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

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Abstract

We explore the gendered effects 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). Our findings show that e-commerce significantly increases women's labor force participation and working hours, while leaving male labor supply unchanged. Additionally, it enhances women's bargaining power, increasing their control over financial resources, reducing time spent on household chores, and improving satisfaction with household task-sharing. E-commerce also leads to improved educational and health outcomes for girls, with no significant effects on boys. These results suggest that digital transformation can reduce gender disparities and improve women's and girls' socioeconomic outcomes in rural areas.

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

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

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1. Introduction

The rapid rise of e-commerce has dramatically reshaped global labor markets, providing flexible, remote, and self-employment opportunities, particularly for women (OECD, 1999; Bauer & Fernández, 2023). Between 2014 and 2023, global e-commerce sales surged 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, accounting for USD 1.9 trillion in sales—30% of the country's total retail transactions. E-commerce offers women employment opportunities that are less dependent on physical labor, which has traditionally dominated male-dominated sectors such as agriculture (Luo & Niu, 2019; UNCTAD, 2023). In developing economies, e-commerce has enabled women to access income-generating activities beyond traditional sectors, allowing them to balance market work with household responsibilities more effectively (Goldin & Katz, 2016; Olivetti & Petrongolo, 2016). This transition has the potential to reduce gender gaps in employment, earnings, and decision-making power 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 focused on the broader economic effects of e-commerce—such as its impact on consumer welfare (Dolfen et al., 2023), living costs (Couture et al., 2021), spatial consumption inequality (Fan et al., 2018), and retail employment (Chun et al., 2023)—few studies have examined 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, especially in developing regions where gender inequalities are more pronounced. This paper addresses this gap by using the staggered rollout of the RECD project to estimate its effects on labor force participation, household bargaining power, and child outcomes in rural China, focusing on the differential impacts on men and women.

In China, the government has explicitly positioned e-commerce as a key tool for addressing both economic and social challenges, particularly in rural areas. The *Rural E-Commerce Comprehensive Demonstration Project* (RECD), launched in 2014, aligns closely with broader

national strategies aimed at poverty alleviation, rural revitalization, and promoting gender equity. This project leverages digital platforms to empower women by providing them with economic opportunities that allow for greater work flexibility, balancing market work with household responsibilities (Luo & Niu, 2019; UNCTAD, 2023). The phased implementation of this project provides a quasi-experimental setting, allowing us to estimate the causal effects of e-commerce expansion on gendered labor outcomes. Drawing on nationally representative panel data from the China Family Panel Studies (CFPS) spanning 2012 to 2020, we apply a difference-in-differences (DID) strategy and event study methodology to evaluate the impact of RECD on women's labor force participation, intra-household bargaining power, and child outcomes. Our analysis focuses on the differential effects of e-commerce expansion on men and women, exploring how digital platforms reshape labor market behavior, household dynamics, and the well-being of children.

Our main findings show that e-commerce has a significant impact on labor force participation (LFP) and working hours for rural women, while having no notable effect on men. Specifically, exposure to the RECD program leads to an approximately 3 percentage point (pp) increase in female LFP (equivalent to 4% of the mean) and a 2.5-hour increase in weekly working hours (8% of the mean). We observe heightened participation in online commercial activities and entrepreneurship among women, whereas these trends remain unchanged for men. Additionally, household income rises, particularly through increased sales of agricultural products and growth in non-agricultural business income. Collectively, these findings suggest that e-commerce reduces the gender gap in labor supply and alters the household production function.

Further, our analysis reveals shifts in household dynamics following e-commerce expansion, with notable reductions in gender inequality. Women's control over financial resources strengthens, as evidenced by an increase of 4.1 to 6.1 pp in the likelihood of women managing household finances after RECD implementation. Moreover, women gain 0.2 additional hours of daily leisure time, such as watching TV or movies, while their time spent on household chores declines by an average of 0.5 hours per day. Meanwhile, satisfaction with spousal contributions to household tasks increases by 3.5-6.0 pp. Additionally, changes in household spending patterns have also been observed, showing increases in the percentage of expenditures allocated to cosmetics (0.05-0.12

pp), medical expenses (0.02 pp), and housing costs (1.6-4.1 pp). These results collectively indicate that e-commerce expansion enhances women's bargaining power within households. Finally, we explore the gendered impacts of e-commerce on children. Our findings show that girls benefit disproportionately from improved educational and health outcomes due to e-commerce expansion, while boys remain largely unaffected. Specifically, we document an increase in girls' school enrollment rates by 3-7 pp, alongside improvements in self-assessed health scores by 10 pp. These results suggest that the benefits of e-commerce expansion for women extend beyond the household, particularly enhancing the well-being and opportunities of girls.

To validate our identification strategy, we employ both an event study approach and the CSDID estimator proposed by Callaway and Sant'Anna (2021) to assess the dynamic effects of e-commerce expansion through the RECD program on labor market outcomes, household bargaining, and child welfare. In traditional two-way fixed effects (TWFE) models, treatment effects are often estimated as weighted averages across different treatment periods, which can introduce bias when earlier-treated groups serve as controls for later-treated groups, particularly when treatment effects are heterogeneous (Goodman-Bacon, 2021; De Chaisemartin & d'Haultfoeuille, 2020). By employing event study approach and using the CSDID estimator, we address these biases and generate unbiased estimates of treatment effects. Our event study tracks these effects longitudinally, confirming parallel pre-treatment trends between treated and control counties, with no significant differences observed before RECD implementation, validating the assumptions of our difference-in-differences analysis. Post-implementation, we observe a steady increase in women's labor force participation, household bargaining power, and girls' outcomes. This gradual emergence of benefits reinforces the causal interpretation of our findings. Moreover, the CSDID estimator, which aggregates group-time average treatment effects (ATTs) across multiple treatment groups and periods, consistently supports these results.

To further strengthen our results, we conduct additional robustness checks. We address potential confounding factors by controlling for concurrent policies and regional developments, including China's investments in education, public health, and internet infrastructure. We incorporate various fixed effects and interaction terms to account for unobserved heterogeneity at

the province, year, and individual levels. To rule out composition changes due to migration, we test for changes in residential patterns and find no significant effects of RECD on migration. We also examine sample attrition and find minimal, statistically insignificant impacts of RECD on attrition rates. Finally, we perform a placebo test by randomly assigning treatment to counties, with results showing no significant effects, further supporting our identification strategy. Across these various specifications and tests, our main findings remain robust, reinforcing the causal interpretation of our findings on gendered impacts of e-commerce expansion.

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 child 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 benefitting 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 describes the background of e-commerce promotion in rural China. Section 3 establishes a conceptual framework to guide our empirical analysis. Section 4 summarizes the dataset and measures of the variables used in this study. We then formulate our empirical strategy in Section 5. Sections 6 and 7 include the results on labor supply and household outcomes, respectively. Section 8 conducts robustness checks on the key results. Finally, Section 9 concludes this paper.

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; the program 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. 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 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 Programs 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 program 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 program to accelerate income generation and entrepreneurship, especially for women, in ways that are distinct from other national efforts.

3. Conceptual Framework

Our conceptual framework builds on the economic theories of household decision-making and labor supply, focusing on how the expansion of e-commerce influences women's labor participation, intra-household bargaining power, and child outcomes in rural China. We base our model on the collective household framework (Chiappori, 1992), which posits that household resources are allocated efficiently according to the bargaining power of each member, with bargaining power shaped by their relative contributions to household income. A central assumption of our model is that women hold a comparative advantage in the e-commerce sector. This assumption is grounded in two key observations. First, e-commerce-related jobs frequently require skills such as communication, customer service, and attention to detail—traits that have been shown to align well with women's strengths (Galor and Weil, 1996; Ge and Zhou, 2020). Second, e-commerce platforms offer flexible working conditions that accommodate the time constraints women face due to household responsibilities. This flexibility reduces the opportunity cost of market work for women, making e-commerce a more attractive employment option compared to traditional sectors dominated by physical labor.

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:

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

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:

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

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

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

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.

3.3 Model Implications

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 utilizes data from the China Family Panel Studies (CFPS), a longitudinal, nationally representative survey that provides detailed and comprehensive information on Chinese individuals, families, and communities. The CFPS is ideal for our analysis as it captures key socioeconomic variables, including employment, household structure, education, health, and intra-household decision-making dynamics, all of which are crucial for evaluating the gendered effects of e-commerce expansion in rural China. The longitudinal design of the CFPS enables us to observe temporal changes in these variables, making it particularly well-suited for a 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.[1] We focus on the rural population aged 20–60, the prime working-age group, yielding a

[1] 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:

longitudinal sample of 51,750 individual-year observations from 127 counties, including 64 RECD counties.

The CFPS provides rich information on household structure, employment, education, health, and intra-household dynamics. For each individual, labor market participation is captured through two key measures: a binary indicator for labor force participation (LFP) and weekly working hours. These measures allow us to evaluate both the extensive (participation) and intensive (hours worked) margins of labor supply.

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).

The CFPS data also provide detailed information on household expenditure patterns. We focus on specific expenditure categories associated with women's preferences, such as cosmetics, housing, and healthcare. Drawing on recent empirical studies (Booysen & Guvuriro, 2021; Bobonis, 2009; Porter, 2016; Doepke & Tertilt, 2019; Gu et al., 2022), we calculate the ratios of spending in these categories relative to total household expenditure.[2] Cosmetics include items like haircuts and beauty treatments, housing costs cover rent and utilities, and healthcare expenditures include medical equipment, pharmaceuticals, and services.

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

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http://www.isss.pku.edu.cn/cfps/cjwt/zy/1356888.htm

[2] 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; Bobonis (2009), Porter (2016), and Doepke and Tertilt (2019) identify spending on housing and healthcare as indicators of women's bargaining power; and Gu et al. (2022) find that women's influence over family finances is reflected in spending on beauty products and clothing.

"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 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 86.6% expressing satisfaction compared to 96.5% 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

Stagger 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:

$$Y_{ict} = \alpha + \beta RECD_{ct} + X'_{ict}\phi + \lambda_c + \delta_t + \lambda_c \times t + \varepsilon_{ict} \quad (6)$$

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 gender, education years, and hukou.[3]

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 ($\lambda_c \times t$),

[3] 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.

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[4]. ε_{ict} is the error term. All standard errors are clustered at the county level to allow for arbitrary correlation within counties over time, following the approach recommended by Bertrand et al. (2004).

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 model. 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:

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

where *i*,*c*, and *t* index individuals, counties, and years, respectively. The dependent variable Y_{ict} represents our outcomes of interest. λ_c and γ_t denote county and year fixed effects, respectively, which account for time-invariant county characteristics and common national trends. X'_{ict} is a vector of individual-level covariates. 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

[4] 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.

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:

$$Y_{ict} = \alpha + \sum_{k=0}^{2+} \mu'_k + X'_{ict}\phi + \lambda_c + \delta_t + \lambda_c \times t + \varepsilon_{ict} \tag{8}$$

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 program. We present our results by estimating the average treatment effects of μ'_k in all regressions, in addition to TWFE and CSDD estimators. The regression equation also incorporates the same covariates as in Equation (7).

5.2 Validity of the Identification Strategies

Validity of the Parallel Trends Assumption. For the DID approach to yield unbiased estimates, the parallel trends assumption must hold—meaning that in the absence of the RECD project, treated and control counties would have exhibited similar trends in outcomes. While counties were not randomly selected for the RECD project, we address concerns about potential selection bias in two ways. First, our event study can test whether treated and control counties exhibited similar trends in key outcomes prior to RECD implementation.[5] The results suggest no significant differences in pre-treatment trends, supporting the validity of the parallel trends assumption.

Second, to mitigate concerns about non-random selection, we control for observable county characteristics that influenced the timing of RECD implementation, such as poverty status and per

[5] We follow Lu and Yu (2015) and incorporate these selection criteria characteristics in a flexible function form in specification (6). Specifically, we introduce the interactions of year-fixed effects and selection criteria variables in 2012, which include being poverty county (dummy) and per capita fixed asset investment.

capita fixed asset investment. By interacting these variables with year fixed effects, we allow for differential trends in counties based on these characteristics, further strengthening the credibility of our identification strategy.

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.[6] 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.

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

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.

Through these robustness checks, we confirm the credibility of our DID estimates and provide strong evidence of the RECD project's impact on labor supply, intra-household bargaining, and child outcomes in rural China.

6. Impact of the RECD on Labor Supply

6.1 Main Results

Table 2 presents our primary findings on the impact of the RECD program on labor supply, estimated using the DID specification described earlier. The results highlight a notable gender disparity in the program's effects on labor force participation and weekly working hours.

For women, the estimates from traditional TWFE, CSDID estimators and parametric event study all show statistically significant positive effects. 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 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 A1 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 time 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 program. Appendix Table A2 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. These findings suggest that digital literacy and familiarity with online platforms play a significant role in enhancing the benefits of e-commerce expansion.

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. The consistency of our estimates with these studies underscores the potential of e-commerce as an important tool for promoting female labor market engagement.

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 observe a clear and sustained increase in female labor force participation and working hours. Specifically, RECD implementation leads to an immediate 1.5 pp (2% of the mean) increase in LFP, growing to 2.5 pp (3% of the mean) in the first year and further expanding to 4.2 pp (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.

Consistent with the overall findings, we observe no significant changes in male labor force participation or working hours following RECD implementation. This gender disparity in the labor market effects of the program highlights the unique role e-commerce plays in expanding economic opportunities for women, particularly in rural areas where traditional barriers to female employment are more pronounced.

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 investigate its impact on e-commerce-related activities, particularly focusing on e-commerce adoption and entrepreneurship. E-commerce presents a unique opportunity for rural women, enabling them to engage in economic activities with greater flexibility and fewer physical constraints, which are often barriers in traditional labor markets.

Table 3, Columns (1-3) presents the results of the impact of RECD on e-commerce participation and entrepreneurship. Post-RECD implementation, the likelihood of women engaging in e-commerce activities increases by 1.6 to 4.1 pp, representing a 10% to 24% rise from the mean. Notably, men's involvement in e-commerce activities remains unchanged, further emphasizing the gender-specific effects of the program. These findings are consistent with the broader literature suggesting that women are more likely to leverage digital platforms for entrepreneurial ventures and income generation, particularly in rural contexts where traditional employment opportunities are limited.

[Insert Table 3 here]

One limitation of our survey data is that it does not distinguish between buying and selling activities online. This limitation may affect the interpretation of these results, as we cannot ascertain whether the increase in e-commerce participation primarily reflects consumption activities (i.e., online purchases) or entrepreneurial activities (i.e., selling goods or services 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 A3 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. These findings suggest that e-commerce not only broadens the scope of women's economic activities but also plays a vital role in enhancing agricultural sales, which is a key income-generating activity in rural areas.

Columns (4-6) of Table 3 examine the effects of RECD on entrepreneurship, defined as being a sole proprietor or owner of a private firm. The traditional two-way fixed effects (TWFE) estimator suggests that RECD increases the probability of female entrepreneurship by 2.3 pp, equivalent to a 34% increase from the mean. The estimates from the CSDID and parametric event study results are consistent, with a magnitude of about 2 pp. These results highlight the transformative potential of e-commerce to foster entrepreneurship, particularly among women, who may otherwise face significant barriers to entering traditional business sectors.

[Insert Table 4 here]

We also examine the effect of RECD on household income. Table 4 shows that RECD implementation is associated with an increase in total household income of approximately 3,000 CNY for households with female members. Notably, business income, including revenues from the sale of agricultural products and non-agricultural operational income, rises by about 1,000 CNY, accounting for roughly one-third of the total income increase. These findings provide further evidence that e-commerce expansion contributes to income growth, particularly through the promotion of female entrepreneurship and agricultural sales. This underscores the important role that digital platforms play in supporting women's economic empowerment and driving rural development.

7. Impact of RECD on Household Outcomes

7.1 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) the division of household chores, and (3) the allocation of household expenditures.

Panel A, B and C of Table 5 presents our main findings. 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 week, suggesting a reallocation of responsibilities that frees up time for market work or personal development.

[Insert Table 5 here]

Moreover, the RECD program 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 3 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. In contrast, the probability of men being designated as household heads is on a downward trend. 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 (measured as TV or movie watching hours). 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.

[Insert Figure 3 here]

We next examine how RECD influences household expenditure patterns, focusing on women's spending preferences. Table 6 shows that RECD implementation is associated with a 0.05 to 0.12 pp increase in the share of cosmetic expenditures, a 0.01 to 0.03 pp increase in medical expenditures, and a 1.6 to 4.1 pp rise in housing expenditures. These trends suggest that as women's bargaining power increases, they gain greater influence over household financial decisions and tend to prioritize goods that align with their preferences, particularly public goods that benefit the family. These results remain robust even after controlling for total household income (Appendix Table A4).

[Insert Table 6 here]

Event study analysis in Figure 4 provides additional insights into the dynamics of RECD's impact on household expenditure patterns. The share of household expenditures allocated to cosmetics, medical needs, and housing generally increases over time following RECD implementation, although the magnitude of these effects varies across categories. These patterns further confirm the role of RECD in reshaping intra-household financial decisions.

[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 A5 show negligible effects on marriage decision, alleviating this concern and supporting the validity of our main results.

Taken together, these findings suggest that e-commerce expansion through RECD strengthens

women's intra-household bargaining power, leading to a more balanced distribution of household responsibilities and greater influence over financial decisions. These results underscore the potential of e-commerce to promote gender equity in rural China by empowering women economically and enhancing their roles within households.

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 program on child outcomes. Table 7 presents regression 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 3.3 to 6.8 pp, representing a 3.5% to 7.2% increase relative to the mean. In contrast, no significant change is observed in boys' enrollment rates. This finding aligns with the hypothesis that mothers tend to invest more in daughters when their bargaining power increases.

[Insert Table 7 here]

In terms of health outcomes, we observe improvements exclusively among girls, with an increase in self-assessed health status by 10 pp. These effects suggest that mothers, empowered by the RECD program, 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 panels a to c of 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 A6. Overall, our results are consistent with the baseline findings.

8.1 Confounding Factors

Our estimates could potentially be biased by concurrent policies or other factors, such as China's investments in education, healthcare, and digital infrastructure, which coincide with the RECD implementation. To address these concerns, we control for these factors by incorporating data on China's Broadband Expansion and Smart City Development policies, which aim to enhance internet infrastructure and stimulate local economic development. Additionally, we include community-level controls, such as the number of schools and healthcare institutions, and the distance to the county seat, to capture local infrastructure changes that could affect 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 program 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 A6, 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 A6, 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 program 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 programs, 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

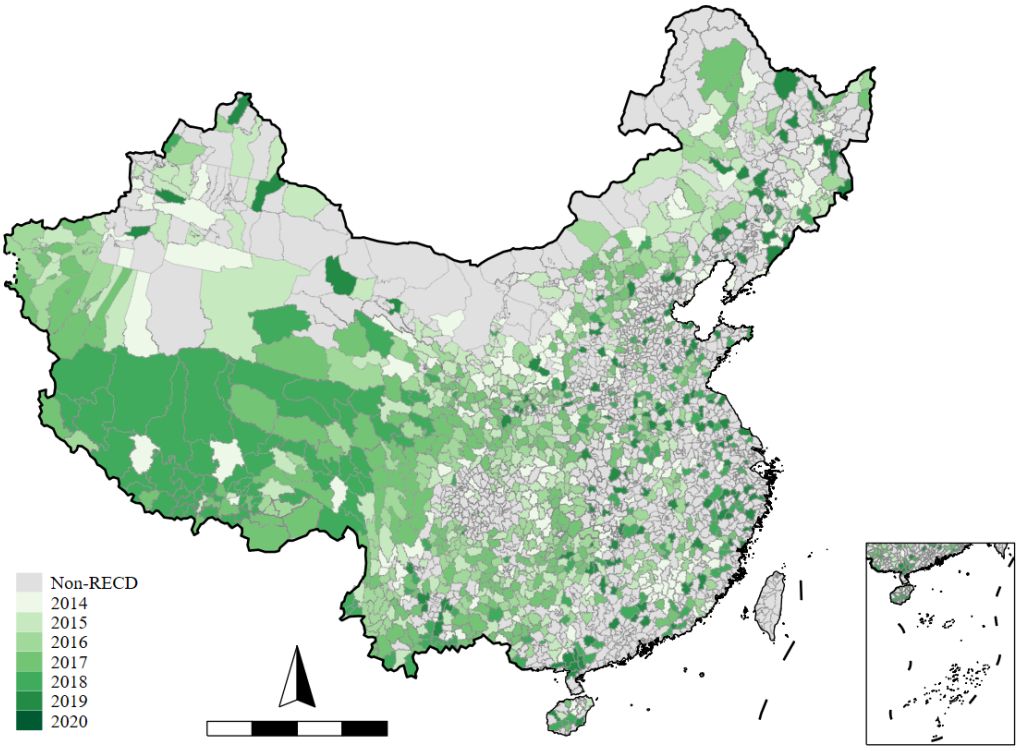
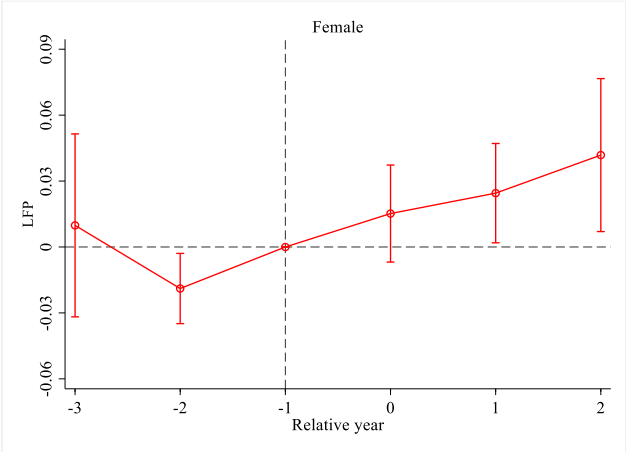
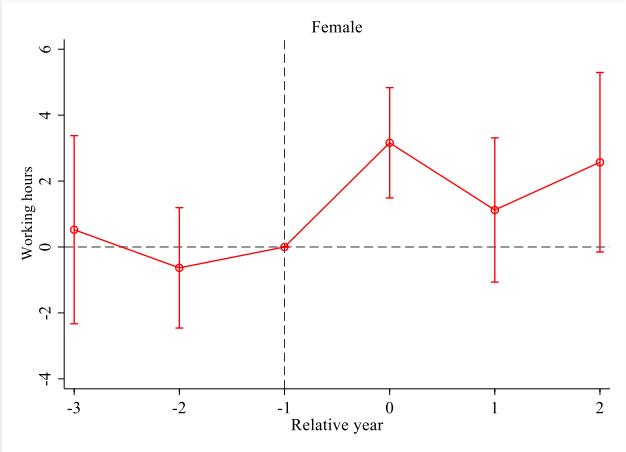


Figure 1: Staggered Implementation of the RECD Project

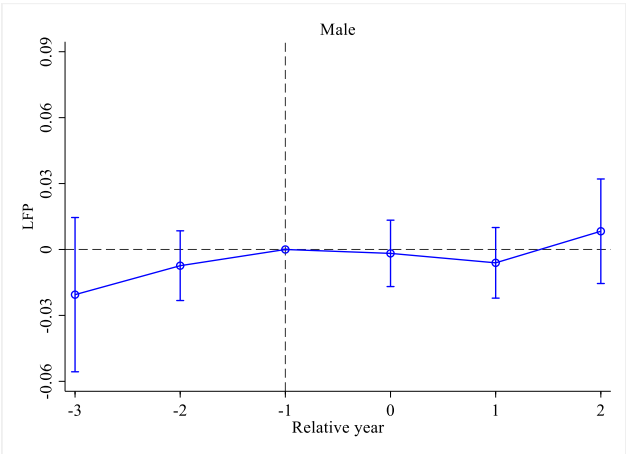
Source: The list of RECD counties (2014-2020) released by the Ministry of Commerce



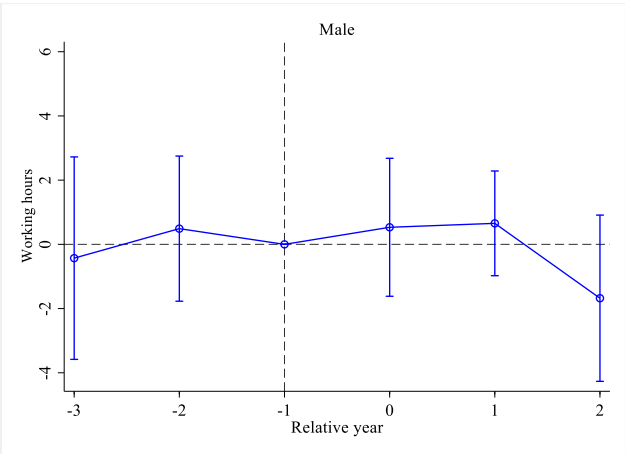
(a) Female LFP



(b) Female working hours



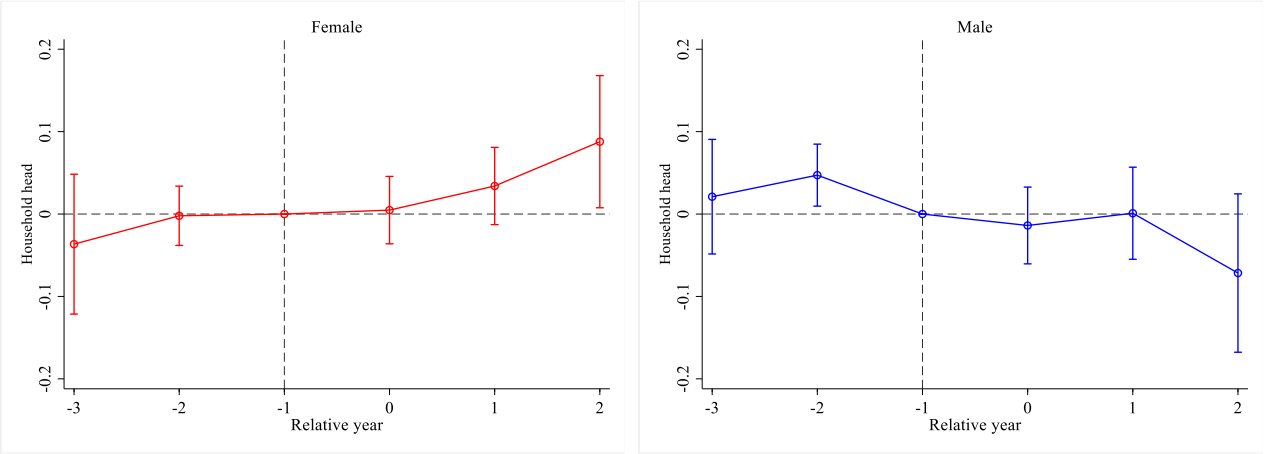
(c) Male LFP



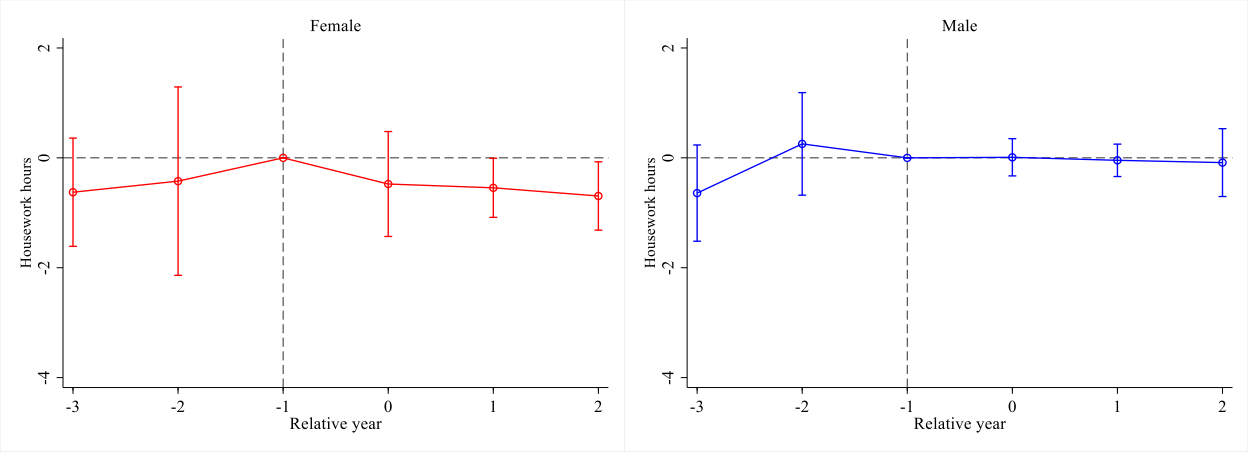
(d) Male working hours

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

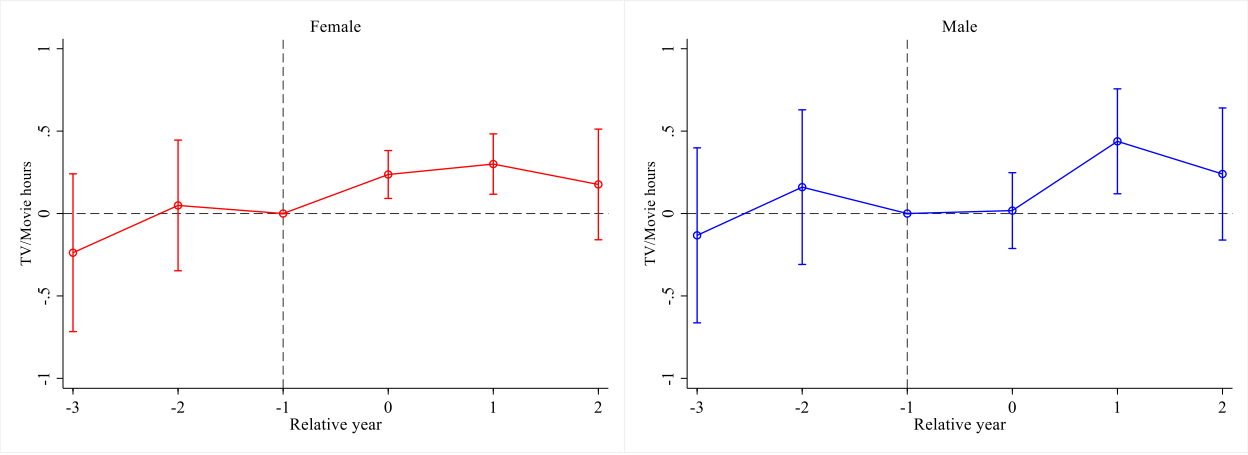
Notes: The figures plot the estimated coefficients and 90% confidence intervals of the estimators suggested by Callaway and Sant'Anna (2021). *X* axis is the year relative to the RECD implementation, and relative year = −1 serves as the reference group. *Y* axis is the estimated coefficients. The sample comes from CFPS 2012–2020 and includes rural residents aged 20-60.



(a) Household head



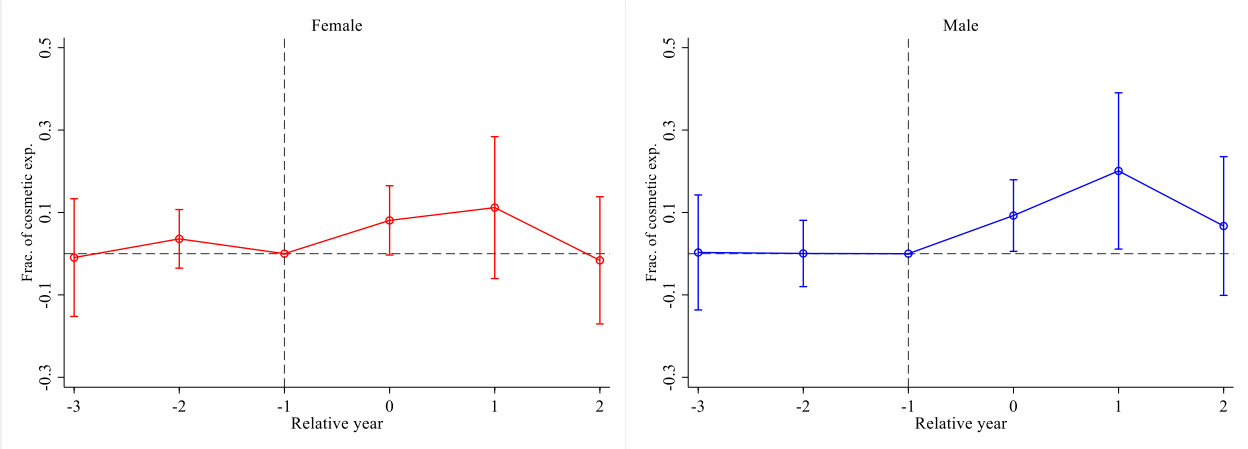
(b) Housework hours



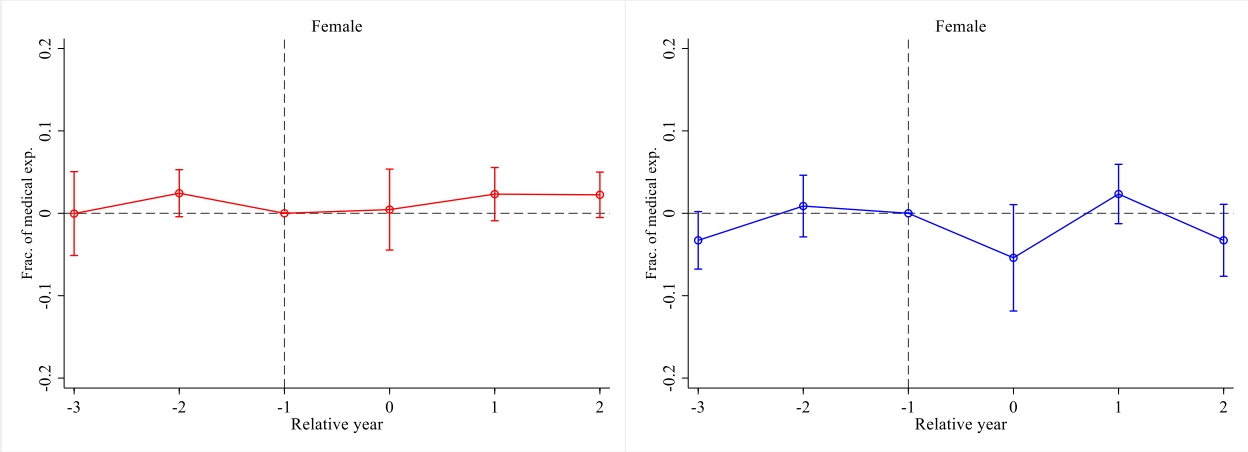
(c) TV/Movie hours

Figure 3: Event-Study Estimates: Impacts of RECD on Household Head and Time Use

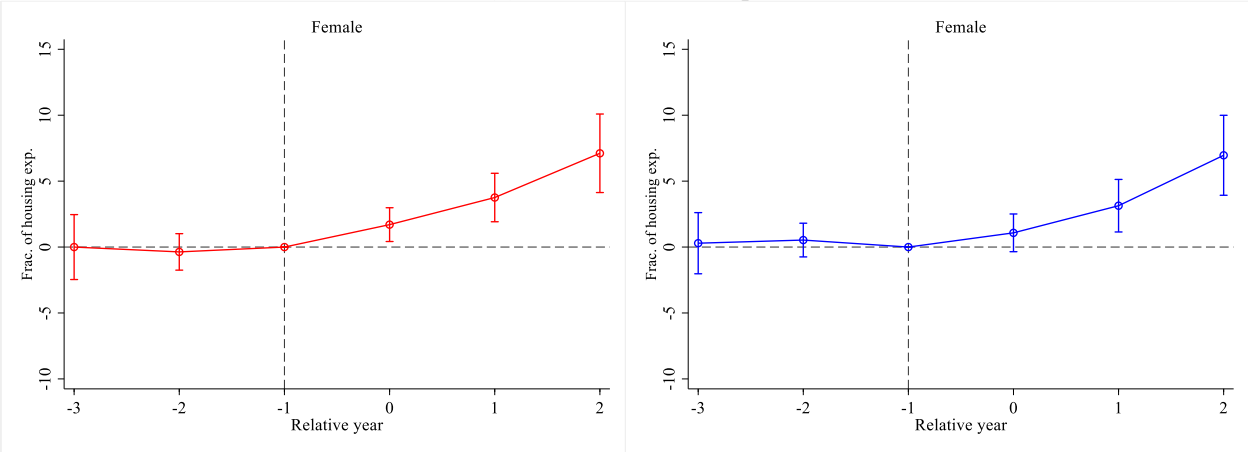
Notes: The figures plot the estimated coefficients and 90% confidence intervals of the estimators suggested by Callaway and Sant'Anna (2021). *X* axis is the year relative to the RECD implementation, and relative year = −1 serves as the reference group. *Y* axis is the estimated coefficients. The sample includes rural residents aged 20-60. Sample for Figure (a) comes from CPFS 2012–2020, while sample for Figures (b) and (c) come from CFPS 2014–2020.



(a) Frac. of cosmetic exp.



(b) Frac. of medical exp.



(c) Frac. of housing exp.

Figure 4: Event-Study Estimates: Impacts of RECD on Household Expenditures

Notes: The figures plot the estimated coefficients and 90% confidence intervals of the estimators suggested by Callaway and Sant'Anna (2021). *X* axis is the year relative to the RECD implementation, and relative year = −1 serves as the reference group. *Y* axis is the estimated coefficients. The sample comes from CFPS 2012–2020 and includes female aged 20-60.

Tables

Table 1: Descriptive statistics

	Female			Male		
Variable	Obs.	Mean	Std.dev	Obs.	Mean	Std.dev
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
Rural 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
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
Frac. of cosmetic expenditure	21,808	0.648	0.880	19,814	0.631	0.862
Frac. of medical expenditure	21,901	0.083	0.331	19,906	0.082	0.326
Frac. of house expenditure	21,671	9.845	10.900	19,635	9.730	10.754
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

Notes: The sample comes from CFPS 2012–2020 and includes rural residents aged 20-60. 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.

Table 2: Impacts of the RECD on LFP and Working Hours

	LFP			Working Hours		
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	CSDID	Para. ES	TWFE	CSDID	Para. ES
Panel A: Female						
RECD	0.035**	0.024**	0.027**	2.774**	2.292***	1.994**
	(0.017)	(0.011)	(0.012)	(1.138)	(0.846)	(0.903)
Observations	25,953	10,707	10,707	25,953	10,707	10,707
Mean of *Y*		0.817			30.685	
Panel B: Male						
RECD	0.020	0.001	0.002	1.218	0.410	0.010
	(0.013)	(0.007)	(0.008)	(0.926)	(0.740)	(0.818)
Observations	25797	10,555	10,555	25797	10,555	10,555
Mean of *Y*		0.887			42.105	
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y

Notes: The sample comes from CFPS 2010–2020 and includes rural residents aged 20-60. Panel A report estimates for female, while Panel B report estimates for male. Columns (1) and (4) report TWFE estimates, columns (2) and (5) report CSDID estimates suggested by Callaway and Sant'Anna (2021), while columns (3) and (6) report average treatment effects of parametric event study. 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 2: Impacts of the RECD on LFP and Working Hours

	LFP	Working Hours
	(1)	(2)
Female Sample		
Panel A: TWFE		
RECD	0.035**	2.774**
	(0.017)	(1.138)
Observations	25,953	25,953
Panel B: CSDID		
RECD	0.024**	2.292***
	(0.011)	(0.846)
Observations	10,707	10,707
Panel C: Parametric ES		
RECD	0.027**	1.994**
	(0.012)	(0.903)
Observations	10,707	10,707
Mean of *Y*	0.817	30.685
Male Sample		
Panel A: TWFE		
RECD	0.020	1.218
	(0.013)	(0.926)
Observations	25797	25797
Panel B: CSDID		
RECD	0.001	0.410
	(0.007)	(0.740)
Observations	10,555	10,555
Panel C: Parametric ES		
RECD	0.002	0.010
	(0.008)	(0.818)
Observations	10,555	10,555
Mean of *Y*	0.887	42.105
Controls	Y	Y
County FE	Y	Y
Year FE	Y	Y
County linear year trend	Y	Y
Selection criteria × Year FE	Y	Y

Table 3: Impacts of RECD on E-commerce Participation and Entrepreneurship

	E-commerce participation			Entrepreneurship		
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	CSDID	Para. ES	TWFE	CSDID	Para. ES
Panel A: Female						
RECD	0.016*	0.039***	0.041***	0.023**	0.021**	0.022**
	(0.010)	(0.011)	(0.013)	(0.012)	(0.009)	(0.010)
Observations	15,806	7,512	7,512	25,953	10,707	10,707
Mean of *Y*		0.169			0.067	
Panel B: Male						
RECD	-0.005	0.018	0.017	-0.021	-0.005	0.001
	(0.013)	(0.012)	(0.013)	(0.020)	(0.014)	(0.015)
Observations	14,667	6,767	6,767	25,797	10,555	10,555
Mean of *Y*		0.168			0.126	
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes rural residents aged 20-60. Panel A report estimates for female, while Panel B report estimates for male. Data on e-commerce participation is only available in CFPS 2014, 2016 and 2018. Columns (1) and (4) report TWFE estimates, columns (2) and (5) report CSDID estimates suggested by Callaway and Sant'Anna (2021), while columns (3) and (6) report average treatment effects of parametric event study. E-commerce participation is defined as engaging in online commercial activities at least once a month (yes =1), while entrepreneurship is defined as being a sole proprietor or owner of private firms (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.

	E-commerce participation	Entrepreneurship	Family income	Business income
	(1)	(2)	(3)	(4)
Female Sample				
Panel A: TWFE				
RECD	0.016*	0.023**	4.029*	1.326*
	(0.010)	(0.012)	(2.121)	(0.773)
Observations	15,806	25,953	25,026	25,175
Panel B: CSDID				
RECD	0.039***	0.021**	2.903*	1.046**
	(0.011)	(0.009)	(1.645)	(0.467)
Observations	7,512	10,707	10,097	10,282
Panel C: Parametric ES				
RECD	0.041***	0.022**	2.589	0.916*
	(0.013)	(0.010)	(1.725)	(0.520)
Observations	7,512	10,707	10,097	10,282
Mean of *Y*	0.169	0.067	47.484	7.208
Male Sample				
Panel A: TWFE				
RECD	-0.005	-0.021	2.145	1.246
	(0.013)	(0.020)	(2.047)	(0.783)
Observations	14,667	25,797	24,753	24909
Panel B: CSDID				
RECD	0.018	-0.005	0.423	0.792
	(0.012)	(0.014)	(1.532)	(0.534)
Observations	6,767	10,555	9,859	10,052
Panel C: Parametric ES				
RECD	0.017	0.001	-0.429	0.736
	(0.013)	(0.015)	(1.680)	(0.593)
Observations	6,767	10,555	9,859	10,052
Mean of *Y*	0.168	0.126	47.641	7.270
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

Table 4: Impacts of RECD on Household Income

	Family income			Business income		
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	CSDID	Para. ES	TWFE	CSDID	Para. ES
Panel A: Female						
RECD	4.029*	2.903*	2.589	1.326*	1.046**	0.916*
	(2.121)	(1.645)	(1.725)	(0.773)	(0.467)	(0.520)
Observations	25,026	10,097	10,097	25,175	10,282	10,282
Mean of *Y*		47.484			7.208	
Panel B: Male						
RECD	2.145	0.423	-0.429	1.246	0.792	0.736
	(2.047)	(1.532)	(1.680)	(0.783)	(0.534)	(0.593)
Observations	24,753	9,859	9,859	24,909	10,052	10,052
Mean of *Y*		47.641			7.270	
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes rural residents aged 20-60. Panel A report estimates for female, while Panel B report estimates for male. Columns (1) and (4) show TWFE estimates, columns (2) and (5) display CSDID estimates recommended by Callaway and Sant'Anna (2021), and columns (3) and (6) present average treatment effects from a parametric event study. Business income refers to income from entrepreneurial projects or self-employment, measured in thousand CNY. 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 5: Impacts of RECD on Household Head, Time, and Satisfaction

	(1) Household head (Female=1)	(2) Housework hours	(3) TV/Movie hours	(4) Satisfaction with spouse's housework
Panel A: TWFE estimates, female sample				
RECD	0.061***	-0.703**	0.138**	0.035*
	(0.022)	(0.334)	(0.064)	(0.021)
Observations	22918	16367	16508	11755
Panel B: CSDID estimates, female sample				
RECD	0.041*	-0.519*	0.227**	0.059*
	(0.024)	(0.316)	(0.097)	(0.036)
Observations	9,701	6,581	6,638	2,620
Panel C: Average treatment effect of parametric event study, female sample				
RECD	0.054*	-0.456	0.222**	0.060*
	(0.028)	(0.348)	(0.110)	(0.036)
Observations	9,701	6,581	6,638	2,620
Mean of *Y*	0.296	2.863	1.383	0.866
Panel D: TWFE estimates among, male sample				
RECD	-0.026	-0.150	0.046	-0.010
	(0.025)	(0.169)	(0.079)	(0.019)
Observations	20887	14534	14657	10577
Panel E: CSDID estimates among, male sample				
RECD	-0.029	-0.069	0.233	0.009
	(0.027)	(0.179)	(0.154)	(0.032)
Observations	8,815	5,761	5,797	2,224
Panel F: Average treatment effect of parametric event study, male sample				
RECD	-0.039	-0.052	0.333*	0.014
	(0.030)	(0.201)	(0.175)	(0.032)
Observations	8,815	5,761	5,797	2,224
Mean of *Y*	0.530	1.585	1.487	0.965
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 married women aged 20-60. Panels A-C provide three estimates for females, while Panels D-F provide three estimates for males. 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 Household Expenditures

	Frac. of cosmetic exp. (1)	Frac. of medical exp. (2)	Frac. of housing exp. (3)	Frac. of cosmetic exp. (4)	Frac. of medical exp. (5)	Frac. of housing exp. (6)	Frac. of cosmetic exp. (7)	Frac. of medical exp. (8)	Frac. of housing exp. (9)
		TWFE			CSDID			Parametric event study	
Panel A: Female									
RECD	0.048	0.026*	1.575*	0.083*	0.018	3.417***	0.064	0.014	4.081***
	(0.055)	(0.013)	(0.898)	(0.048)	(0.015)	(0.729)	(0.054)	(0.016)	(0.838)
Observations	21808	21901	21564	9,243	9,300	9,160	9,243	9,300	9,160
Mean of Y	0.648	0.083	9.845	0.648	0.083	9.845	0.648	0.083	9.845
Panel B: Male									
RECD	0.062	0.029*	1.821*	0.119**	-0.009	2.889***	0.113**	-0.024	3.578***
	(0.049)	(0.016)	(0.940)	(0.049)	(0.017)	(0.804)	(0.056)	(0.019)	(0.969)
Observations	19814	19906	19539	8,337	8,417	8,238	8,337	8,417	8,238
Mean of Y	0.631	0.082	9.730	0.631	0.082	9.730	0.631	0.082	9.730
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes married women aged 20-60. Panel A report estimates for female, while Panel B report estimates for male. The dependent variables are the fraction (%) of various expenditures to total household expenditure. Columns (1)(2)(3) report TWFE estimates, columns (4)(5)(6) report CSDID estimates suggested by Callaway and Sant'Anna (2021), while columns (7)(8)(9) report average treatment effects for parametric event study.. 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 7: Impacts of RECD on Child Outcomes

	(1) School enrollment	(2) Self-assessed health	(3) Saving for education
Panel A: TWFE estimates, girls sample			
RECD	0.068*	0.105**	0.036
	(0.040)	(0.044)	(0.034)
Observations	6,402	3,218	6,360
Panel B: CSDID estimates, girls sample			
RECD	0.033*	0.097*	0.031*
	(0.020)	(0.060)	(0.017)
Observations	4,444	1,843	4,379
Panel C: Average treatment effect of parametric event study, girls sample			
RECD	0.048***	0.093	0.010
	(0.019)	(0.069)	(0.023)
Observations	4,444	1,843	4,379
Mean of *Y*	0.943	0.653	0.135
Panel D: TWFE estimates, boys sample			
RECD	0.035	-0.064	0.012
	(0.048)	(0.073)	(0.032)
Observations	7,330	3,678	7,283
Panel E: CSDID estimates, boys sample			
RECD	0.017	0.034	0.011
	(0.014)	(0.054)	(0.024)
Observations	5,091	2,128	5,010
Panel F: Average treatment effect of parametric event study, boys sample			
RECD	0.007	0.078	-0.011
	(0.014)	(0.058)	(0.030)
Observations	5,091	2,128	5,010
Mean of *Y*	0.945	0.665	0.145
Controls	Y	Y	Y
County FE	Y	Y	Y
Year FE	Y	Y	Y
County linear year trend	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes children who are younger than 15. When observing educational outcomes, we include children aged 6-15, because the Compulsory Education Law in China mandates that children should receive nine years of compulsory education starting from 6 years old. When observing self-rated health, we include children aged 10-15 because data for these variables is available in this age range. Panels A-C provide three estimates for girls, while Panels D-F provide three estimates for boys. 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.

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:

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

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:

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

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:

$$\begin{aligned}\Pi = &\lambda\left[u(C)+v(l_f)+w(H)\right]+(1-\lambda)\left[u(C)+v(l_m)\right]\\ &+\mu(w_f h_f + w_m h_m - C - I)\\ &+\gamma_f(1-l_f-t_f-h_f)+\gamma_m(1-l_m-t_m-h_m)\\ &+\kappa(t_f+t_m-T)\end{aligned} \tag{A11}$$

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.

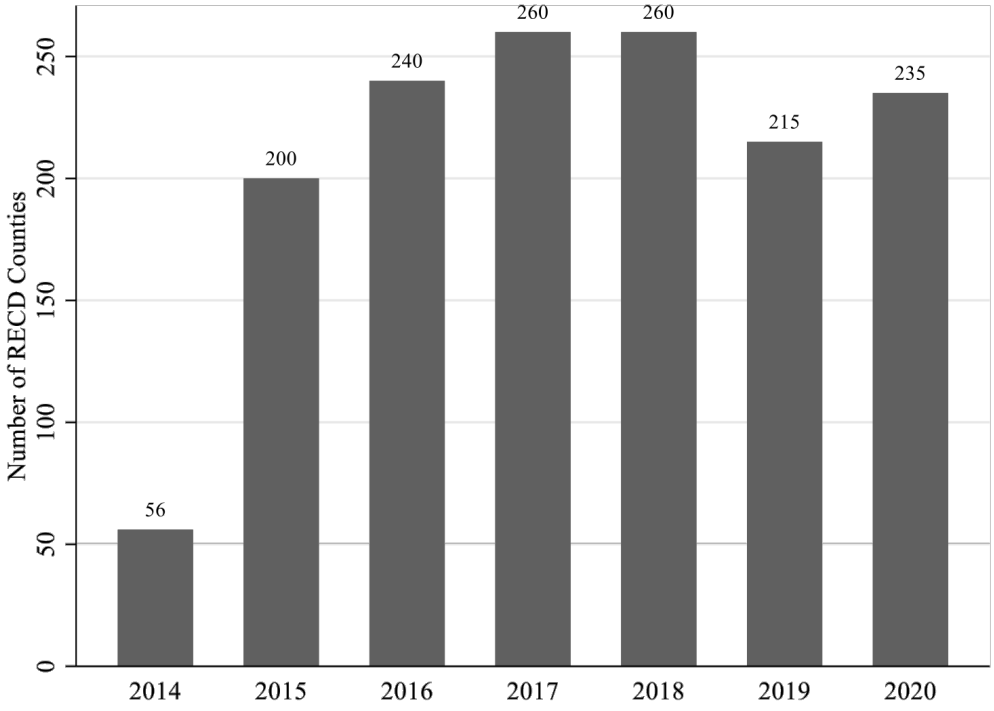


Figure A1: The Number of RECD Counties Approved Each Year

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

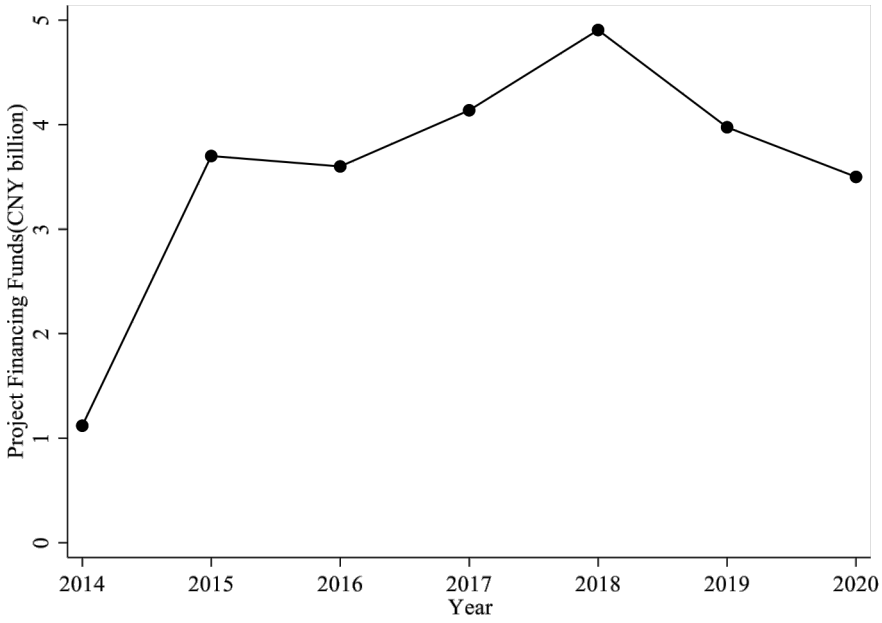


Figure A2: Project Financial Funds Received by Demonstration Counties Each Year

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

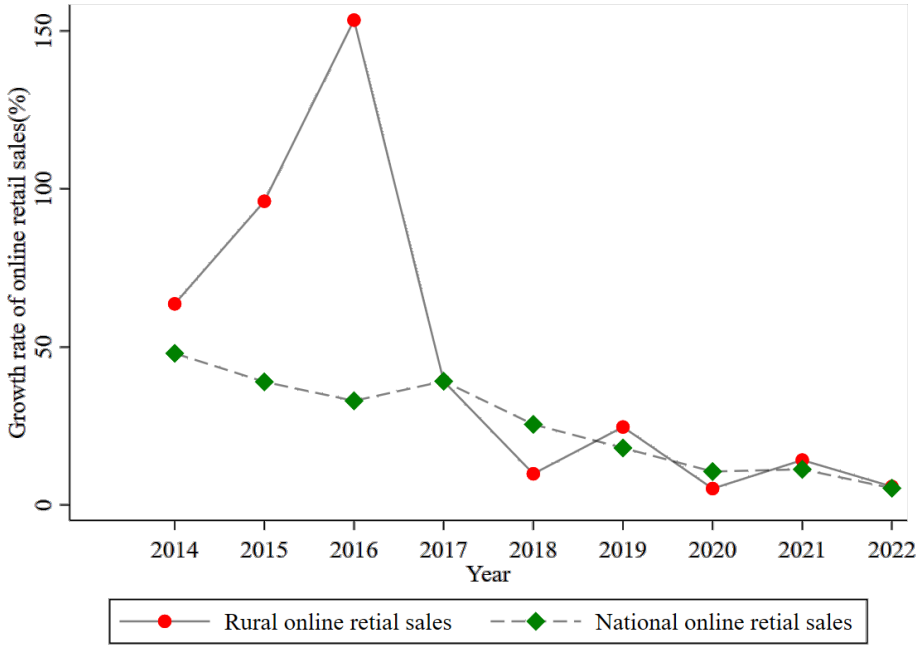
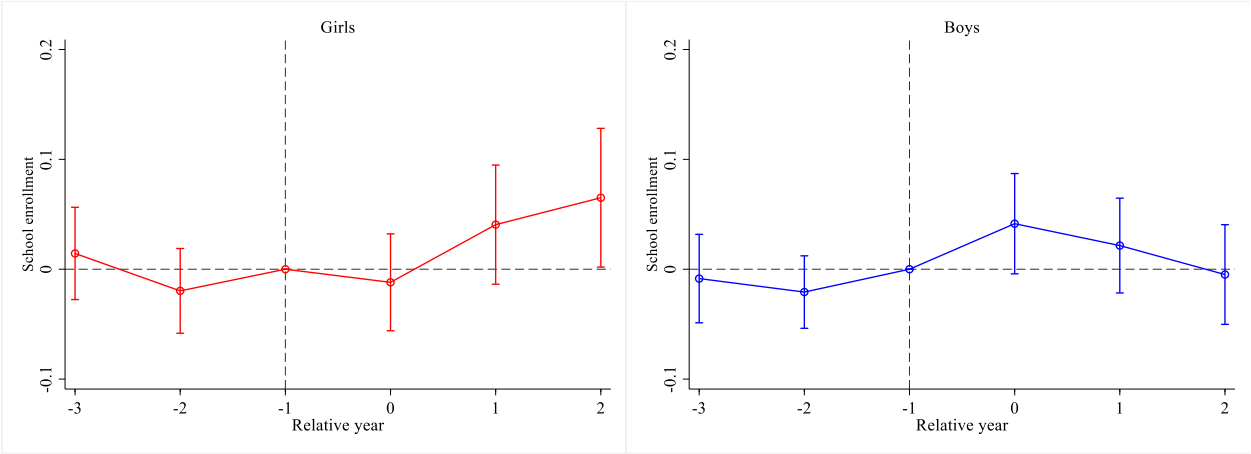
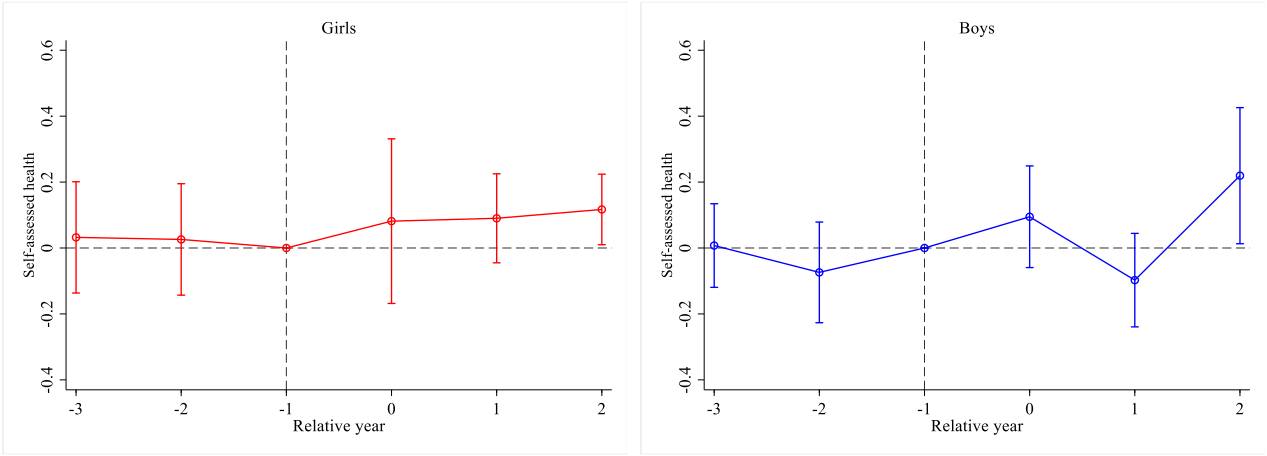


Figure A3: The Annual Growth Rate of Rural Online Retail Sales and National Online Retail Sales

Source: Ministry of Commerce.



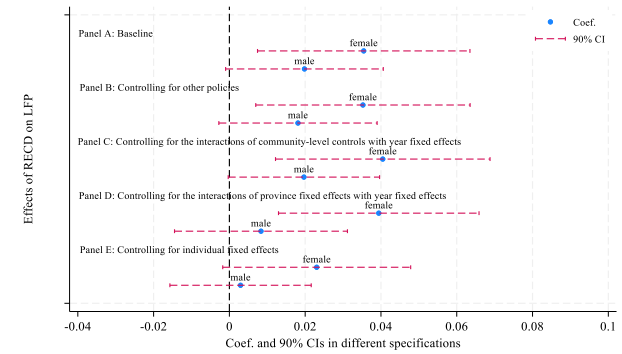
(a) School enrollment

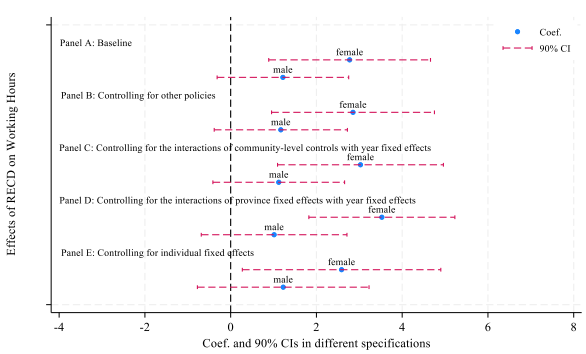


(b) Self-assessed Health

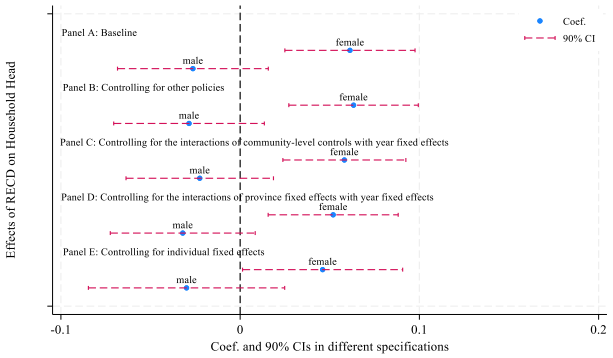
Figure A4: Event-Study Estimates for Self-assessed Health

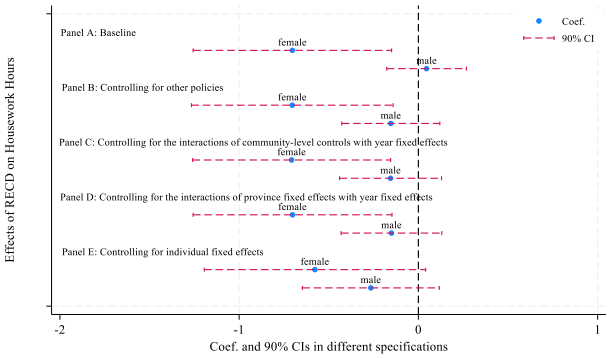
Notes: The figures plot the estimated coefficients and 90% confidence intervals of the estimators suggested by Callaway and Sant'Anna (2021) for main children outcomes. *X* axis is the year relative to the RECD treatment, and relative year = −1 serves as the reference group. *Y* axis is the estimated coefficients. The sample comes from CFPS 2012–2020 and includes children.

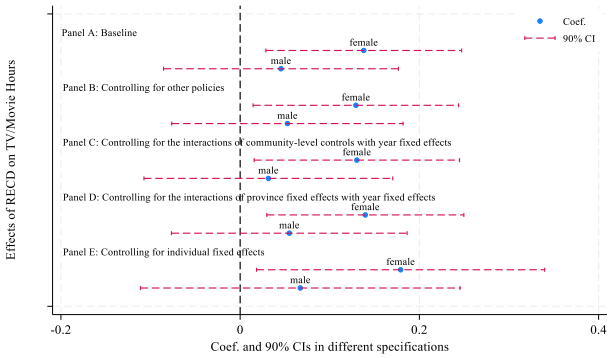


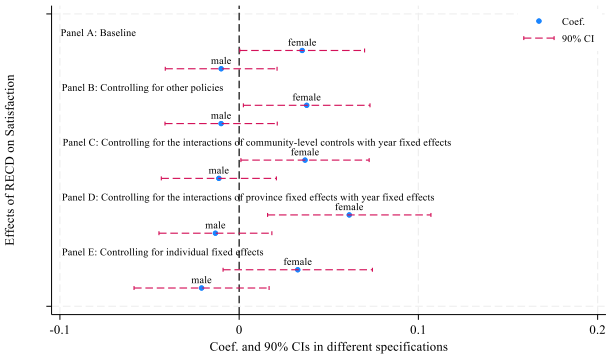


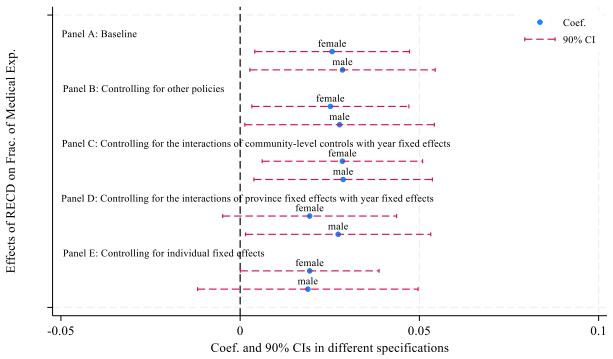
(a) Labor Supply

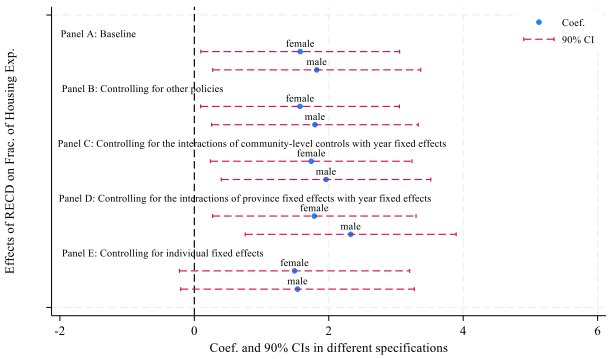




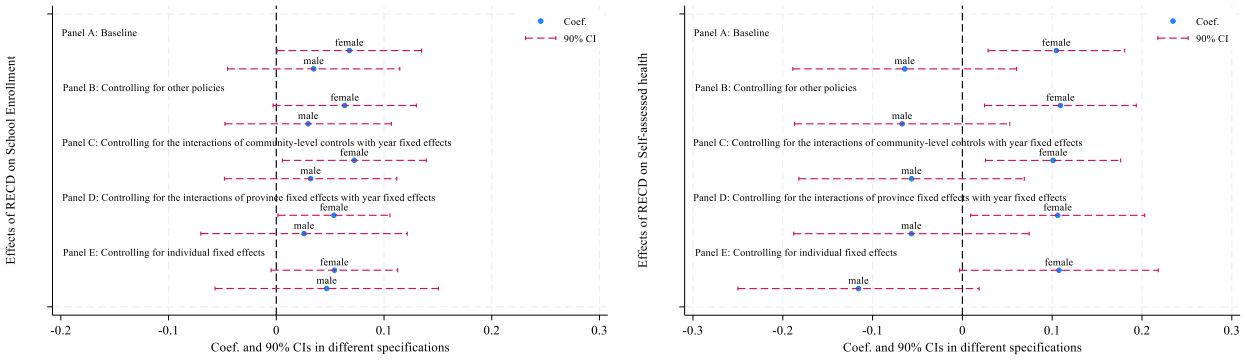








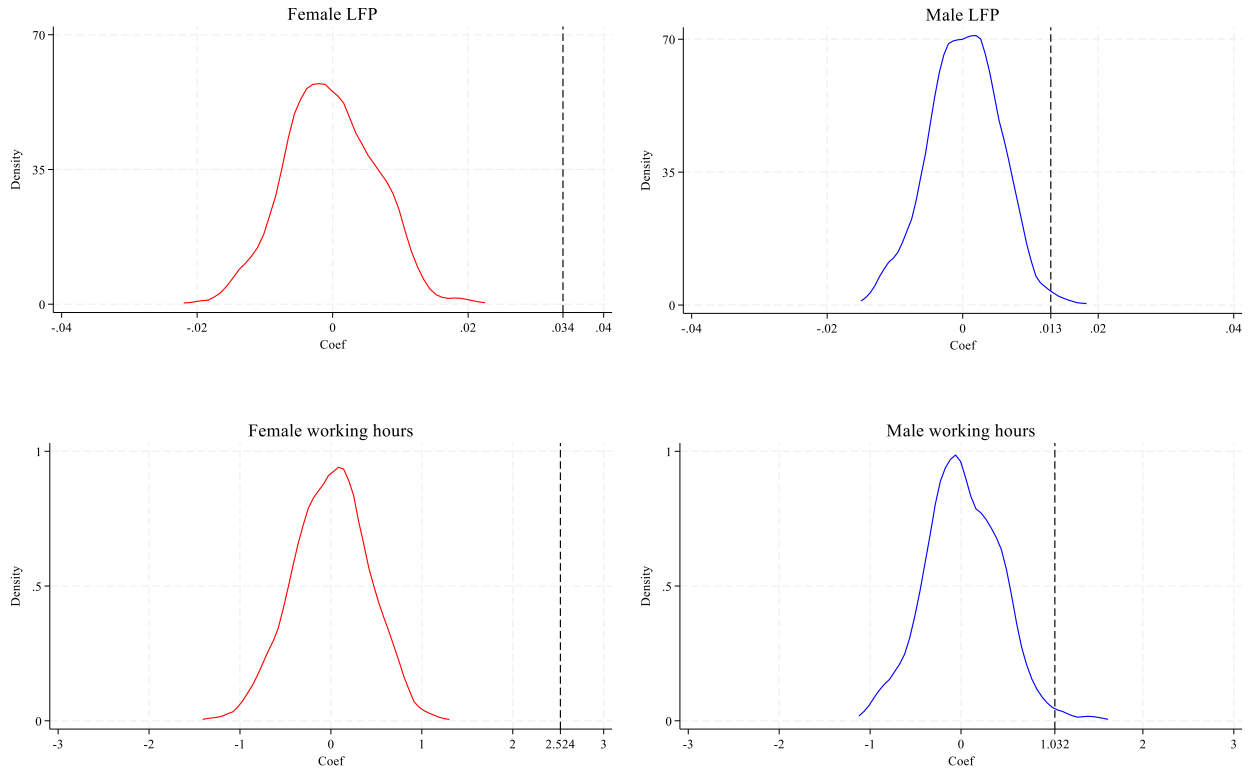
(b) Intra-household Bargaining Power



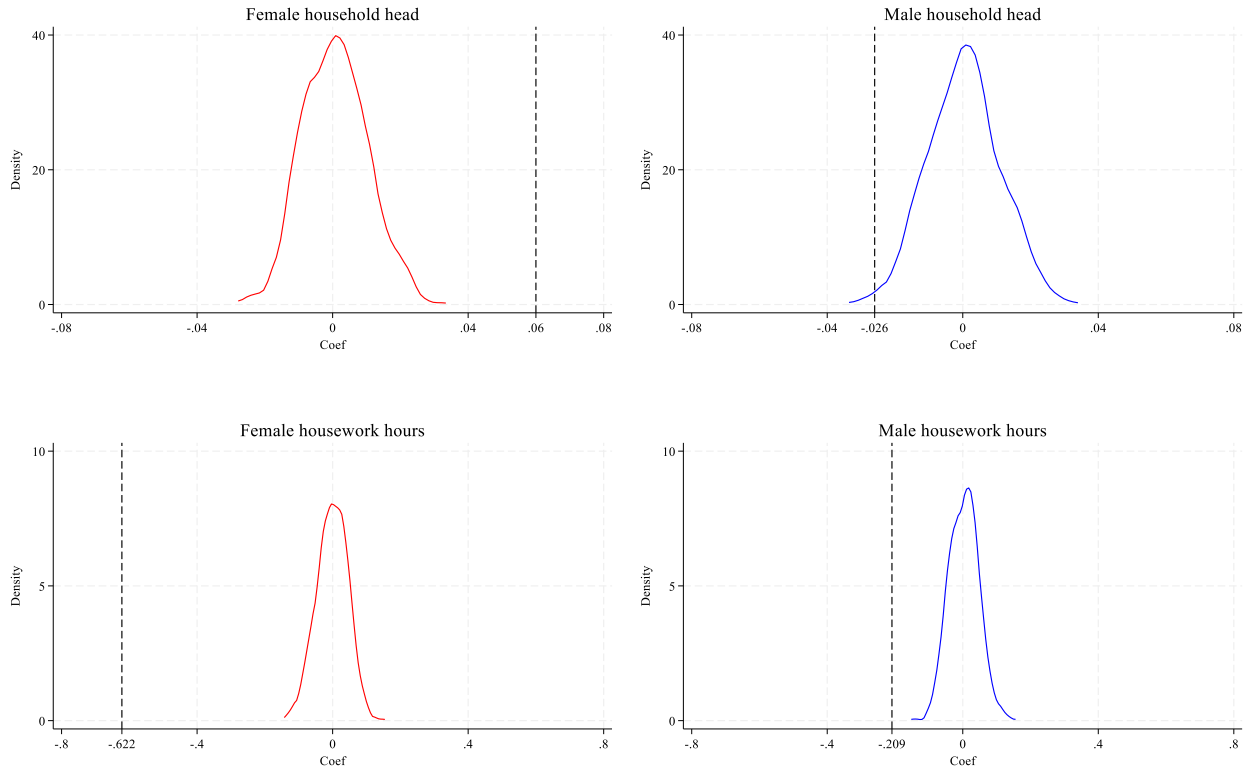
(c) Child Outcomes

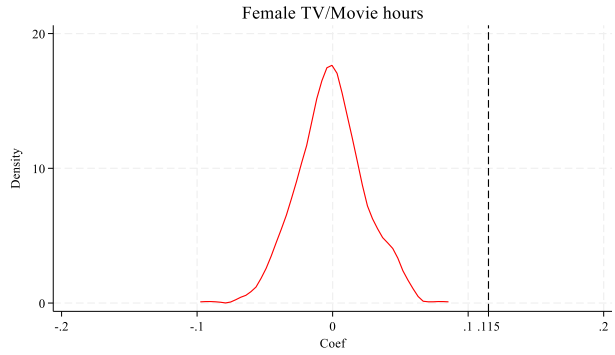
Figure A5: Robustness Checks:Effects of RECD in Different Specifications

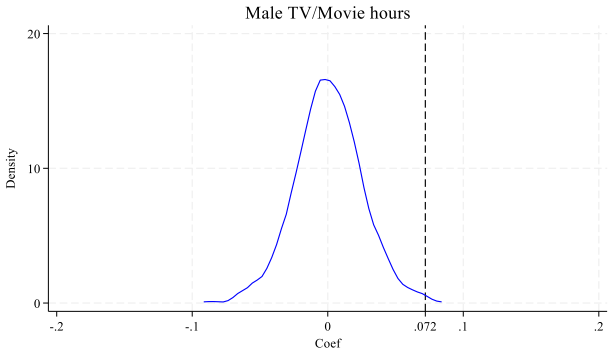
Notes: The figure displays results for women on the left panels and men on the right panels using samples from CFPS 2012–2020. Figure (a) and (b) include rural residents aged 20-60, while figure (c) include rural children. Data on housework hours and TV/movie hours is only available in CFPS 2014, 2016, 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. 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.

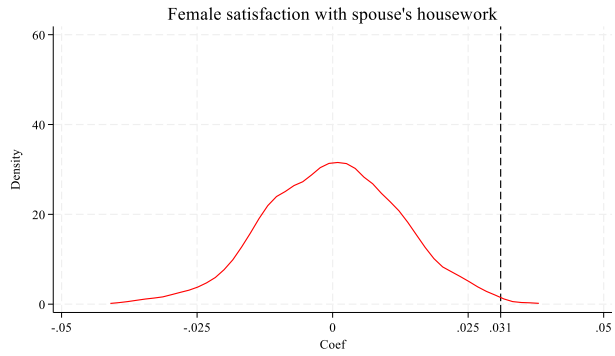


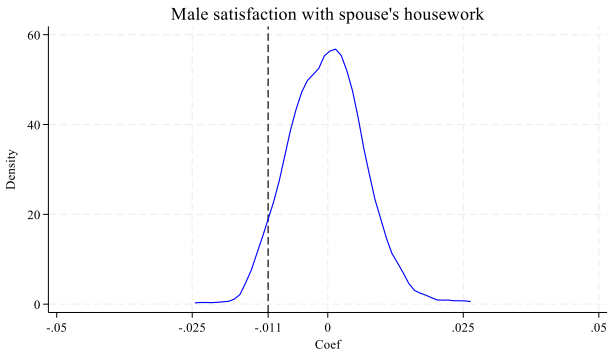
(a) Labor Supply

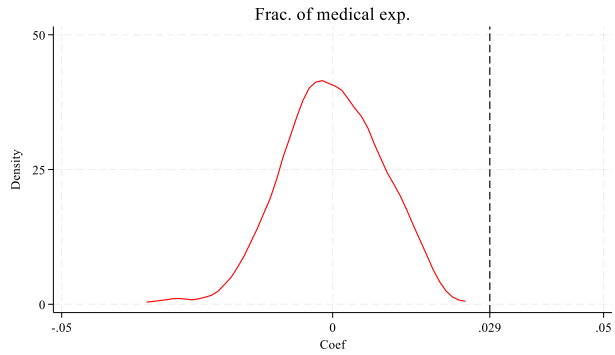


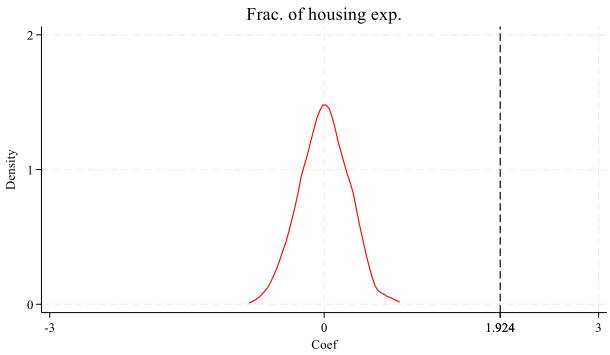




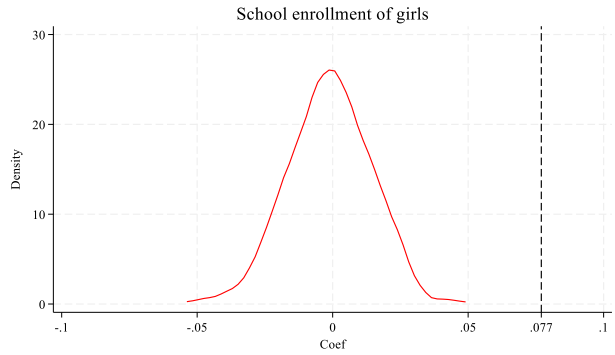


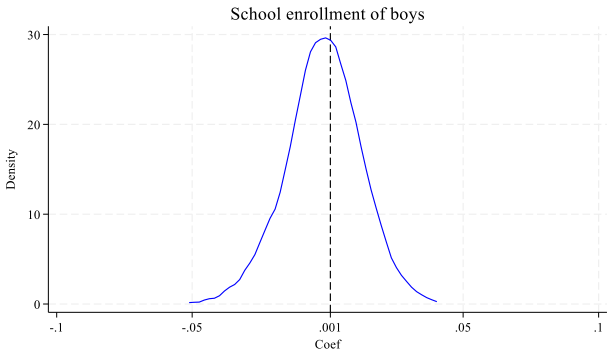


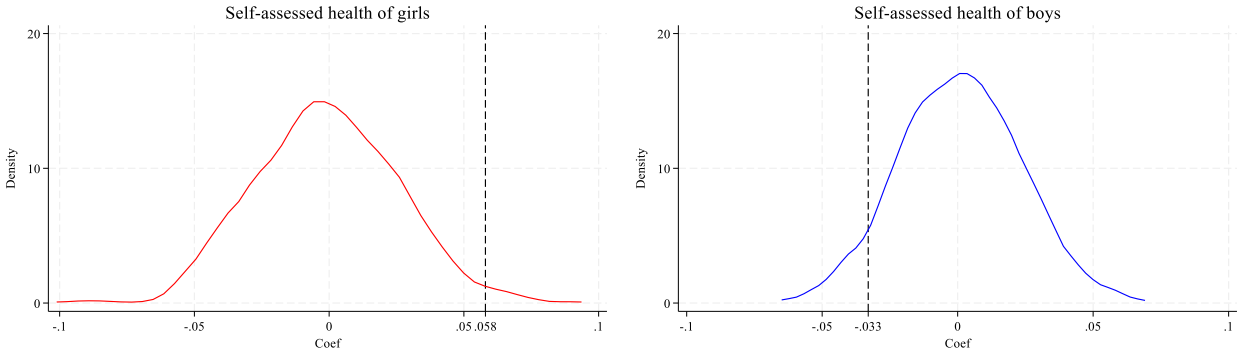




(b) Intra-household Bargaining Power







(c) Child Outcomes

Figure A6: Placebo test

Notes: The figures display placebo test results for women on the left panels and men on the right panels, 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: Impacts of the RECD on LFP and Working Hours with Baseline Controls

	LFP			Working Hours		
	(1)	(2)	(3)	(4)	(5)	(6)
	TWFE	CSDID	Para. ES	TWFE	CSDID	Para. ES.
Panel A: Female						
RECD	0.027	0.018*	0.021*	2.209*	1.677**	1.572*
	(0.018)	(0.010)	(0.012)	(1.233)	(0.796)	(0.891)
Observations	25,953	10,707	10,707	25,953	10,707	10,707
Mean of *Y*		0.817			30.685	
Panel B: Male						
RECD	0.012	-0.003	-0.002	0.351	-0.433	-0.658
	(0.013)	(0.007)	(0.008)	(1.077)	(0.733)	(0.823)
Observations	25,797	10,555	10,555	25,797	10,555	10,555
Mean of *Y*		0.887			42.105	
Controls	N	N	N	N	N	N
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	N	N	N	N	N	N

Notes: The sample comes from CFPS 2010–2020 and includes rural residents aged 20-60. Panel A report estimates for female, while Panel B report estimates for male. Columns (1) and (4) show TWFE estimates, columns (2) and (5) display CSDID estimates recommended by Callaway and Sant'Anna (2021), and columns (3) and (6) present average treatment effects from a parametric event study. 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 A2: 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				
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)
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)
Observations	25953	25797	25953	25797
Mean of *Y*	0.817	0.887	30.685	42.105
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 A3: 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) TWFE	(2) CSDID	(3) Para. ES	(4) TWFE	(5) CSDID	(6) Para. ES
Panel A: Female						
RECD	0.027	0.041**	0.038**	0.012	0.004	0.000
	(0.019)	(0.017)	(0.018)	(0.009)	(0.021)	(0.024)
Observations	6,291	3,235	3,235	9,515	4,207	4,207
Mean of *Y*		0.172			0.167	
Panel B: Male						
RECD	-0.006	0.039**	0.047**	-0.005	-0.036	-0.063**
	(0.024)	(0.018)	(0.019)	(0.014)	(0.023)	(0.028)
Observations	5,880	2,962	2,962	8,785	3,736	3,736
Mean of *Y*		0.170			0.167	
Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes rural residents aged 20-60. Columns (1) and (4) show TWFE estimates, columns (2) and (5) display CSDID estimates recommended by Callaway and Sant'Anna (2021), and columns (3) and (6) present average treatment effects from a parametric event study. 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 A4: Impacts of RECD on Household Expenditures Conditional on Household Income

	Frac. of cosmetic exp. (1)	Frac. of medical exp. (2)	Frac. of housing exp. (3)	Frac. of cosmetic exp. (4)	Frac. of medical exp. (5)	Frac. of housing exp. (6)	Frac. of cosmetic exp. (7)	Frac. of medical exp. (8)	Frac. of housing exp. (9)
		TWFE			CSDID			Para. ES	
Panel A: Female									
RECD	0.032	0.020*	1.486*	0.079*	0.020	3.404***	0.062	0.015	3.979***
	(0.054)	(0.011)	(0.866)	(0.048)	(0.016)	(0.728)	(0.056)	(0.017)	(0.864)
Observations	21015	21101	20802	8,623	8,675	8,576	8,623	8,675	8,576
Mean of Y	0.656	0.084	9.840	0.656	0.084	9.840	0.656	0.084	9.840
Panel B: Male									
RECD	0.043	0.023	1.763*	0.078	-0.003	3.185***	0.059	-0.019	3.837***
	(0.049)	(0.014)	(0.910)	(0.050)	(0.018)	(0.775)	(0.057)	(0.021)	(0.949)
Observations	19024	19106	18838	7,727	7,791	7,711	7,727	7,791	7,711
Mean of Y	0.638	0.083	9.729	0.638	0.083	9.729	0.638	0.083	9.729
Household Income	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
County linear year trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020 and includes married women aged 20-60. The dependent variables are the fraction (%) of various expenditures to total household expenditure. Columns 1 to 3 use TWFE estimators, while columns 4 to 6 use estimators suggested by Callaway and Sant'Anna (2021). 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 A5: 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: TWFE estimates, female sample					
RECD	0.007	-0.002	-0.005	-0.000	-0.153
	(0.007)	(0.007)	(0.003)	(0.002)	(0.094)
Observations	25953	25953	25953	25953	23653
Panel B: CSDID estimates, female sample					
RECD	-0.001	0.003	-0.003	0.002	-0.033
	(0.006)	(0.005)	(0.004)	(0.002)	(0.030)
Observations	10,707	10,707	10,707	10,707	10,137
Panel C: Average treatment effect of parametric event study, female sample					
RECD	-0.002	0.003	-0.003	0.002	-0.014
	(0.006)	(0.005)	(0.004)	(0.003)	(0.038)
Observations	10,707	10,707	10,707	10,707	10,137
Mean of *Y*	0.908	0.082	0.006	0.003	21.775
Panel D: TWFE estimates among, male sample					
RECD	0.004	-0.015*	0.004	0.007*	-0.120
	(0.008)	(0.008)	(0.004)	(0.004)	(0.104)
Observations	25797	25797	25797	25797	21772
Panel E: CSDID estimates among, male sample					
RECD	-0.005	-0.009*	0.010**	0.002	0.046
	(0.007)	(0.005)	(0.004)	(0.002)	(0.042)
Observations	10,555	10,555	10,555	10,555	9,273
Panel F: Average treatment effect of parametric event study, male sample					
RECD	-0.006	-0.009	0.012**	0.002	0.057
	(0.008)	(0.006)	(0.005)	(0.003)	(0.050)
Observations	10,555	10,555	10,555	10,555	9,273
Mean of *Y*	0.822	0.148	0.025	0.004	23.719
Controls	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
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: The sample comes from CFPS 2012–2020 and includes rural residents aged 20-60. Panels A-C provide three estimates for females, while Panels D-F provide three estimates for males. 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: Robustness Checks: Possible Composition Change and Attrition Test

	Cross-county migrants (=1) (1)	Urban-to-rural migrants (=1) (2)	Attrition (=1) (3)
Panel A: TWFE estimates			
RECD	-0.003	0.003	0.019
	(0.006)	(0.017)	(0.023)
Observations	51,750	51,750	99,552
Panel B: CSDID estimates			
RECD	0.001	0.006	-0.002
	(0.003)	(0.005)	(0.009)
Observations	21,262	21,262	47,766
Panel C: Average treatment effect of parametric event study			
RECD	0.000	0.007	-0.002
	(0.003)	(0.006)	(0.010)
Observations	21,262	21,262	47,766
Mean of *Y*	0.044	0.040	0.480
Controls	Y	Y	Y
County FE	Y	Y	Y
Year FE	Y	Y	Y
County linear year trend	Y	Y	Y
Selection criteria × Year FE	Y	Y	Y

Notes: The sample comes from CFPS 2012–2020. Column (3) use a balanced panel dataset consisting of individuals aged 20-60 who were interviewed in the first wave, while the other columns use the same sample as the baseline regression. 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.