45.252	45.993			
Frac. of consumption (%)						
Cosmetic	25,959	0.621	0.927			
Education	25,915	7.171	13.021			
Medical	25,923	11.871	16.664			
Housing	25,725	11.157	13.894			
Culture & entertainment	25,994	0.106	0.348			
Tourism	26,045	0.277	1.162			
Food	25,907	33.965	21.348			

Notes: The table presents summary statistics for key variables from the China Family Panel Studies (CFPS) conducted between 2012 and 2020. Panel A and B include rural residents aged 20–60 in a five-year individual-year panel (2012, 2014, 2016, 2018, 2020). In Panel B, data on housework hours and TV/movie hours is available only for CFPS 2014, 2016, 2018, and 2020. Data on satisfaction is available only for CFPS 2014, 2018 and 2020. Panel C includes children aged 6-15 in a five-year children-year panel. Panel D uses a five-year household-year panel. Except for Panel D, the other panels present results by gender.

Table 2: Impacts of the RECD on Labor Market Dynamics

	LFP (Yes = 1)	Working Hours	E-commerce participation (Yes = 1)	Entrepreneurship (Yes = 1)
	(1)	(2)	(3)	(4)
Panel A: Female sample				
Mean of *Y*	0.817	30.685	0.169	0.067
TWFE	0.035**	2.774**	0.016*	0.023**
	(0.017)	(1.138)	(0.010)	(0.012)
CSDID	0.024**	2.292***	0.039***	0.021**
	(0.011)	(0.846)	(0.011)	(0.009)
Para. ES	0.027**	1.994**	0.041***	0.022**
	(0.012)	(0.903)	(0.013)	(0.010)
Observation	25,953	25,953	15,806	25,953
Panel B: Male sample				
Mean of *Y*	0.887	42.105	0.168	0.126
TWFE	0.020	1.218	-0.005	-0.021
	(0.013)	(0.926)	(0.013)	(0.020)
CSDID	0.001	0.410	0.018	-0.005
	(0.007)	(0.740)	(0.012)	(0.014)
Para. ES	0.002	0.010	0.017	0.001
	(0.008)	(0.818)	(0.013)	(0.015)
Observation	25,797	25,797	14,667	25,797
Controls	Y	Y	Y	Y
County FE & Year FE	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample consists of rural residents aged 20–60 from CFPS 2012–2020. E-commerce participation is defined as engaging in online commercial activities at least once a month (yes =1), while entrepreneurship is defined as being the sole proprietor or owner of private firms (yes =1). All regressions include individual-level controls such as age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at the county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 3: Impacts of RECD on Household Income and Expenditures

	Household income (1,000 yuan)	Business income (1,000 yuan)	Household expenditures (1,000 yuan)
	(1)	(2)	(3)
Mean of Y	41.363	6.408	45.246
TWFE	3.955*	2.196**	3.409**
	(2.007)	(0.927)	(1.537)
CSDID	5.876***	1.714***	2.946
	(1.565)	(0.523)	(1.876)
Para. ES	5.059***	2.278***	4.353**
	(1.805)	(0.590)	(2.205)
Observations	26,365	26,408	26,060
Controls	Y	Y	Y
County FE & Year FE	Y	Y	Y
County linear year trend	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample consists of rural households from the CFPS 2012–2020. Business income includes revenues from agricultural product sales and non-agricultural business operations, measured in thousand CNY. All regressions include controls such as the number of family members, household head's gender, age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 4: Impacts of RECD on Household Expenditure Patterns

Frac. of expenditures by categories (%)	Cosmetic (1)	Education (2)	Medical (3)	Housing (4)	Cul. & Ent. (5)	Tourism (6)	Food (7)
Mean of Y	0.621	7.171	11.871	11.157	0.106	0.277	33.965
TWFE	0.077*	0.511	1.567*	1.862**	0.012	-0.033	-1.858
	(0.042)	(0.327)	(0.929)	(0.860)	(0.013)	(0.030)	(1.355)
CSDID	0.077**	1.074**	1.342*	2.027**	0.001	-0.017	-0.476
	(0.038)	(0.434)	(0.790)	(0.971)	(0.012)	(0.034)	(1.087)
Para. ES	0.076*	0.728*	1.796**	2.696**	-0.002	-0.013	-0.132
	(0.045)	(0.388)	(0.839)	(1.316)	(0.015)	(0.040)	(1.277)
Observations	25,950	25,908	25,913	25,715	25,984	26,035	25,898
Controls	Y	Y	Y	Y	Y	Y	Y
County FE & Year FE	Y	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample consists of rural households from the CFPS from 2012–2020. The dependent variables are the fraction of various expenditures to total household expenditure. All regressions include controls such as the number of family members, household head's gender, age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5: Impacts of RECD on Household Head, Time, and Satisfaction

	Household head (Female=1)	Housework hours	TV/Movie hours	Satisfaction with spouse's housework
	(1)	(2)	(3)	(4)
Panel A: Female sample				
Mean of *Y*	0.296	2.863	1.383	0.866
TWFE	0.061***	-0.703**	0.138**	0.035*
	(0.022)	(0.334)	(0.064)	(0.021)
CSDID	0.041*	-0.519*	0.227**	0.059*
	(0.024)	(0.316)	(0.097)	(0.036)
Para. ES	0.054*	-0.456	0.222**	0.060*
	(0.028)	(0.348)	(0.110)	(0.036)
Observation	22,918	16,367	16,508	11,755
Panel B: Male sample				
Mean of *Y*	0.530	1.585	1.487	0.965
TWFE	-0.026	-0.150	0.046	-0.010
	(0.025)	(0.169)	(0.079)	(0.019)
CSDID	-0.029	-0.069	0.233	0.009
	(0.027)	(0.179)	(0.154)	(0.032)
Para. ES	-0.039	-0.052	0.333*	0.014
	(0.030)	(0.201)	(0.175)	(0.032)
Observation	20,887	14,534	14,657	10,577
Controls	Y	Y	Y	Y
County FE & Year FE	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample for household heads comes from CFPS 2012, 2014, 2016, 2018, and 2020. The sample for time use comes from CFPS 2014, 2016, 2018, and 2020. The sample for satisfaction comes from CFPS 2014, 2018, and 2020. All samples include married rural residents aged 20–60. All regressions include individual-level controls like age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 6: Impacts of RECD on Child Outcomes

	(1) School enrollment	(2) Self-assessed health	(3) Saving for education
Panel A: Girls sample			
Mean of *Y*	0.943	0.653	0.135
TWFE	0.033**	0.052*	0.027
	(0.017)	(0.031)	(0.032)
CSDID	0.029*	0.097*	0.031*
	(0.017)	(0.060)	(0.017)
Para. ES	0.040*	0.093	0.010
	(0.022)	(0.069)	(0.023)
Observation	6,402	3,218	6,360
Panel B: Boys sample			
Mean of *Y*	0.945	0.665	0.145
TWFE	-0.002	-0.043	-0.013
	(0.025)	(0.044)	(0.023)
CSDID	0.017	0.060	0.011
	(0.014)	(0.059)	(0.024)
Para. ES	0.007	0.078	-0.011
	(0.014)	(0.058)	(0.030)
Observation	7,330	3,678	7,283
Controls	Y	Y	Y
County FE & Year FE	Y	Y	Y
County linear year trend	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample comes from CFPS 2012–2020 and includes children age 6–15. We focus on children aged 6-15, aligning with the Compulsory Education Law in China, which mandates nine years of compulsory education starting at age 6. For analyses of self-rated health, we restrict the sample to children aged 10–15, as data on self-rated health is only available for this age range. All regressions include individual-level controls like age and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Appendix

Detailed Conceptual Model

In this appendix, we provide the full mathematical derivations and proofs that support our conceptual framework.

A.1 Model Setup

Consider a household consisting of two adults—a female (*f*) and a male (*m*)—and one child. Each adult allocates time between leisure, home production, and market labor. The total time endowment for each individual is normalized to one:

$$l_i + t_i + h_i = 1, \quad i \in \{f, m\} \tag{A1}$$

where l_i denotes leisure time, t_i is time spent on home production (e.g., childcare, household chores), and h_i is time allocated to market labor.

Labor Market

Individuals can work in either the traditional sector or the e-commerce sector. The level of e-commerce development is represented by the parameter *E*, where higher values of *E* indicate greater e-commerce development. We assume that wages depend on *E*, with women's wages being more positively affected by e-commerce development due to their comparative advantage. Specifically, the wage rates are:

$$w_f = w_0 + \alpha_f E \tag{A2}$$

$$w_m = w_0 + \alpha_m E \tag{A3}$$

where $w_0 > 0$ is the base wage in the traditional sector, $\alpha_f > \alpha_m \geqslant 0$ capture the differential impact of e-commerce development on women's and men's wages.

Home Production

Home production requires a total of *T* units of time, which must be fulfilled by the adults:

$$t_f + t_m = T \tag{A4}$$

Child Human Capital Production

The child's human capital *H* depends on parental investment *I*:

$$H = H(I) \tag{A5}$$

with $H'(I) > 0$, $H''(I) < 0$.

Budget Constraint

Household income consists of earnings from market labor:

$$C + I = w_f h_f + w_m h_m \tag{A6}$$

where C is household consumption, h_f and h_m refer to the time women and men allocate to the labor market, respectively.

Household Utility Functions

We adopt a collective household model where decisions are Pareto efficient and reflect the bargaining power of each spouse. The household maximizes:

$$\underset{C,I,l_f,l_m,t_f,t_m,h_f,h_m}{max} \lambda U_f + (1-\lambda)U_m \tag{A7}$$

where $\lambda \in [0, 1]$ is the female's bargaining power, endogenously determined within the household. Individual utilities are:

$$U_f = u(C) + v(l_f) + w(H) \tag{A8}$$

$$U_m = u(C) + v(l_m) \tag{A9}$$

where $u(\cdot)$, $v(\cdot)$, and $w(\cdot)$ are twice continuously differentiable, strictly increasing, and strictly concave functions.

Intra-household Bargaining Power

The female's bargaining power λ depends on her share of household earnings:

$$\lambda = \lambda(s_f), s_f = \frac{w_f h_f}{w_f h_f + w_m h_m} \tag{A10}$$

with $\lambda'(s_f) > 0$.

A.2 Household Optimization

The household maximizes the weighted sum of utilities subject to time and budget constraints. The Lagrangian for the optimization problem is:

$$\Pi = \lambda\left[u(C) + v\left(l_f\right) + w(H)\right] + (1-\lambda)[u(C) + v(l_m)] + \mu\left(w_f h_f + w_m h_m - C - I\right)$$

$$+\gamma_f\left(1 - l_f - t_f - h_f\right) + \gamma_m(1 - l_m - t_m - h_m) + \kappa(t_f + t_m - T) \tag{A11}$$

A.3 Comparative Statics and Proofs

Proposition 1: An increase in e-commerce development (E) reduces the gender gap in labor supply by increasing women's labor supply more than men's.

Proof:

From the FOCs for home production:

$$\frac{\partial \Pi}{\partial t_i} = -\gamma_i + \kappa = 0 \tag{A12}$$

From the FOCs for market labor:

$$\frac{\partial \Pi}{\partial h_i} = \frac{\partial \lambda}{\partial h_i}(U_f - U_m) + \mu w_i - \gamma_i = 0 \tag{A13}$$

Combining the above two formulas:

$$\mu w_i = \kappa - \frac{\partial \lambda}{\partial h_i}(U_f - U_m) \tag{A14}$$

An increase in E raises women's wages more than men's:

$$\frac{\partial w_f}{\partial E} = \alpha_f > \alpha_m = \frac{\partial w_m}{\partial E} \tag{A15}$$

Assuming μ and κ are constant, the increase in w_f leads to a larger increase in h_f compared to the increase in h_m. Therefore:

$$\frac{\partial h_f}{\partial E} - \frac{\partial h_m}{\partial E} > 0 \tag{A16}$$

Proposition 2: An increase in women's labor supply and earnings due to ecommerce development (E) enhances their bargaining power within the household.

Proof:

As women's labor supply h_f and wages w_f increase with E, their share of household income s_f rises. Since $\lambda = \lambda(s_f)$ with $\lambda'(s_f) > 0$, it follows that:

$$\frac{\partial \lambda}{\partial E} = \lambda'(s_f)\frac{\partial s_f}{\partial E} > 0 \tag{A17}$$

Therefore, the female's bargaining power λ increases with E.

Proposition 3: Enhanced female bargaining power leads to higher investment in children's human capital, particularly benefiting daughters if mothers have gender-specific preferences.

Proof:

From the FOC for investment I:

$$\lambda w'(H)H'(I) = \mu \tag{A18}$$

Differentiating with respect to E:

$$w'(H)H'(I)\frac{\partial \lambda}{\partial E} + \lambda w''(H)[H'(I)]^2\frac{\partial I}{\partial E} = 0 \tag{A19}$$

Since $H''(I) < 0$ and $\partial\lambda / \partial E > 0$, we have:

$$\frac{\partial I}{\partial E} > 0 \tag{A20}$$

Therefore, investment in the child's human capital I increases with E. If the mother places more emphasis on daughters' outcomes, this increased investment particularly benefits girls.

To test the propositions derived from the model, we exploit the county-by-county rollout of e-commerce expansion as a natural experiment. We analyze how e-commerce impacts women's labor market outcomes, intra-household bargaining power, and child outcomes. The empirical analysis aims to understand the effects of e-commerce on gender roles in rural China.

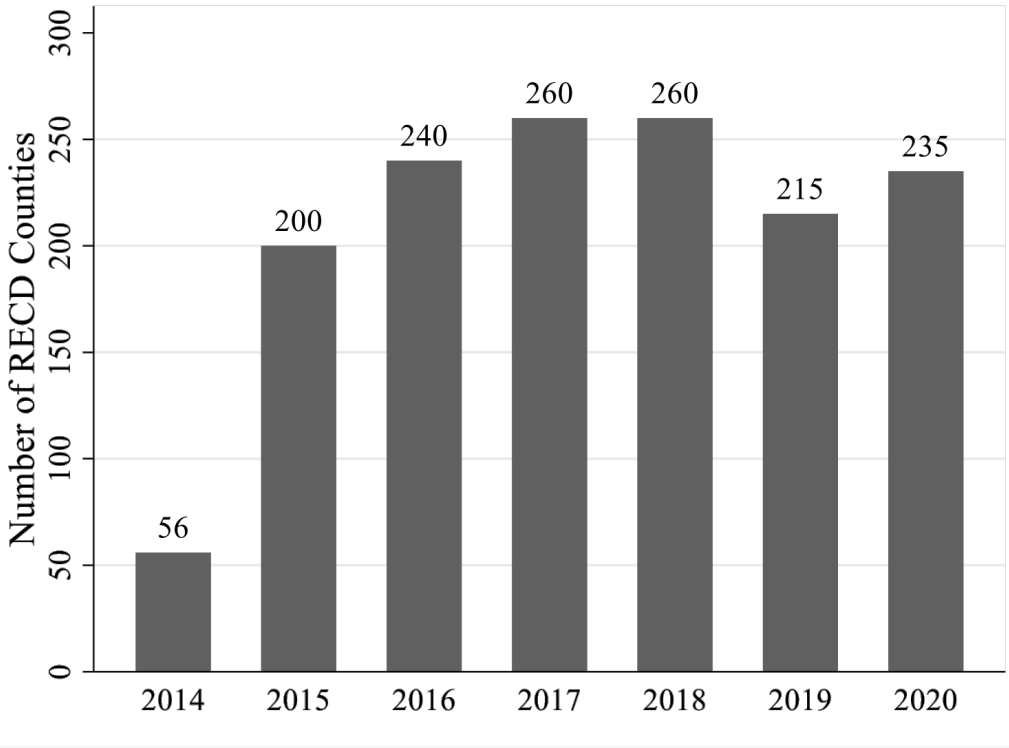


Figure A1: The Number of RECD Counties Approved Each Year

Notes: This figure illustrates the annual number of approved Rural E-Commerce Comprehensive Demonstration (RECD) counties in China from 2014 to 2020.

Source: The list of RECD counties (2014-2020) released by the Ministry of Commerce.

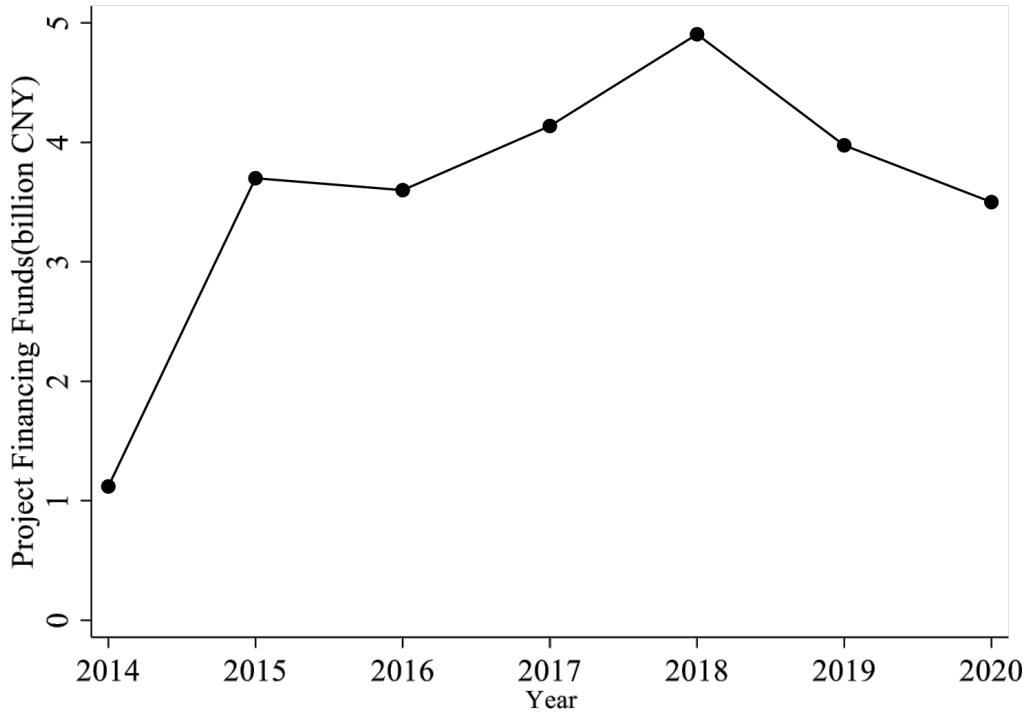


Figure A2: Project Financial Funds Received by Demonstration Counties Each Year

Notes: This figure illustrates the annual financial funds support received by Rural E-Commerce Comprehensive Demonstration (RECD) counties in China from 2014 to 2020.

Source: "Notice on the Implementation of Rural E-commerce Comprehensive Demonstration" released by the Ministry of Finance and Ministry of Commerce each year.

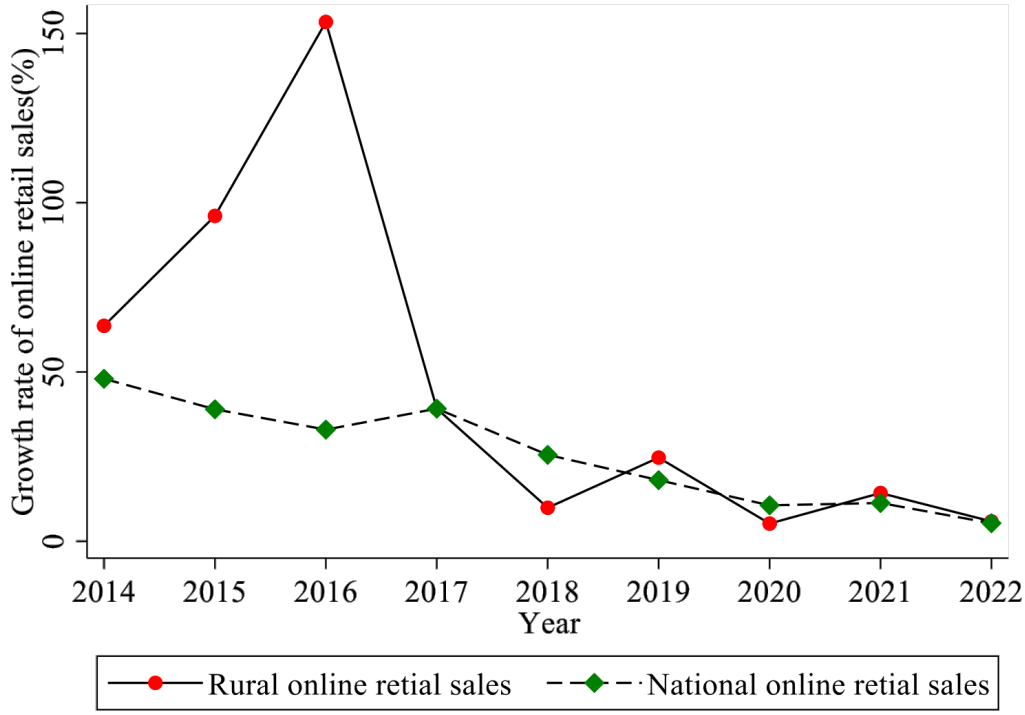
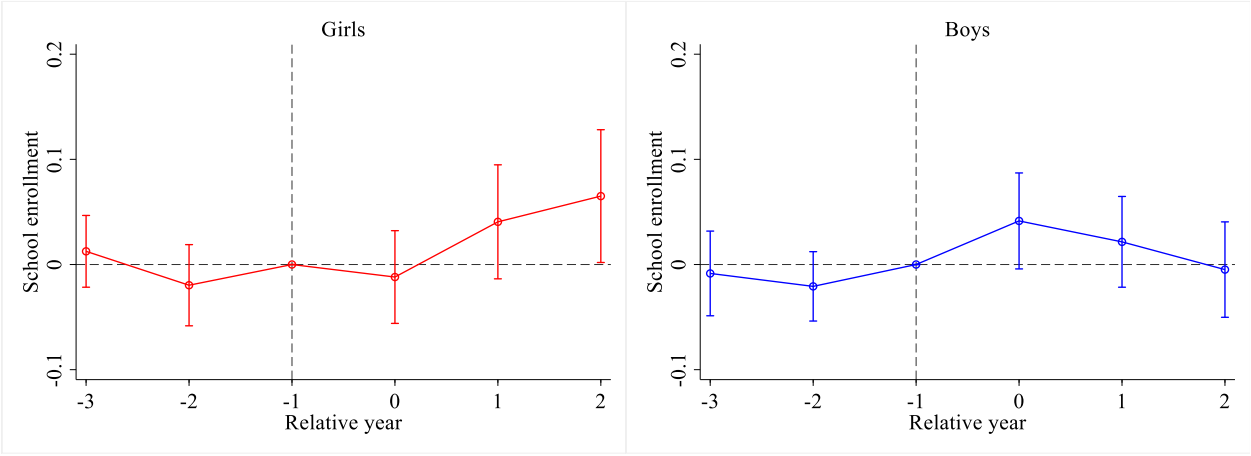


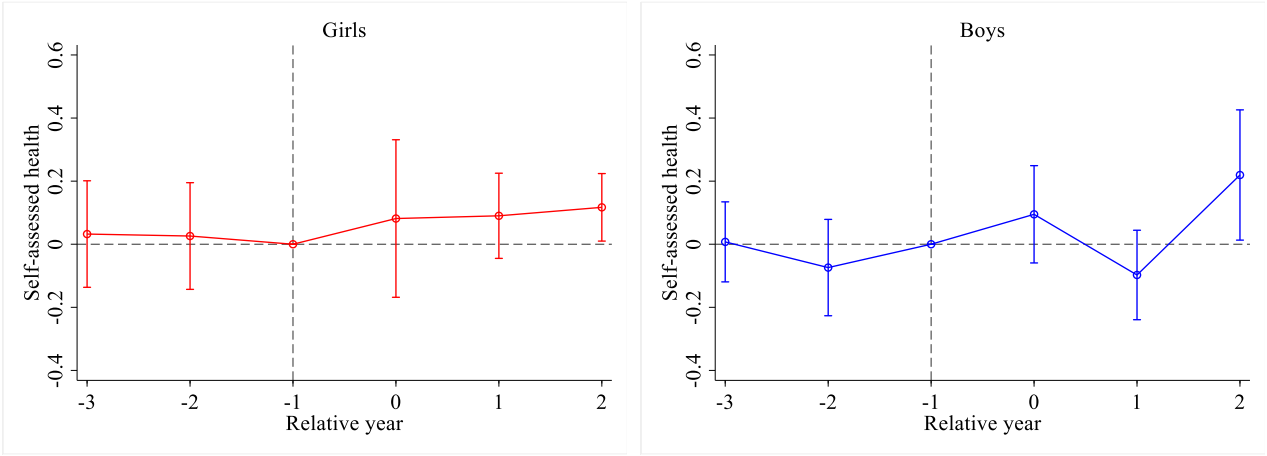
Figure A3: The Annual Growth Rate of Rural Online Retail Sales and National Online Retail Sales

Notes: This figure illustrates the Annual Growth Rate of Rural Online Retail Sales and National Online Retail Sales in China from 2014 to 2022.

Source: Ministry of Commerce.



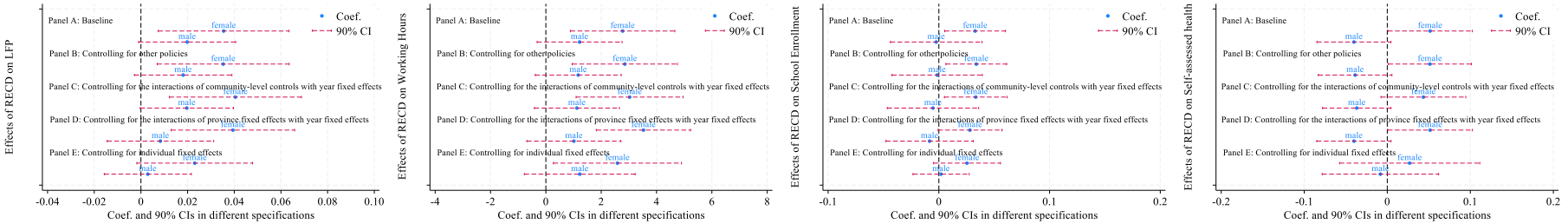
(a) School enrollment



(b) Self-assessed health

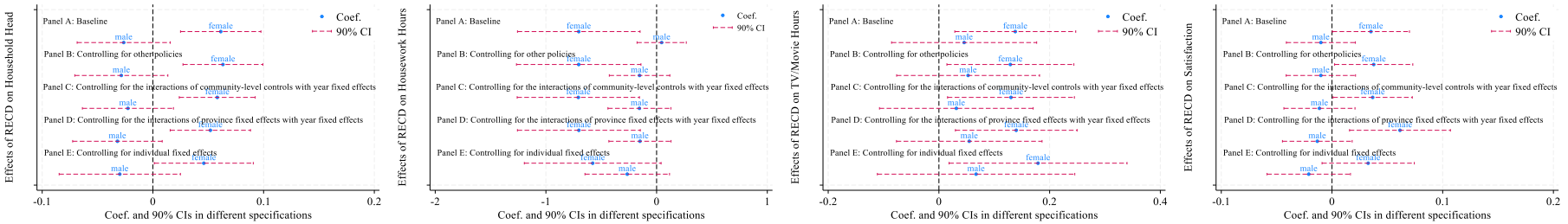
Figure A4: Event-Study Estimates: Impacts of RECD on Children Outcomes

Notes: The figure shows the dynamic effects of the RECD project on key children's outcomes by gender, using the estimators proposed by Callaway and Sant'Anna (2021). The sample is drawn from the China Family Panel Studies (CFPS) 2012–2020, including children age 6–15. The figure comprises two panels: (a) School enrollment, and (b) Self-assessed health. Each panel presents point estimates with corresponding 90% confidence intervals. The x-axis represents years relative to the RECD implementation (with -1 as the reference year), while the y-axis displays the magnitude of the estimated effects.



(a) Labor Supply

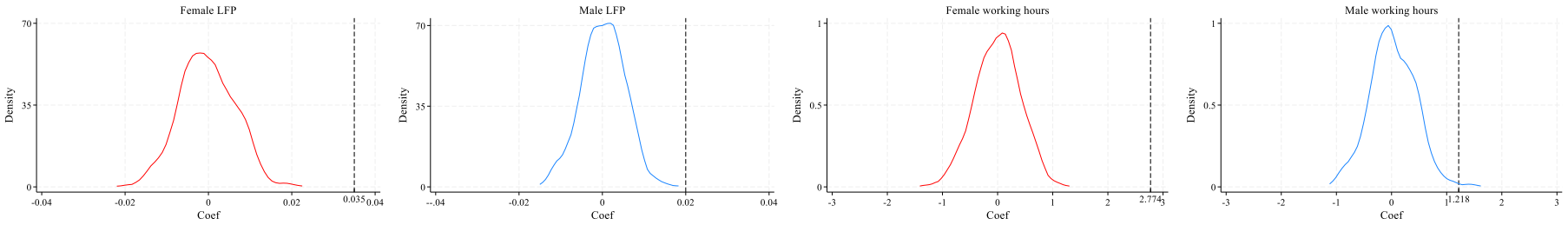
(c) Child Outcomes



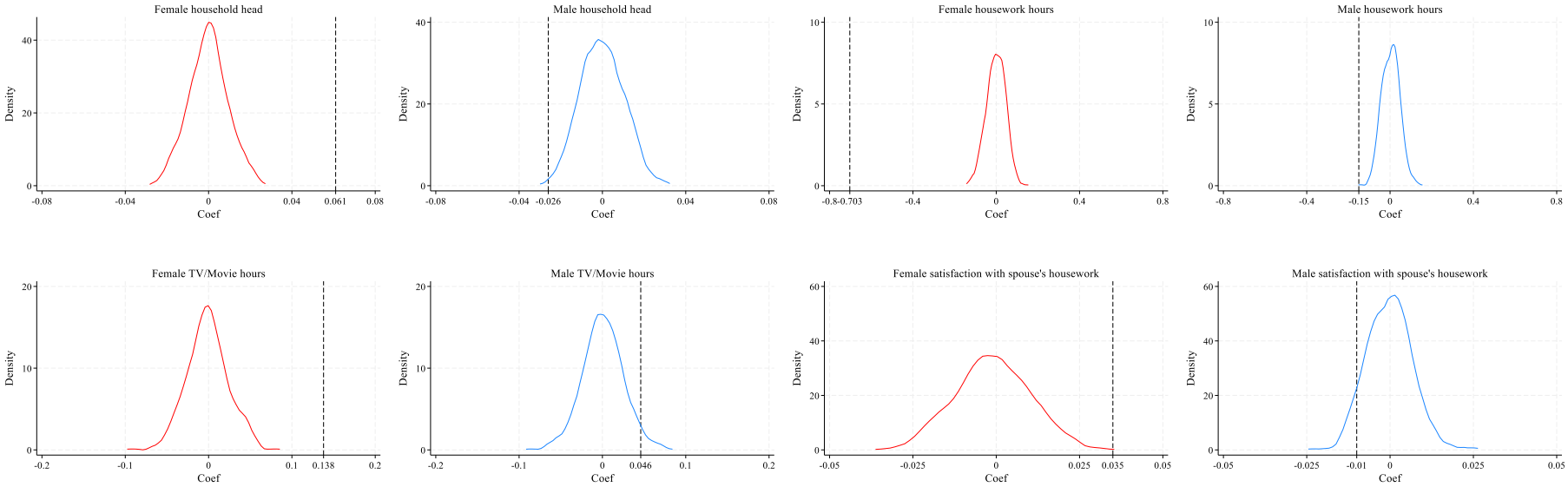
(b) Intra-household Bargaining Power

Figure A5: Robustness Checks: Effects of RECD in Different Specifications

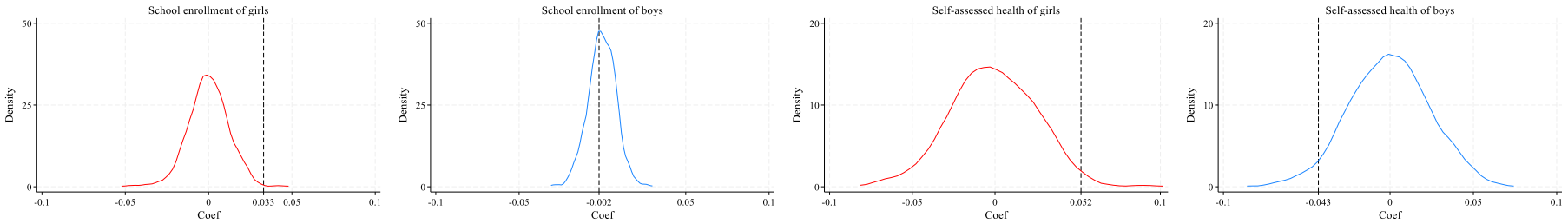
Notes: The figure displays robustness checks in different specifications. Figure (a) and (b) include rural residents aged 20-60, while figure (c) include rural children. Each panel displays point estimates and 90% confidence intervals, with results for females (girls) shown at the top and results for males (boys) shown at the bottom. Data on housework hours and TV/movie hours is only available in CFPS 2014, 2016, 2018, and 2020. Data on satisfaction is only available in CFPS 2014, 2018 and 2020. All regressions use TWFE estimators and control for individual-level controls, county fixed effects, year fixed effects, county-specific linear year trend and the interactions of selection criteria with year fixed effects. Panel A presents the baseline results. Panel B additionally controls for China's broadband pilot policy and smart city pilot policy. Panel C additionally controls for the interactions of community-level controls (Number of kindergartens, primary schools, middle schools, medical institutions and the distance to the county seat) with year fixed effects. Panel D additionally controls for the interactions of province fixed effects with year fixed effects. Panel E additionally controls for the individual fixed effects. Standard errors are clustered at the county level.



(a) Labor Supply



(b) Intra-household Bargaining Power



(c) Child Outcomes

Figure A6: Placebo test

Notes: The figure displays placebo test results for women (girls) indicated by the red line and men (boys) indicated by the blue line, based on 500 permutations of the implementation timing of RECD. The sample comes from CFPS 2012–2020. Figure (a) and (b) include rural residents aged 20–60, while figure (c) include rural children. Data on housework hours and TV/movie hours is only available in CFPS 2014, 2016, 2018, and 2020. Data on satisfaction is only available in CFPS 2014, 2018 and 2020. All regressions use TWFE estimators and control for individual-level controls, county fixed effects, year fixed effects, county-specific linear year trend and the interactions of selection criteria with year fixed effects.

Table A1: Source of variations in RECD implementation

	RECD Implementation			
	(1)	(2)	(3)	(4)
Province FE × Year FE	YES	YES		
City FE × Year FE			YES	YES
Observations	25,632	1,458	25,605	441
R^2	0.306	0.393	0.472	0.641
Adj. R^2	0.299	0.292	0.401	0.468
Mean of *Y*	0.197	0.166	0.168	0.129

Notes: The data consists of a panel dataset of counties from 2012 to 2020. Columns (1) and (3) include full 2,848 counties, while Columns (2) and (4) include 162 counties sampled by CFPS. The regressions are estimated by OLS estimator.

Table A2: Balance test

	Non-RECD counties (N=856)	RECD counties (N=1260)	Unconditional diff.	Conditional diff.
	(1)	(2)	(3)	(4)
Selection criteria				
Poverty county (dummy)	0.000	0.632	0.632***	
	[0.000]	[0.483]	(0.014)	
Per capita fixed asset investment (CNY)	31676	19426	-12250***	
	[25174]	[16231]	(974)	
Other characteristics				
Area (sq.km)	2903.410	4335.420	1432.010***	0.000
	[5418.393]	[6210.952]	(254.782)	(0.000)
log(GDP) (10 thousand CNY)	14.213	13.251	-0.962***	-0.041
	[0.851]	[1.131]	(0.043)	(0.031)
log(population) (10 thousand people)	3.774	3.435	-0.339***	0.046
	[0.758]	[0.976]	(0.038)	(0.037)
Primary sector share (%)	16.661	23.297	6.637***	0.001
	[10.875]	[11.153]	(0.487)	(0.002)
Secondary sector share of GDP (%)	51.246	42.708	-8.537***	0.001
	[14.147]	[15.256]	(0.647)	(0.001)
Per capita fiscal expenditure (CNY)	6007.027	6093.213	86.186	-0.000
	[5296.477]	[4816.933]	(226.245)	(0.000)
Distance from the prefectures (km)	43.484	65.074	21.590***	0.001***
	[40.918]	[46.795]	(1.922)	(0.000)

Notes: The sample is derived from cross-sectional data of 2,116 counties in 2012. Columns (1)–(2) present the mean and standard deviation [in brackets] for RECD and non-RECD counties; column (3) shows unconditional differences and standard errors (in parentheses) between two groups; column (4) shows the differences and standard errors (in parentheses) conditional on the two selection criteria. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A3: Impacts of the RECD on LFP and Working Hours with Baseline Controls

	LFP	Working Hours
	(1)	(2)
Panel A: Female		
Mean of *Y*	0.817	30.685
TWFE	0.027	2.209*
	(0.018)	(1.233)
CSDID	0.018*	1.677**
	(0.010)	(0.796)
Para. ES	0.021*	1.572*
	(0.012)	(0.891)
Observation	25,953	25,953
Panel B: Male		
Mean of *Y*	0.887	42.105
TWFE	0.012	0.351
	(0.013)	(1.077)
CSDID	-0.003	-0.433
	(0.007)	(0.733)
Para. ES	-0.002	-0.658
	(0.008)	(0.823)
Observation	25,797	25,797
Controls	N	N
County FE & Year FE	Y	Y
County linear year trend	Y	Y
Selection criteria × Year FE	N	N

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample comes from CFPS 2012–2020 and includes rural residents aged 20–60. We only incorporate county fixed effects, year fixed effects and county-specific linear year trends. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A4: The Heterogeneous Effects of RECD on Labor Supply by Age and Education

	LFP		Working hours	
	(1) Female	(2) Male	(3) Female	(4) Male
Panel A: By age				
Mean of *Y*	0.817	0.887	30.685	42.105
RECD	0.105***	0.089***	0.973	1.756
	(0.036)	(0.029)	(2.436)	(1.880)
RECD × Age	-0.002**	-0.002***	0.043	-0.013
	(0.001)	(0.001)	(0.049)	(0.037)
Observation	25,953	25,953	25,953	25,953
Panel B: By education				
RECD	0.026	0.008	3.082***	1.759*
	(0.018)	(0.013)	(1.179)	(0.975)
RECD × High Edu.	0.025*	0.020**	-0.793	-0.943
	(0.015)	(0.008)	(1.009)	(0.772)
Observation	25,797	25,797	25,797	25,797
Controls	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes rural residents aged 20–60. The group with high education levels is defined as those who have completed nine years of compulsory education. All regressions use TWFE estimators and control for individual-level controls, county fixed effects, year fixed effects, county-specific linear year trend and the interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A5: Impacts of RECD on E-commerce Participation for Counties w/ and w/o Agricultural Specialty Products

	Counties with agricultural specialty products	Counties without agricultural specialty products
	E-commerce participation	
	(1)	(2)
Panel A: Female		
Mean of Y	0.172	0.167
TWFE	0.028	0.012
	(0.019)	(0.009)
CSDID	0.041**	0.004
	(0.017)	(0.021)
Para. ES	0.038**	0.000
	(0.018)	(0.024)
Observation	6,291	9,515
Panel B: Male		
Mean of Y	0.170	0.167
TWFE	-0.006	-0.005
	(0.024)	(0.014)
CSDID	0.030	-0.014
	(0.020)	(0.022)
Para. ES	0.037*	-0.027
	(0.022)	(0.026)
Observation	5,880	8,785
Controls	Y	Y
County FE & Year FE	Y	Y
County linear year trend	Y	Y
Selection criteria × Year FE	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample comes from CFPS 2014, 2016 and 2018 and includes rural residents aged 20–60. E-commerce participation is defined as engaging in online commercial activities at least once a month (yes =1). All regressions include individual-level controls like age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A6: Impacts of RECD on Household Expenditure Patterns Conditional on Household Income

Frac. of expenditures by categories	Cosmetic	Education	Medical	Housing	Cul. &ent.	Tourism	Food
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean of Y	0.620	7.181	11.867	11.130	0.106	0.278	33.939
TWFE	0.076*	0.465	1.595*	1.829**	0.011	-0.035	-1.745
	(0.041)	(0.328)	(0.929)	(0.875)	(0.013)	(0.030)	(1.371)
CSDID	0.077	1.213*	1.429*	2.100**	0.001	-0.020	-0.222
	(0.074)	(0.722)	(0.849)	(0.978)	(0.013)	(0.037)	(1.107)
Para. ES	0.074	0.833	1.884**	2.877**	-0.003	-0.017	0.134
	(0.102)	(1.047)	(0.955)	(1.140)	(0.015)	(0.044)	(1.181)
Observations	25,533	25,490	25,498	25,334	25,583	25,609	25,493
Household Income	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
County FE & Year FE	Y	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample consists of rural households from the CFPS 2012–2020. The dependent variables are the fraction of various expenditures to total household expenditure. All regressions include controls such as household income, the number of family members, household head's gender, age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A7: Impacts of RECD on Marital Decisions

	Married (=1)	Single (=1)	Divorced (=1)	Cohabiting (=1)	Age at first marriage
	(1)	(2)	(3)	(4)	(5)
Panel A: Female					
Mean of *Y*	0.908	0.082	0.006	0.003	21.775
TWFE	0.007	-0.002	-0.005	-0.000	-0.153
	(0.007)	(0.007)	(0.003)	(0.002)	(0.094)
CSDID	-0.001	0.003	-0.003	0.002	-0.033
	(0.006)	(0.005)	(0.004)	(0.002)	(0.030)
Para. ES	-0.002	0.003	-0.003	0.002	-0.014
	(0.006)	(0.005)	(0.004)	(0.003)	(0.038)
Observation	25,953	25,953	25,953	25,953	23,653
Panel B: Male					
Mean of *Y*	0.822	0.148	0.025	0.004	23.719
TWFE	0.004	-0.015*	0.004	0.007*	-0.120
	(0.008)	(0.008)	(0.004)	(0.004)	(0.104)
CSDID	-0.005	-0.009*	0.010**	0.002	0.046
	(0.007)	(0.005)	(0.004)	(0.002)	(0.042)
Para. ES	-0.006	-0.009	0.012**	0.002	0.057
	(0.008)	(0.006)	(0.005)	(0.003)	(0.050)
Observation	25,797	25,797	25,797	25,797	21,772
Controls	Y	Y	Y	Y	Y
County FE & Year FE	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). The sample comes from CFPS 2012–2020 and includes rural residents aged 20–60. All regressions include individual-level controls like age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table A8: Robustness Checks: Possible Composition Change and Attrition Test

	Cross-county migrants (=1)	Urban-to-rural migrants (=1)	Attrition (=1)
	(1)	(2)	(3)
Panel A: Female			
Mean of *Y*	0.066	0.032	0.198
TWFE	-0.008	0.016	0.032
	(0.007)	(0.016)	(0.022)
CSDID	-0.000	0.004	-0.019
	(0.003)	(0.006)	(0.013)
Para. ES	-0.000	0.005	-0.012
	(0.002)	(0.007)	(0.013)
Observation	25,953	25,953	36,675
Panel B: Male			
Mean of *Y*	0.067	0.045	0.202
TWFE	0.000	-0.011	0.034
	(0.010)	(0.019)	(0.024)
CSDID	0.003	0.004	-0.018
	(0.007)	(0.009)	(0.013)
Para. ES	0.003	0.004	-0.011
	(0.007)	(0.010)	(0.013)
Observation	25,797	25,797	38,045
Controls	Y	Y	Y
County FE & Year FE	Y	Y	Y
County linear year trend	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y

Notes: This table presents TWFE estimates, CSDID estimates, and average treatment effects from a parametric event study based on Callaway and Sant'Anna (2021). Column (3) use a balanced panel dataset consisting of rural individuals aged 20-60 who were interviewed in the first wave, while the other columns use the same sample as the baseline regressions. All regressions include individual-level controls like age, education levels, and agricultural hukou dummies. We also incorporate county fixed effects, year fixed effects, county-specific linear year trends, and interactions of selection criteria with year fixed effects. Standard errors clustered at county level are reported in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.