From Dishes to Dollars: The Effects of Online Food Delivery Platforms on Housework and Employment

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Abstract

This paper investigates the impact of online food delivery platforms on housework and employment by leveraging a unique quasi-experiment. We find that the introduction of such services into a city led to a significant reduction in the time spent on housework, particularly among women. Household consumption expenditures on food increased, as a substitution for labor. Furthermore, our findings demonstrate positive effects on narrowing the gender gap in labor supply and well-being. Our paper offers insights and implications for optimizing the allocation of resources between households and society.

Keywords: digital platforms, household production, specialization, female labor supply

JEL Codes: D13, J16, J22

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1 Introduction

The allocation of time between market hours and home hours is widely recognized to have important economic implications.[1] Based on the home production model, time allocation reflects the relative productivity between the market sector and the home sector. However, despite a substantial increase in market wage rate relative to home productivity, the time dedicated to household work has not decreased correspondingly in relation to market hours (Bridgman, 2016; Fang and Zhu, 2017).[2] In the United States, this ratio experienced a slight decline from 41% to 35% during the period 1965-2013.[3] Despite this declining trend, the household sector remains responsible for a sizeable part of economic activity across most countries. According to data from 36 countries, predominantly OECD members, the average ratio of home hours to total hours worked is 46% between 1961 and 2012 (Bridgman, Duernecker, and Herrendorf, 2018). In China, the ratio stood at 38% in 2018.[4] Existing literature has studied substantial changes to household decisions, such as electricity, broadband Internet, and large home appliances, which could reduce home hours, and consequently facilitate female labor supply (Greenwood, Seshadri, and Yorukoglu, 2005; de V. Cavalcanti and Tavares, 2008; Dettling, 2017; Vidart, 2023).

Recently, the emergence of online food delivery platforms provides a highly flexible and cost-effective solution for outsourcing household work to society, facilitating the potential to reallocate time from the home sector to the market sector. Over the past decade, online food delivery platforms have experienced rapid growth in China, significantly impacting people's daily lives. By 2021, these platforms had gained popularity among approximately 38 percent of the Chinese population, and sales accounted for around 1 percent of the GDP (The State Information Center, 2022).

In this paper, we aim to examine the effects of the introduction of online food delivery platforms on the time spent on household work and labor supply. The staggered introduction of online food delivery platforms in cities across China between 2008 and 2018 provides us with a unique quasi-experiment to identify the causality. We utilize three main datasets.

[1]For example, see Becker (1965), Greenwood, Seshadri, and Yorukoglu (2005), Herrendorf, Rogerson, and Valentinyi (2014), Fang and Zhu (2017), Bridgman, Duernecker, and Herrendorf (2018), and Vidart (2023).

[2]For example, Bridgman (2016) finds that home productivity experienced a meager average growth of only 0.1 percent from 1978 to 2010, whereas market labor productivity grew at a rate of 1.6 percent per year in the United States.

[3]The data is from the American Time Use Survey (ATUS) conducted by the Bureau of Labor Statistics, and calculated by Fang and Zhu (2017).

[4]The market hours and home hours are 4.4 and 2.7, respectively. We obtain the data from the second wave of National Time Use Survey, conducted by National Bureau of Statistics of China. For detailed information, please refer to the website at `http://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900224.html`.

The first is the China Family Panel Studies (CFPS) survey data, a large-scale nationally representative longitudinal survey conducted by the Institute of Social Science Survey (ISSS) of Peking University, which provides time use, labor supply, and other information on respondents and their households. The second data source specifies the dates on which Eleme, a leading online food delivery platform in China, was introduced in cities. The last dataset we use is the China Statistical Yearbooks for Regional Economy, which provides city-level characteristics.

We estimate the introduction of Eleme on time used for housework using a Difference-in-Differences (DID) approach, that builds on two sources of variation. First, cities were covered by Eleme at different times. Second, within the same city, individuals completed the CFPS survey at different times. We find that the introduction of Eleme into a city significantly reduced the amount of time spent on housework. Specifically, the introduction of Eleme leads to a reduction of roughly 11.8 minutes in time spent on housework per day, which accounts for approximately 10 percent of the sample mean. The magnitude of the coefficient is comparable to a 5.8 percent decrease in maid service price, as estimated by Stratton (2012).

The identification assumption is that in the absence of the Eleme roll-out, the housework outcomes of respondents living in cities with different Eleme expansion points of time would have evolved along parallel trends. One might worry that cities in different provinces or different Eleme expansion groups, indicating varying entry times across the expansion groups, might have different trends in terms of housework time. We address this concern in five ways. First, we perform the event study and check for pre-trends. Second, to the extent that the trends in housework time are linear, we would be able to account for them by including province (expansion-group-level) linear time trends. Third, we can also include province-by-survey-wave (expansion-group-by-survey-wave) fixed effects to control for any unobserved time-varying province-specific (expansion-group-specific) shocks. Fourth, we allow the trends to be correlated to the city's initial characteristics that may be possibly correlated with Eleme roll-out timing by including the interaction terms between city initial characteristics and wave fixed effects. Fifth, we specifically focus on the time period characterized by the intensive entry of online food delivery platforms. During this period, the entry decisions of these platforms are relatively more exogenous, allowing for a cleaner identification strategy. These strategies could assuage concerns about violations of the parallel trend assumption in our setting and identify the causality.

We further investigate the effects on household expenditures. The results show that the introduction of Eleme significantly increases the expenditures on food and related items while reducing the expenditures on fuel for cooking. These findings suggest that the introduction of Eleme has directly changed the lifestyle of local individuals, particularly their eating habits, and more importantly, further confirm that the observed effects are driven by food delivery platforms instead of other factors. Additionally, we find the effects of the Eleme entry on housework time are more pronounced for women, families with a larger size, and those with coresident elderly and young children, that are perceived to have more housework responsibilities.

Next, we examine the gender gap changes in time allocation between market hours and leisure. First, we find a U-shape pattern in the market hours response of females, compared to males, to the introduction of the online food delivery platform across different age groups, suggesting that the effects could be more pronounced for those with a higher labor supply elasticity (Keane and Wasi, 2016). Second, we show that the positive effects of the online food delivery platform on market hours are significantly larger for highly educated women, who have a higher opportunity cost of time. Third, we also find the introduction of Eleme has a more pronounced positive effect on the leisure and well-being of females compared to males.

Our study contributes to three strands of literature. First, our paper is closely related to the literature that documents the specialization of home production. The dominant economic theory to explain intrahousehold time allocation has been specialization within the household, which was introduced by Becker (1985, 1991), and was extended to collective or semi-cooperative models in the later studies (Gobbi, 2018; Doepke and Tertilt, 2019). According to the home production model, the intrahousehold time allocation is driven by comparative advantages, specifically, the partner with the highest relative earnings should specialize in market production and spend less time on housework (Stratton, 2012; Artmann, Oosterbeek, and van der Klaauw, 2022). This specialization often results in a division of labor based on gender, where men typically concentrate on employment outside the home, while women specialize in domestic activities (Alesina, Giuliano, and Nunn, 2013; Siminski and Yetsenga, 2022). In addition to the focus on intrahousehold allocation, several researchers have explored the possibilities beyond the boundaries of the household. For example, Cortes and Tessada (2011) find that low-skilled immigration increased the labor supply and wage of highly skilled women, by decreasing housework time and increasing expenditures on housekeeping services. Similar findings are represented in Amuedo-Dorantes and Sevilla (2014), East and Velásquez (2022) and Pedrazzi and Peñaloza-Pacheco (2023).

Our paper extends this strand of literature by identifying an advance in technology that enables specialization outside of the household. The introduction of technology allows for the reallocation of housework time from lower-productivity members within households to lower-productivity members in society. This enables a greater number of family members, especially women, to participate in the labor force, leading to increased overall efficiency in society. Furthermore, such technology offers a self-reliant solution that can benefit the local economy, without low-skilled immigrants (Cortes and Tessada, 2011; Amuedo-Dorantes and Sevilla, 2014; East and Velásquez, 2022; Pedrazzi and Peñaloza-Pacheco, 2023), which has important implications for developing countries.

Second, our paper joins a fast-growing literature that studies the impacts of online gig platforms. Recent studies have examined the effects of online gig platforms on various labor market outcomes, including employment (Huang et al., 2020; Abraham et al., 2021; Bracha and Burke, 2021; Glasner, 2023), entrepreneurship (Burtch, Carnahan, and Greenwood, 2018; Barrios, Hochberg, and Yi, 2022), productivity (Choudhury, Foroughi, and Larson, 2021), employer-employee matching (Benson, Sojourner, and Umyarov, 2020), and gender wage gap (Mas and Pallais, 2017; Cook et al., 2021; Adams-Prassl et al., 2023). This literature primarily focuses on the supply side of platforms, indicating the market opportunities created by these platforms. To the best of our knowledge, this paper is the first to empirically explore the effects of online food delivery platforms on the demand side, i.e., consumers of platforms.

Third, our paper adds to the vast literature on technology progress and female work-life balance. Previous literature shows how the advancements in home technology played a major role in home production and labor market participation, that is, the "Household Revolution" (Greenwood, Seshadri, and Yorukoglu, 2005). The main mechanisms explored in the literature are the wider availability and declining price of home appliances (Greenwood, Seshadri, and Yorukoglu, 2005; de V. Cavalcanti and Tavares, 2008), and the increase in market production opportunities (Vidart, 2023). Recently, technological change has also taken the form of the "digital revolution". For example, they have examined the impact of broadband Internet on marriage decisions (Bellou, 2015), fertility behavior (Guldi and Herbst, 2017; Billari, Giuntella, and Stella, 2019), and labor supply (Dettling, 2017), the effects of the robots and automation on employment (Adachi, Kawaguchi, and Saito, 2022), and gender gaps in income and labor force participation (Anelli, Giuntella, and Stella, 2021), as well as the effects of the digital television transition on female labor supply(Nieto, 2023). Compared to substantial changes to household decisions, such as electricity, broadband Internet, and large home appliances, which could reduce home hours, and consequently facilitate female labor supply, we highlight a new labor-saving technology that is divisible and flexible and also could potentially improve the work-life balance.

The remainder of the paper is as follows. In Section 2, we briefly review the background on online food delivery platforms and introduce our dataset. Section 3 discuss the identification strategy. Section 4 presents the main empirical results as well as the validity of identification. We discuss our results in section 5 and section 6 concludes.

2 Background and Data

2.1 Background

Over the past decade, online food delivery platforms have experienced rapid growth in China, significantly impacting people's daily lives. In 2021, the user base of online food delivery platforms in China reached a staggering 544 million, which accounts for approximately 38 percent of the population. Additionally, the sales generated by these platforms exceeded one trillion, equivalent to about 1 percent of the GDP in China (The State Information Center, 2022).

We investigate the effects of online food delivery platforms, with a particular focus on the representative platform Eleme, on housework and labor supply.[5] Our choice of Eleme is without loss of generality for three reasons as follows. Firstly, Eleme holds the distinction of being the first online food delivery platform established in China, originating from Shanghai Jiaotong University in 2008. Prior to 2013, there was essentially only one prominent online food delivery platform operating in China. Between 2011 and 2018, Eleme gradually expanded its services to encompass numerous cities across China, following a staggered fashion, which offers variations for identification.

Second, Eleme has held a large market share and has been the leading online food delivery platform during its expansion period. According to reports from Eleme, the platform held a significant market share, representing over half of the market before 2014, indicating that Eleme was a dominant player in the online food delivery industry during that period. As the industry evolved and more competitors entered the market, Eleme maintained its position in the top two, with a market share of over 30 percent before 2020.[6]

Third, the entry of other competitors does not bias our estimation. After 2014, with the entry of more competitors into the market, all of these major platforms experienced rapid expansion, spanning over two hundred cities in less than six months (Li, Mo, and Zhou, 2022). Eleme also followed a similar expansion pattern, as illustrated in Figure 1. Such simultaneity further confirms the representative of Eleme on the whole online food

[5]The website address for the Eleme platform is `https://www.ele.me`.

[6]During this period, the other prominent food delivery platform, Meituan (`https://waimai.meituan.com`), was established in November 2013, considerably later than Eleme. Unfortunately, due to data limitations, we are unable to identify the precise entry time of Meituan.

delivery industry. In such cases where their competitors might enter new markets not yet covered by Eleme, our estimation provides a conservative lower bound.

2.2 Data

Our analysis draws on three primary data sources. The first is the CFPS survey data, which provides information on the respondents and their households. The second data source specifies the dates on which Eleme was introduced in cities. The last is the China Statistical Yearbooks for Regional Economy for our city-level covariates for our analysis.

China Family Panel Studies (CFPS) survey data Our first main data source consists of approximately 56,000 responses, from about 20,000 households in 128 cities to the CFPS survey, covering five waves conducted in 2010, 2014, 2016, 2018, and 2020.[7] The CFPS is a large-scale nationally representative longitudinal survey conducted by the Institute of Social Science Survey (ISSS) of Peking University. It contains rich information on the economic and non-economic well-being of Chinese individuals and households, including time use, labor market performance, and detailed demographics and socioeconomic status.

The CFPS employs a three-stage sampling design. Administrative units and socioeconomic status are the main stratification variables. Counties are selected as the primary sampling units, followed by neighborhood communities as the second-stage sampling units, and households as the third-stage sampling units. The average response rate across the survey waves is 73 percent (CFPS 2010–2018).[8] The random sampling design, high response rate, and large sample size of the CFPS assure the high quality of the data.

One advantage of the CFPS survey data is that we have access to the exact month in which each respondent was surveyed. However, it is worth noting that the survey months for each wave are typically concentrated in the summer months, from June to September. To address this issue, we transform the coding format from wave-month to wave-quarter, which helps to smooth out the distribution of survey time.

Eleme expansion dates data We obtained information on the entry time of the Eleme platform into each city in our sample from the Wayback Machine. This online archive contains snapshots of various websites at different points in time, enabling users to visit old

[7]Due to the unavailability of data on time use, which is our primary dependent variable, we exclude the data from the 2012 wave of the survey.

[8]The cross-sectional response rates for individuals are 84.1%, 74.1%, 72.8%, 69% (track response rate for the gene respondents in baseline 2010 wave), and 67.4% for waves 2010, 2012, 2014, 2016, and 2018. The information on response rate for the 2020 wave has not been disclosed yet.

versions of those websites.[9] Specifically, the front pages of Eleme's website showed the list of cities that had access to Eleme's services before that point in time, which allows us to identify the entry time of Eleme into each city in our sample.[10] As an example, Appendix Figure A1 shows the front page of Eleme as of May 7th, 2014, recovered via the Wayback Machine. As shown in the figure, Eleme was open to 31 cities at that point in time.

Armed with a time-series of snapshots of the front page of Eleme's website, it is possible to reconstruct tentative dates in which Eleme was rolled out in each city. Specifically, the roll-out date in a certain city should be between the date of the first snapshot in which the city is listed and the date of the previous snapshot. When the distance between the snapshots is more than one day, we consider the first date on which a city is listed on Eleme's front page as the introduction date.

Our analysis benefits from the high temporal resolution snapshots of Eleme's website provided by the Wayback Machine during its rapid expansion period (2014-2015), allowing for a precise imputation of the introduction dates of Eleme in each city. During the period in which Eleme expanded from 12 to 316 cities (January 2014 to November 2015), the average number of days between consecutive snapshots was 3.7 days. Therefore, the imputed introduction dates should be within four days of the actual introduction dates, which is reasonable given the quarterly time frame of our analysis. Importantly, at least one snapshot was captured on the Wayback Machine in each quarter from 2010 to 2015, further supporting that our imputed introduction points of time are reliable between 2010 and 2015. Figure 2 illustrates the regional variation in the timing of Eleme's introduction in cities before November 2015.

However, between November 24th, 2015, and September 4th, 2018, the pages captured by the Wayback Machine did not disclose the list of cities that had Eleme service, which makes it difficult to impute introduction dates during this period. Fortunately, until November 2015, 316 cities had access to Eleme's services, which covered most cities in China. Moreover, 125 cities (out of 128 cities) in the CFPS were accessible to Eleme.[11]

[9] Braghieri, Levy, and Makarin (2022) also use this online archive to access previous versions of Facebook pages, thereby enabling them to pinpoint the precise time when Facebook was introduced into US colleges in the mid-2000s.

[10] The earliest page captured on the Wayback Machine was on December 17th, 2008, which coincides with the start of Eleme food delivery service among colleges in Shanghai. Notably, Shanghai Lazas Information Technology Corporation, the company that owns Eleme, was formally registered on the National Enterprise Credit Information Publicity System on July 7th, 2010.

[11] The Wayback Machine first captured information about the three cities in our sample on September 4th, 2018, and this date was imputed as the introduction date of Eleme in those cities. Additionally, we exclude those cities in our robustness checks to ensure that our results are not driven by imprecise imputation. Please see Appendix Figure A4 for detailed results.

Hence, the infrequency of front pages in Wayback Machine after 2016 is almost irrelevant to our analysis as it does not confound the entry time of cities.

China Statistical Yearbooks for Regional Economy data We also gathered city-level data from the China Statistical Yearbooks for Regional Economy for the period between 2010 and 2020. The Yearbooks provide comprehensive economic statistics on China's cities, including data on regional economic growth, population, industry structure, and employment, which help us to control for the time-variant city-level characteristics. In addition, we collect information on the accommodation and catering industry in each city to analyze the expansion patterns of online food delivery platforms.

2.3 Variables and Summary Statistics

Construction of the housework variables To measure the time spent on housework, we rely on two sets of questions from the CFPS individual questionnaire. The first question asks, "In general, how long do you spend on housework every day?" which allows us to construct the *Daily Housework variable*. The second set of questions asks, "In general, how long do you spend on housework on weekdays?" and "In general, how long do you spend on housework on weekends?" which we use to construct the *Housework on Weekdays* and *Housework on Weekends* variables, respectively.

The answers to these two sets of questions are mutually exclusive for two reasons. Firstly, the 2010 wave only includes responses to the housework on weekdays and weekends questions, while the 2014 wave only includes responses to the daily housework question. Secondly, respondents in 2016, 2018, and 2020 waves were only asked these questions if they had indicated that their household work was divided into weekdays and weekends in an earlier question. Otherwise, they were asked about time spent on general daily housework.

To make the most information on housework, we construct imputed housework variables as follows: if respondents answered the first set of questions (i.e., *Daily Housework* variable), the imputed housework is equal to their reported daily housework. Otherwise, it is equal to the mean of the housework on weekdays and weekends. As an alternative measure, we impute the weighted mean of housework on weekdays and weekends, using the share of weekdays and weekends per week (i.e., 5/7 for weekdays and 2/7 for weekends) as weights.[12]

[12]The weighting method is based on the National Time Use Survey conducted by the National Bureau of Statistics of China. For detailed information on the weighting methodology, please refer to the website of the National Bureau of Statistics of China at http://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900224.html.

We also winsorize the housework hours at the 1st and 99th percentile to guard against outliers.

Construction of the treatment indicator The construction of our treatment indicator is straightforward. A respondent to the CFPS survey is classified as treated if, at the time the respondent took the survey, Eleme was available in the city, and not treated otherwise. As mentioned above, all cities in our sample had access to Eleme before September 2018. Thus, in the 2020 wave, all respondents were classified as treated.

Summary statistics We merge the dataset, which includes information on the timing of Eleme's introduction and city-level economic data, with the CFPS dataset using a unique city identifier. Our sample is restricted to individuals aged 16 to 59, who are expected to participate in the labor force. About 73% of the individuals in our CFPS sample fall into this age range. Furthermore, we exclude observations with missing values on key variables. To ensure greater comparability between the control and treatment groups and to identify the clean causal effects of the introduction of online food delivery platforms, we only include respondents who completed the CFPS survey within two years (eight quarters) before or after Eleme's entry. We end up with unbalanced panel data consisting of 32,013 individuals in 113 cities during the quarterly periods spanning from 2010 to 2020. Table 1 presents descriptive statistics of the main variables used in our empirical analysis. See Table A1 in Appendix for the definition of these variables.

3 Empirical Strategy

3.1 Identification Strategy

We estimate the introduction of online food delivery platforms on time used for housework using a Difference-in-Differences (DID) approach, that builds on two sources of variation. First, cities were covered by Eleme at different times. Second, within the same city, individuals completed the CFPS survey at different times. We compare how the time spent on housework changes in cities where Eleme has entered to those where it has not yet entered at the survey time. Our estimates are based on the following regression:

$$Y_{icqt} = \alpha + \beta \times Treat_{cqt} + X_{icqt} \cdot \gamma + X_{ct} \cdot \eta + \theta_c + \delta_t + \varepsilon_{icqt} \quad (1)$$

where Y_{icqt} represents the outcome of individual i who participated in the q^{th} quarter of survey wave t and resides in city c; $Treat_{cqt}$ is an indicator for whether, before the q^{th} quarter of survey wave t, Eleme platform was available; X_{icqt} is a vector of individual-level control variables, which includes demographic characteristics such as gender, age, and age squared of the respondents, as well as socioeconomic status such as hukou status (urban or rural), marital status, highest education level, employment status, and internet usage; X_{ct} is a vector of time-variant city-level control variables, including GDP (in natural log), population (in natural log), and the share of the service industry; θ_c and δ_t indicates city and wave fixed effects, respectively. The standard errors are clustered at the city level.

Under the assumption that, in the absence of the Eleme roll-out, the housework outcomes of respondents living in cities with different Eleme expansion points of time would have evolved along parallel trends, the coefficient of interest β identifies the average treatment effect on the treated (ATT) of the introduction of Eleme on the time spent on housework. Therefore, our baseline specification model allows us to rule out various concerns that could otherwise impair our ability to interpret the results as causal.

3.2 Threats to Identification

First, it is unlikely that Eleme randomly enters cities, and features of a city (e.g., size, location, economic characteristics) may make it an attractive target for Eleme's entry while simultaneously affecting the time use of local people. This could, in turn, result in selection effects and bias in our estimations. Accordingly, we can safeguard against the possible bias by including city fixed effects, which can rule out that the results are driven by time-invariant differences in time use across cities, and controlling for time-variant characteristics of cities, such as GDP, population, and industrial structure.

Another potential concern in our setting is the plausibility of the parallel trend assumption. In our baseline specification, the time period fixed effects (δ_t) are assumed to be constant across cities, which rules out possibly heterogeneous trends. One might worry that cities in different provinces or different Eleme expansion groups, indicating varying entry times across the expansion groups, might have different trends in terms of housework outcomes.[13] We address this concern in five ways. First, we estimate a fully dynamic version of equation (1), i.e., the event study, and check for potential pre-trends. Second, to the

[13] According to the Chinese administrative geography, provinces are divided into cities, and cities are further divided into counties. The province level is a higher administrative level than the city level, and cities are governed by their respective provinces, and adhering to the policies issued by those provinces. Consequently, different cities in one province often share some common characteristics and development patterns.

extent that the trends are linear, we would be able to account for them in a robustness check that includes province (expansion-group-level) linear time trends. Third, we can also include province-by-wave (expansion-group-by-wave) fixed effects to control for any unobserved time-varying province-specific (expansion-group-specific) shocks. Fourth, we allow the trends to be correlated to the city's initial characteristics that may be possibly correlated with Eleme roll-out timing by including the interaction terms between city initial characteristics and wave fixed effects. Fifth, we focus on the cities that experienced intensive entry, which provides a relatively more exogenous and cleaner identification strategy. These strategies, which we explore in detail in later sections, should assuage concerns about violations of the parallel trend assumption in our setting.

Although the introduction of Eleme is at the city level, the panel feature of data provides us with the opportunity to exploit individual-level variation. To obtain a more precise specification, we include individual fixed effects and quarter fixed effects to control for time-invariant individual-specific characteristics and seasonal effects, respectively. Appendix Table A4 shows that key results are not sensitive to the inclusion of alternative fixed effects. However, the marginal benefit of controlling individual and quarter-fixed effects is limited, with potential costs. Firstly, the distribution of survey time is highly concentrated in a particular quarter. Specifically, 88 percent of individuals in the same city completed the CFPS survey in the same quarter. Moreover, since the CFPS dataset is an unbalanced panel, controlling for individual fixed effects would result in a significant reduction in observations, with the estimation being more influenced by outliers and measurement errors (Angrist and Pischke, 2009).

4 Results

In this section, we present the results of our baseline specification, examine the validity of identification, and discuss the robustness of our findings through various checks.

4.1 Baseline Results

4.1.1 Housework Time

Table 2 presents estimates of β in equation (1) on our imputed housework outcome, and shows that the introduction of Eleme in a city had a negative impact on the time spent on housework. The first column in the table shows results for our simple specification, which includes only individual demographic controls, city fixed effects, survey-wave fixed effects, and an indicator for treatment status. In the second and third columns, we also include individual socioeconomic status control variables and city-level control variables, respectively. In the fourth column, we add the province linear time trends, in order to account for the possibility that cities belonging to different provinces might be on different linear housework trends. In the fifth column, we control for province-by-wave fixed effects to account for any unobserved time-varying province-specific shocks. Our results are fairly stable and statistically significant across specifications.

The effect size on the amount of time spent on the housework in our preferred specification, namely the one that includes all individual level and city level control variables, as well as city and wave fixed effects, is -0.197, as shown in the third column of Table 2. Specifically, the estimate suggests that the introduction of Eleme leads to a reduction of roughly 11.8 ($= -0.197 \times 60$) minutes in time spent on housework per day, which accounts for approximately 10 percent of the sample mean (1.997). The magnitude of the coefficient is comparable to the literature that examines the effect of services by maids on housework time. Specifically, Stratton (2012) finds that a 10% decrease in the cost of maid service reduces female housework time by about 14.2 minutes or about 17% per day.

As mentioned below, unobservable heterogeneous time trends that may be correlated with the entry timing of Eleme are of crucial concern to the DID strategy. To alleviate this concern, we introduce province linear trends and province-by-wave fixed effects, respectively. By doing so, we not only control for the linear trends (if the trends are linear) but also allow the trends to differ across provinces. The results, shown in columns (4) and (5), remain largely unchanged and in line with those found in column (3), lending support to the argument that our baseline estimates are not affected by the province-specific heterogeneous time trends.

4.1.2 Household Consumption Expenditures

We then consider the possible changes in household consumption expenditures driven by the introduction of Eleme. One may worry about that the individuals, covered in our data, did not use the Eleme food delivery services before. We have to acknowledge that the point estimate above captures both the direct effect of Eleme on individuals who used the platform and the indirect effect of Eleme on individuals who did not use the platform, but whose neighbors did. The CFPS survey does not include any questions on the online food delivery services use; therefore, it is not possible for us to determine whether a particular survey respondent used Eleme services. Fortunately, we can investigate the household consumption expenditures changes after the entry of Eleme. Specifically, we estimate the following model at the household level:

$$Y_{hcqt} = \alpha + \beta \times Treat_{cqt} + X_{hcqt} \cdot \gamma + X_{ct} \cdot \eta + \theta_c + \delta_t + \varepsilon_{hcqt} \quad (2)$$

where Y_{hcqt} represents the consumption expenditures (or shares) outcomes of household h who participated in the q^{th} quarter of survey wave t and resides in city c; $Treat_{cqt}$ is an indicator for whether, before the q^{th} quarter of survey wave t, Eleme platform was available; X_{hcqt} and X_{ct} are vectors of household-level and city-level controls, including the family structure, city-level GDP, population and industrial structure. θ_c and δ_t indicate city and wave fixed effects, respectively. The standard errors are clustered at the city level.

Figure 3 presents results on the local household consumption expenditures and the corresponding shares of expenditures. The results demonstrate that the introduction of Eleme leads to a significant increase of more than 60 yuan (approximately 2.5 percent, as shown in Figure 3b) in expenditures on food and related items while reducing the expenditures on fuel for cooking.[14] Additionally, the expenditures on water and electricity, and local transportation have a slightly increasing effect, whereas the expenditures on communication have a slightly decreasing effect.

These findings indicate that the introduction of online food delivery platforms has had a direct impact on the lifestyle of local individuals, specifically in terms of their eating habits. The observed changes in expenditure patterns show that these changes are attributed to the introduction of online food delivery platforms, rather than being influenced by other coinciding shocks in time and location.

4.1.3 Event Study

In order to test for parallel trends and study the dynamics of treatment effects, we estimate an event-study version of the difference-in-differences model with indicators for distance to/from the introduction of the online food delivery platform. Specifically, we estimate the following specification:

$$Y_{icqt} = \alpha + \beta_k \times \sum_{k=-8}^{8} \mathrm{D}_{k(cqt)} + X_{icqt} \cdot \gamma + X_{ct} \cdot \eta + \theta_c + \delta_t + \varepsilon_{icqt} \quad (3)$$

[14] Based on the average currency exchange rate between the Chinese Yuan (RMB) and US dollars (USD) during our sample period of 2010-2020, which is sourced from the International Monetary Fund, 60 yuan is approximately equivalent to 9.2 dollars.

where Y_{icqt} represents the housework outcomes of individual i who participated in the q^{th} quarter of survey wave t and resides in city c; $D_{k(cqt)}$ is a set of indicators that take value one if, for city c in the q^{th} quarter of survey wave t, the entry of Eleme was k quarters away. X_{icqt} and X_{ct} are vectors of individual-level and city-level controls, respectively, which are in line with equation (1). θ_c and δ_t indicate city and wave fixed effects, respectively. The standard errors are clustered at the city level.

Figure 4 presents the event-study results, indicating that the estimates are consistent with the parallel trends assumption: the coefficients on the quarters prior to the introduction of Eleme in a city are all statistically close to zero and exhibit no discernible pre-trends. Furthermore, Figure 4 illustrates the dynamics of treatment effects, revealing that the negative effect of Eleme entry on the amount of time dedicated to household work grows for one year after the implementation and then stabilizes, and remains significant at the 5 percent level. The increase in treatment effects over time may be attributed to the broader expansion area and higher intensity usage of Eleme services. Appendix Figure A2 shows the event study figure for the alternative outcome, i.e. the weighted housework, which also confirms that the parallel trends assumption holds.

4.2 Validity of Identification and Robustness

The key assumption underlying our baseline DID strategy is the parallel trend assumption: in the absence of the Eleme roll-out, the housework outcomes of respondents living in cities with different Eleme expansion timings would have evolved along parallel trends. While the counterfactual is certainly unobservable, we perform a battery of exercises that test the parallel trend assumption and probe the validity of our identification strategy.

4.2.1 Heterogenous Time Trends

The rollout of Eleme across cities was not random: as shown in Appendix Figure A3, cities with higher levels of development and larger populations had earlier accessibility to Eleme compared to other cities. This fact might raise the concern that unobservable heterogeneous trends that may be correlated with the entry timing of Eleme. The event study estimates in Figure 4 and the results that account for province linear trends and province-specific time effects in Table 2 may partially alleviate this concern in the above section. To further address this concern, we follow Braghieri, Levy, and Makarin (2022) and consider the possible heterogeneous time trends between the different expansion groups.

Based on the order in which the Eleme entered cities, we roughly divide them into four expansion groups, ranging from earliest to latest. The first expansion group comprises 6 cities that were covered by Eleme between 2008 and 2013. All of these cities are province capitals located in the developed eastern region. They have a high level of economic development and attract the entrance of online platforms, including Eleme. The second expansion group is the largest, consisting of 84 cities that were covered by Eleme in 2014, which is the rapid expansion period of Eleme. These cities exhibit varying levels of economic development and high diversity, as represented by the distribution (standard deviations) of their GDP and population shown in Appendix Figure A3. The third expansion group includes 20 cities covered by Eleme in 2015, while the fourth expansion group consists of only 3 cities covered by Eleme between 2016 and 2018. These expansion groups exhibit significant differences among themselves.

To alleviate this concern, we include the expansion group by survey wave fixed effects, which sweep out the between-expansion-group variation, focusing solely on the within-group variation. Similar to Chen et al. (2020) and Braghieri, Levy, and Makarin (2022), we additionally estimate a specification that incorporates the interaction terms between survey wave fixed effects and city-level characteristics that could be correlated with the timing of Eleme's roll-out. These characteristics include average housework hours, the number of firms in the accommodation and catering industry, the ratio of sales in the accommodation and catering industry to GDP, and the ratio of employment in the accommodation and catering industry to total employment in 2010.

Together, we not only allow the time trends to differ across expansion groups, but we also allow the trends to be correlated to the city's initial characteristics that may be possibly correlated with Eleme roll-out timing. The estimation results are presented in Table 3, and demonstrate that the inclusion of these controls does not substantially alter our baseline findings.

4.2.2 Choice of Sample and Time Window

We specifically focus on the time period characterized by the intensive entry of online food delivery platforms. During this period, the entry decisions of these platforms are relatively more exogenous, allowing for a cleaner identification strategy. Specifically, we narrow the time window to the period from the 3rd quarter of 2014 to the 3rd quarter of 2016, which is more focused and concentrated, aiming to reduce potential sources of noise that could threaten our parallel trend assumption. The results are shown in Table 4 and keep in line with our baseline results. We also find that even though the standard errors are clustered at the expansion group and wave (2×2) level to account for all of the potential sources of correlation in the residuals, the effects of Eleme on the time spent on housework are still significantly negative at the 10 percent level.

We further restrict our samples to cities that experienced intensive entry in August 2014, as depicted in Figure 1, which shows the highest number of cities newly covered by Eleme during that period. We acknowledge that Eleme's selection of cities during this period is primarily driven by coverage and market share considerations rather than specific city characteristics, leading to a diverse set of cities with varying development patterns.[15] Additionally, to address potential weighting bias arising from different treated lengths of time, we follow Norris and Xiong (2023) and balance our sample in event time.[16] Therefore, we restrict the sample to these cities and explore different bandwidths to access the robustness of our estimates. The results, presented in Figure 5, align with our baseline findings, reinforcing the validity of our conclusions.

4.2.3 Other Robustness Checks

To obtain a more precise specification, we additionally include survey-quarter fixed effects, survey-year-by-quarter fixed effects, and individual fixed effects to control for seasonal effects and time-invariant individual-specific characteristics. Results are shown in Appendix Table A4. The coefficients consistently exhibit significant negative values, and their magnitudes remain relatively stable without substantial changes. The observed increase in standard errors could potentially be attributed to outliers and measurement errors, as discussed in the section 3.

To alleviate concerns regarding the influence of outliers, we exclude the earliest and latest expansion groups, along with the survey wave conducted in 2020, which could be affected by the COVID-19 pandemic. We demonstrate that the results, depicted in Appendix Figure A4, remain robust and are not driven by the earliest or latest Facebook expansion group, nor by the specific survey wave.

Furthermore, the possible serial correlation in housework at the higher level may cause the standard errors to be biased downward (Bertrand, Duflo, and Mullainathan, 2004; Dube, Lester, and Reich, 2010). To account for this bias, we change the level at which standard

[15]The distributions of GDP and population in cities, that newly introduced Eleme in August 2014, are shown in Appendix Figure A3.

[16]Norris and Xiong (2023) explored the effects of Uber entry and noted that each β_k in (3) is estimated from a different sub-sample of cities, with greater weight given to cities where Uber entered earlier, which could potentially introduce bias if the entry time is correlated with a city's growth path. To mitigate this bias, they restrict the sample to be balanced in event time instead of calendar time.

errors are clustered. Appendix Table A5 shows that our baseline results are robust to clustering standard errors at the province level and at the Eleme expansion group by wave level.

5 Discussion

5.1 Heterogeneity

In this subsection, we explore how the availability of an online food delivery platform like Eleme has led to a differential reduction in the time devoted to home production.

Previous studies have indicated that home production is an increasing function of family size, and the burden of housework and childcare disproportionately weighs on women, particularly in cases where they have young children or belong to larger families (Menta and Lepinteur, 2021). Building on this premise, we propose the hypothesis that the availability of online food delivery platforms would have a more pronounced effect in reducing housework time for this group and potentially narrow the gender gap in home hours.

To test this hypothesis, we estimate the heterogeneous effects of the introduction of Eleme on the time spent on housework by family size and gender. It is important to note that we use the number of family members who typically eat at home as a proxy for family size. This variable is directly related to housework for cooking, which can potentially be outsourced to the online food delivery services.

The results, as presented in Table 5, show that the reducing effect of Eleme on the time spent on housework for large families is more than twice that for small families, as indicated in the first and third columns. From the gender perspective, the second and fourth columns demonstrate that the introduction of Eleme has a significantly larger effect on women than men, particularly for women in large families. These results align with the traditional household specialization pattern in China, where women have been more responsible for cooking and other household chores. These findings also suggest that the introduction of Eleme helps narrow the gender gap in terms of time allocation for household work.

Furthermore, it is essential to consider heterogeneity by family structure. We divide the sample into four groups based on detailed family members' information: (1) families without coresident elderly above 65 and children under 18, which are expected to have the least housework burden; (2) families with coresident elderly above 65, where adults often assume additional responsibilities to their elderly parents in need of care; (3) families with both coresident elderly and young children under 18, in which adults not only should take care of the elderly, but their school-age children; (4) families with both coresident elderly and young children under 7, in which adults bear the heaviest burden of housework for childcare and elderly care. Table 6 shows the corresponding results, demonstrating that compared to families without coresident elderly and young children, the effect of Eleme is approximately twice as large for families with coresident elderly aged above 65 (-0.166 versus -0.298), and three times as large for families with both coresident elderly aged above 65 and young children under 18 (-0.166 versus -0.435). While the coefficient magnitude increases for families with young children under 7 in the fourth column, it does not reach statistical significance, possibly due to the small sample size.

Combined, the results suggest that the introduction of Eleme alleviates the burden of household work, particularly for women, families with a larger size, and those with coresident elderly, and young children. These findings support our hypothesis and are consistent with Menta and Lepinteur (2021).

5.2 Labor Supply and Leisure

As discussed previously, our findings demonstrate that the introduction of online food delivery platforms leads to a significant reduction in the time spent on housework, especially for women with heavy housework burdens. A natural question thus arises: how do they allocate the time saved from household chores?

Labor supply responses by age The existing literature suggests that advancements in labor-saving technology can lead to the reallocation between home production and market production and an increased female labor supply. Two potential mechanisms explain this relationship. Firstly, the declining price and wider availability of home appliances increase the opportunity costs of time spent on household chores, making it more attractive for women to enter the labor market (Greenwood, Seshadri, and Yorukoglu, 2005; de V. Cavalcanti and Tavares, 2008). Secondly, the progress in labor-saving technology, such as the broadband Internet and electricity, can improve job flexibility and market production opportunities, allowing individuals to work more and balance work and home responsibilities more effectively (Dettling, 2017; Mas and Pallais, 2017; Vidart, 2023).

We additionally incorporate the labor supply elasticity into our analysis. Recent research on labor supply has extended traditional labor supply models to incorporate the life-cycle perspective, as the labor supply elasticities vary systematically over the life-cycle for individuals (Keane and Wolpin, 2010; Keane and Wasi, 2016; Attanasio et al., 2018).

They particularly highlight such age-variation in labor supply elasticities is crucial, especially in optimal tax analysis and policy implication (Keane, 2016; Iskhakov and Keane, 2021). Building on this understanding, we propose a hypothesis that the availability of Eleme has the potential to motivate individuals to shift their time from home production to market production. The magnitude of this shift is expected to be heterogeneous by age.

The results are presented in Figure 6. [17] We find a U-shape pattern in the market hours response of females (with males as the reference group) to the introduction of Eleme across different age groups. Specifically, we find that the number of hours worked by females, conditional on non-farm employment, significantly increased by approximately five hours before the age of 25. It then declines to near zero between the ages of 25 and 55 before reaching its peak of nine hours for the 55-60 age group.[18] Our findings are in line with Rogerson and Wallenius (2009) and Keane and Wasi (2016), who predict a U-shape for labor supply elasticities in a life-cycle model. It suggests that the impact of Eleme on market hours could be more pronounced for those with a higher labor supply elasticity, possibly due to that they are more inclined to respond to the opportunities provided by the platform and adjust their time allocation between market work and home production (Fang and Zhu, 2017).[19]

Opportunity cost of time Education is an important indicator of one's opportunity cost of time (Stratton, 2012; Erosa, Fuster, and Kambourov, 2016; Bridgman, Duernecker, and Herrendorf, 2018; Iskhakov and Keane, 2021).[20] Individuals with higher education levels often have greater potential for career advancement and higher salaries in the labor market. Therefore, if they choose to spend time on housework, they are likely to forgo higher opportunity costs compared to individuals with lower education levels. This implies that individuals with higher education levels may be more motivated to seek time-saving solutions, such as utilizing platforms like Eleme, to reduce their time spent on housework

[17] Specifically, we estimate the following modification of equation (1):

$$MarketHours_{g(i),icqt} = \alpha+\beta_{g,1}Treat_{cqt}+\beta_{g,2}Treat_{cqt}\times Female_i+X_{g(i),icqt}\cdot\gamma+X_{ct}\cdot\eta+\theta_c+\delta_t+\varepsilon_{g(i),icqt} \quad (4)$$

where $g(i)$ represents the age group in Figure 6 or the education level in 7 of individual i. The coefficient of interest, denoted as $\beta_{g,2}$, identifies the heterogeneous treatment effects by gender within specific age or education groups.

[18] The largest labor supply responses are observed in the 55-60 age group, which may be attributed to the difference in legal retirement age between males and females in China. The retirement age for females is 55, while for males it is 60.

[19] We additionally present the results for the extensive margins in Appendix Figure A5 and Figure A6.

[20] The opportunity cost of time is captured using their predicted natural log of net hourly earnings, which are based on their education and potential experience as well as household data on non-labor income receipt (Stratton, 2012).

and allocate more time to market activities (Bridgman, Duernecker, and Herrendorf, 2018). Therefore, we investigate the heterogenous effects of Eleme on market hours by highest education level.

Results presented in Figure 7 reveal that the introduction of Eleme has no effects on market hours for low-educated females (junior high school and below) compared to males with the same education level, while it has pronounced positive effects on market hours for highly-educated females (senior high school and above). Moreover, the positive effects of Eleme on market hours for females with college and above education are statistically significant at the 10 percent level. These findings align with previous literature suggesting that home technology progress or low-skilled immigration benefits high-skilled women more, as they have a higher opportunity cost of time and are more likely to outsource their housework (Cortes and Tessada, 2011; Bridgman, Duernecker, and Herrendorf, 2018; East and Velásquez, 2022).

Leisure We next look at leisure, which is the remaining component of time allocation apart from home hours and market hours in the time constraints function. We proxy leisure as the sleep hours and weighted sleep hours, following the same construction methodology used for housework hours and weighted housework hours. Additionally, we are interested in the changes in female well-being, which are measured by the indicators of good self-reported health and life satisfaction.

Results are reported in Table 7. We find that the average treatment effects of online food delivery platforms on leisure and well-being are positive but almost insignificant. However, the interaction term between treatment status and gender indicator are significantly positive, indicating that the introduction of Eleme has a particularly favorable impact on females. This finding suggests that the online food delivery platform contributes to a reduction in the gender gap concerning leisure and well-being.

5.3 Economic Importance

Transformation from home production to market production We examine the economic significance of the transformation from home production to market production brought about by food delivery platforms. The reduction of home production can be imputed using estimations of household production value by Bridgman, Duernecker, and Herrendorf (2018). They found that the 2005–2010 average shares of household production range from 10 percent to 50 percent across 33 countries. Our estimation of a 10 percent reduction in housework time could potentially correspond to at least a 1 percent increase in GDP.[21] The value added of market production can be proxied by sales. In 2021, the sales generated by these platforms exceeded one trillion, equivalent to about 1 percent of the GDP in China (The State Information Center, 2022). This suggests that the economic impact of the transformation from home production to market production facilitated by platforms could be substantial.

Furthermore, the economic importance of the transformation from home production to market production is particularly significant for developing countries. Unlike relying on cheap home services provided by low-skilled immigration from less developed areas (Cortes and Tessada, 2011; East and Velásquez, 2022; Pedrazzi and Peñaloza-Pacheco, 2023), online food delivery platforms like Eleme offer a domestic solution that can benefit the local economy. This is especially relevant in developing countries such as China, where there is a polarization in income distribution. The introduction of platforms like Eleme has the potential to tap into the substantial opportunities that arise from shifting from home production to market production, thereby creating new economic prospects. By enabling individuals to outsource household chores and allocate more time to market work, these platforms contribute to economic growth, job creation, and the overall development of the country.

Long-run impacts The effects of online food delivery platforms, as a new labor-saving technology, may extend to subsequent cohorts. Lewis (2014) investigates how advancements in home production technologies affect female employment and investment in daughters. The study reveals that household electrification did not have an immediate impact on female employment. However, it is associated with increased school attendance, particularly among teenage daughters, and ultimately leads to improvements in the labor market outcomes of subsequent generations of women.

Our findings, as illustrated in Figure 6, indicate that the introduction of online food delivery platforms has a substantial and significant positive effect on market hours for young women, who may potentially represent daughters in households included in our sample.[22] This highlights the potential for online food delivery platforms to have long-term effects on female labor supply and the welfare of future cohorts. By facilitating a reduction in household chores and increasing time available for market production, these platforms could

[21] Our baseline results indicate that the introduction of online food delivery platforms could lead to a 10 percent reduction in housework time. Based on the lower bound of estimations from Bridgman, Duernecker, and Herrendorf (2018), we perform a back-of-the-envelope calculation and derive a rough estimate that the share of value added produced in the home sector is approximately 1 percent (= 10 percent × 10 percent).

[22] As depicted in Table 1, the average age of our sample is approximately 41 years old.

potentially contribute to improved labor market outcomes and economic opportunities for women in the long run.

6 Conclusion

In this paper, we estimate the effects of an online food delivery platform on the time spent on housework and labor supply. By leveraging the staggered introduction of Eleme across cities in China, we find that the introduction of Eleme into a city significantly reduced the amount of time spent on housework. We also find a significant increase in food expenditures and a decrease in water and electricity expenditures, which confirms the effects are driven by food delivery platforms. Additionally, these effects are pronounced for groups that face the most time constraints due to previous existing heavy housework burdens. Moreover, our study demonstrates that the introduction of Eleme leads to an increase in female market hours relative to males, with variations across different age groups and levels of education. Finally, it also has a more pronounced positive effect on the leisure and well-being of females compared to males.

Our paper contributes to the existing literature by highlighting the transformative impact of technology in enabling specialization outside of the household. By examining the introduction of online food delivery platforms, we show that this technological advancement allows for the reallocation of housework time from less productive household members to lower-productivity members in society. As a result, more family members, particularly women, can participate in the labor force, leading to increased overall efficiency in society. Importantly, this technology-driven solution offers a self-reliant alternative that can benefit local economies, without relying on low-skilled immigration (Cortes and Tessada, 2011; Amuedo-Dorantes and Sevilla, 2014; East and Velásquez, 2022; Pedrazzi and Peñaloza-Pacheco, 2023). This finding holds significant implications, particularly for developing countries, where the adoption of such technologies can stimulate economic growth and foster overall development.

Furthermore, our research highlights the potential of the home sector, particularly in the post-pandemic era, where the revival of economic activity is of utmost importance. By emphasizing the liberation of home production, our paper offers insights and implications for optimizing the allocation of resources between households and society. This liberation of home production has the potential to generate economic growth, reduce unemployment, and enhance work-life balance. As we navigate the challenges posed by the pandemic, understanding and harnessing the potential of the home sector becomes increasingly crucial in promoting sustainable and inclusive economic development.

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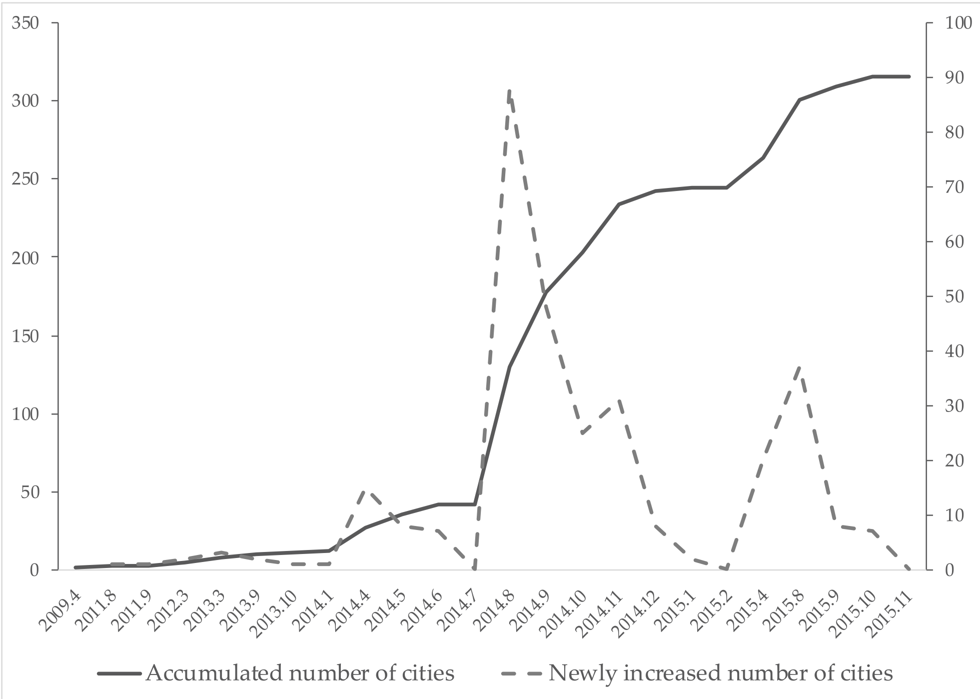


Figure 1: Eleme Expansion Timeline

Notes: This figure shows the number of cities that had access to Eleme's services during the Eleme expansion period. The x-axis represents the expansion months, indicating the periods during which at least one city gained access to Eleme, excluding the initial and final points. The dashed line indicates the number of newly introduced cities each month, while the solid line represents the cumulative number of cities before the expansion months.

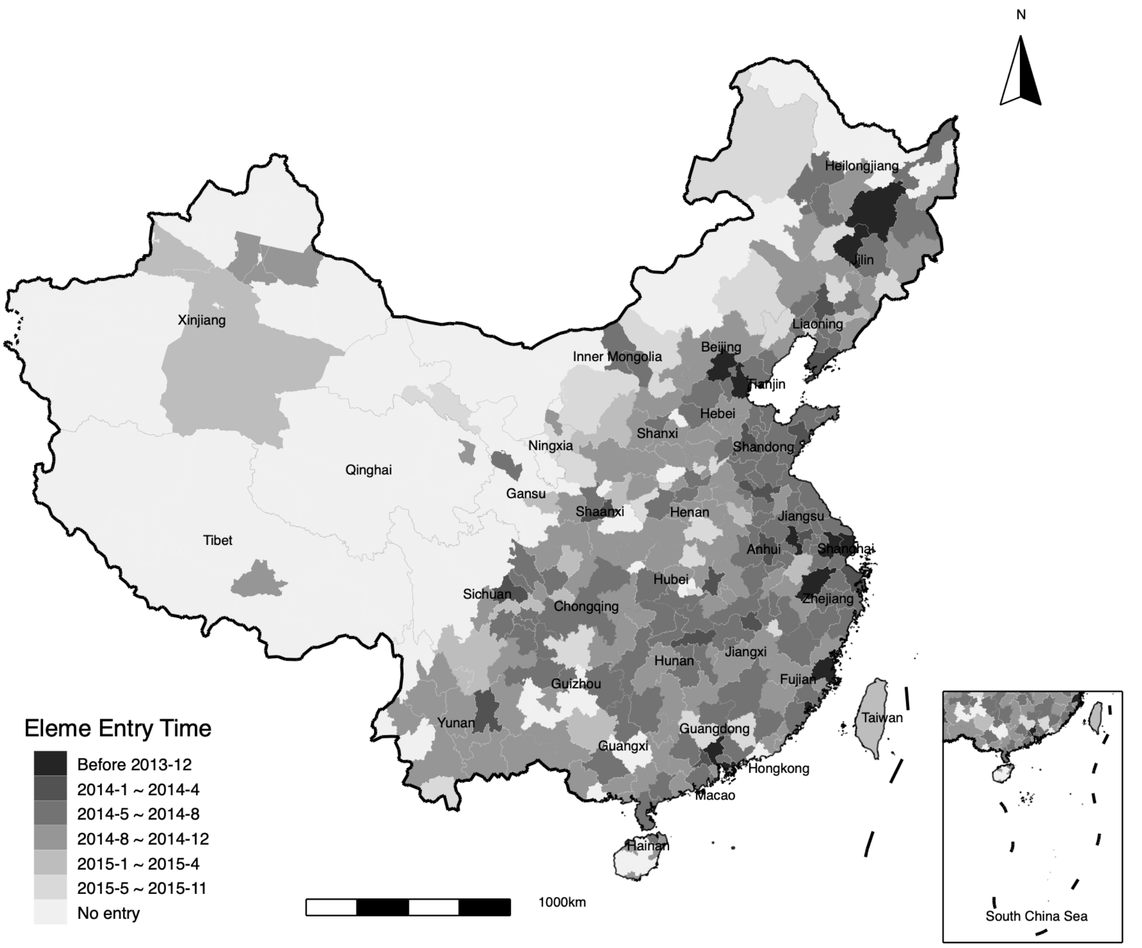
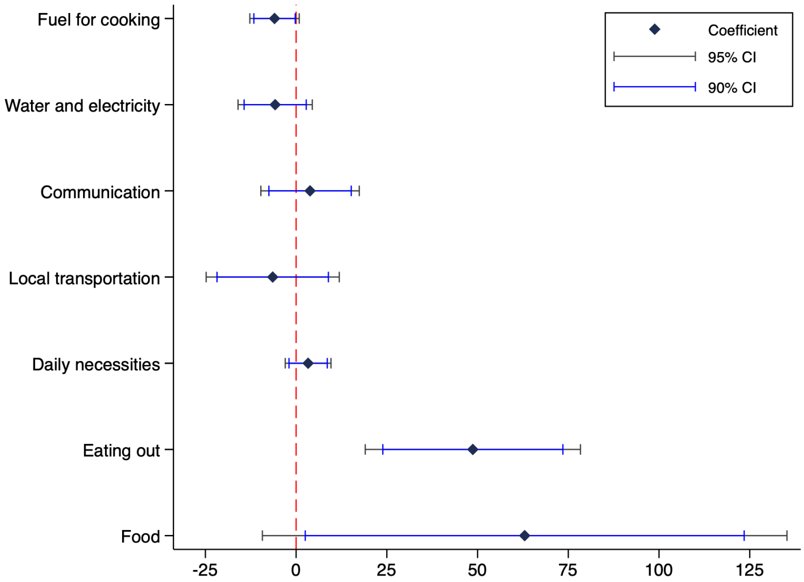
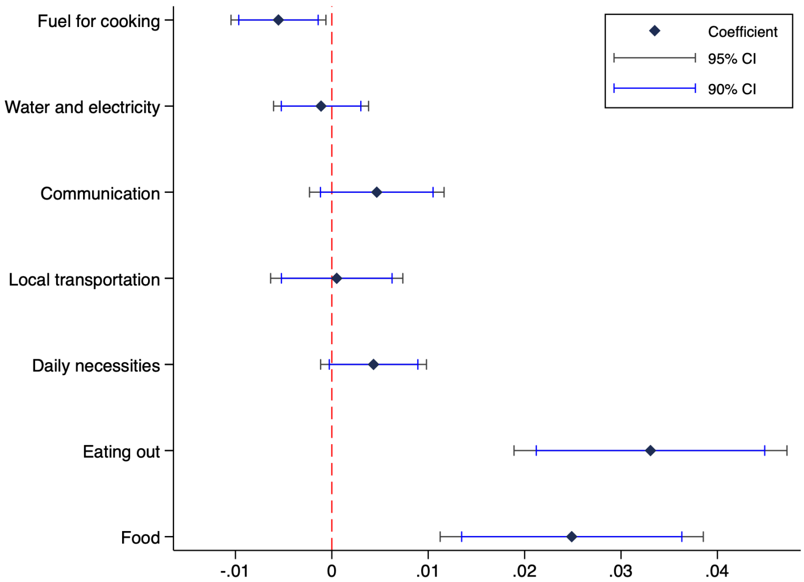


Figure 2: Eleme Entry Time in Each City

Notes: This figure shows the regional distribution of the timing of Eleme's introduction in cities before November 2015. The colors represent the variation in the timing of Eleme's introduction, with darker colors indicating earlier introductions in cities.



(a) Expenditures (RMB)



(b) Shares of Expenditures (%)

Figure 3: Effects of Eleme on the Household Expenditures

Notes: This figure shows the estimates based on the equation (2). In the top panel of the figure, the dependent variables are the monthly household consumption expenditures allocated to various items, such as food, eating out, daily necessities, local transportation, communication, water and electricity, and fuel for cooking. In the bottom panel, the dependent variables are the shares of monthly household consumption expenditures allocated to the same items. The x-axis represents the coefficients of Eleme introduction, while each point corresponds to a separate regression conducted for each dependent variable. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

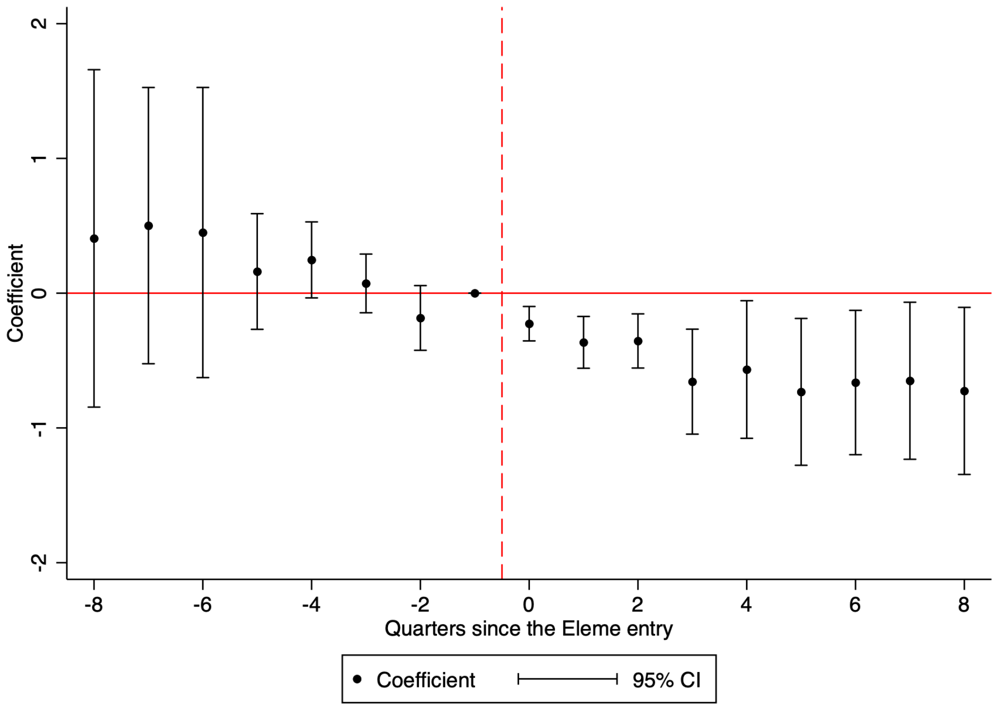


Figure 4: Effects of Eleme on the Time Spent on Housework

Notes: This figure shows the event study estimates based on equation (3). The dependent variable is the mean imputed housework hours per day. The bars represent 95% confidence intervals. Standard errors are clustered at the city level.

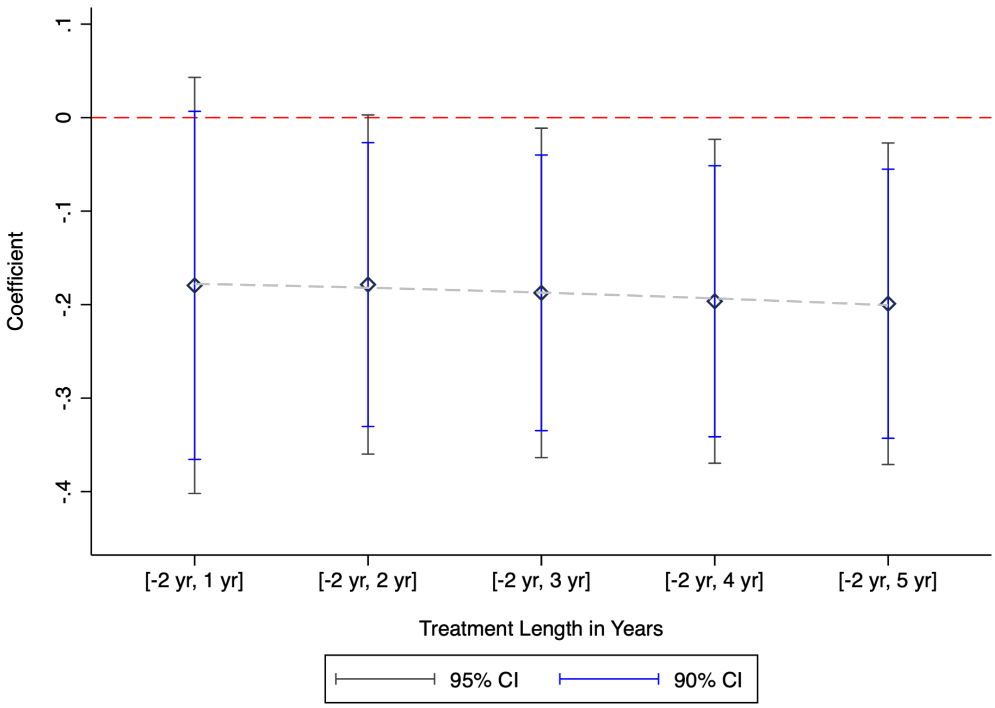


Figure 5: Different Bandwidths of the Largest Expansion Group

Notes: This figure shows the estimates based on equation (1) with a restricted sample consisting of cities that were covered by Eleme in August 2014, representing the largest expansion group. The dependent variable is the mean imputed housework hours. Each diamond point represents a separate regression conducted with different bandwidths ranging from 1 year to 5 years. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

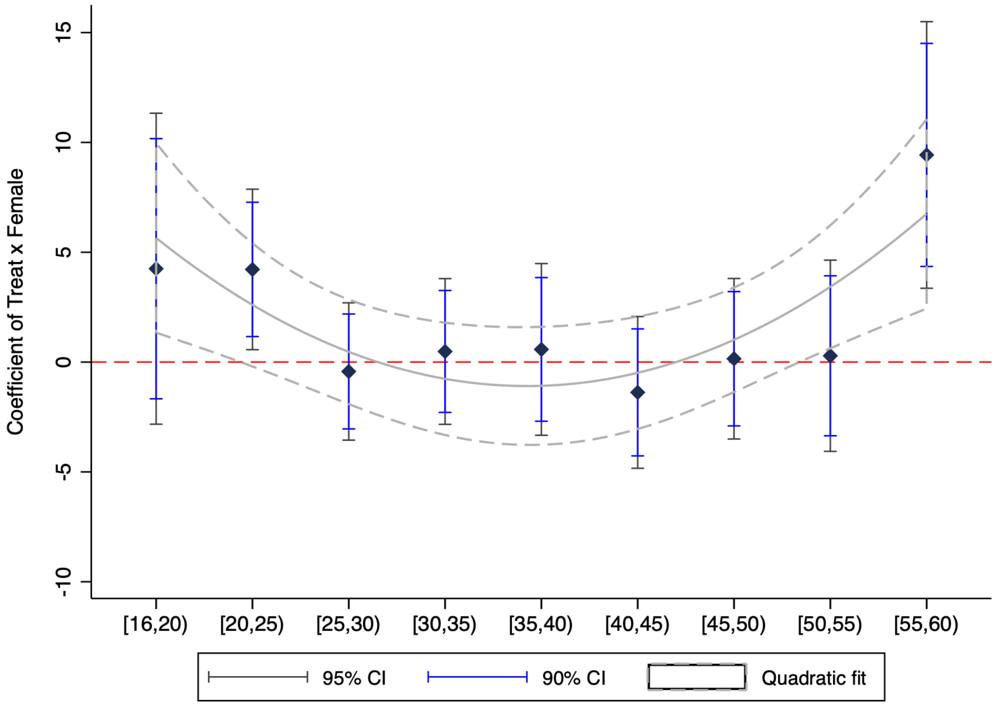


Figure 6: Effects of Eleme on the Labor Supply by Age

Notes: This figure shows the estimates of coefficient $\beta_{g,2}$ from equation (4). The dependent variable is the number of market hours per week conditional on non-farm employment. Each diamond point represents the coefficient of the interaction between treatment status and the female indicator within each specific age group. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

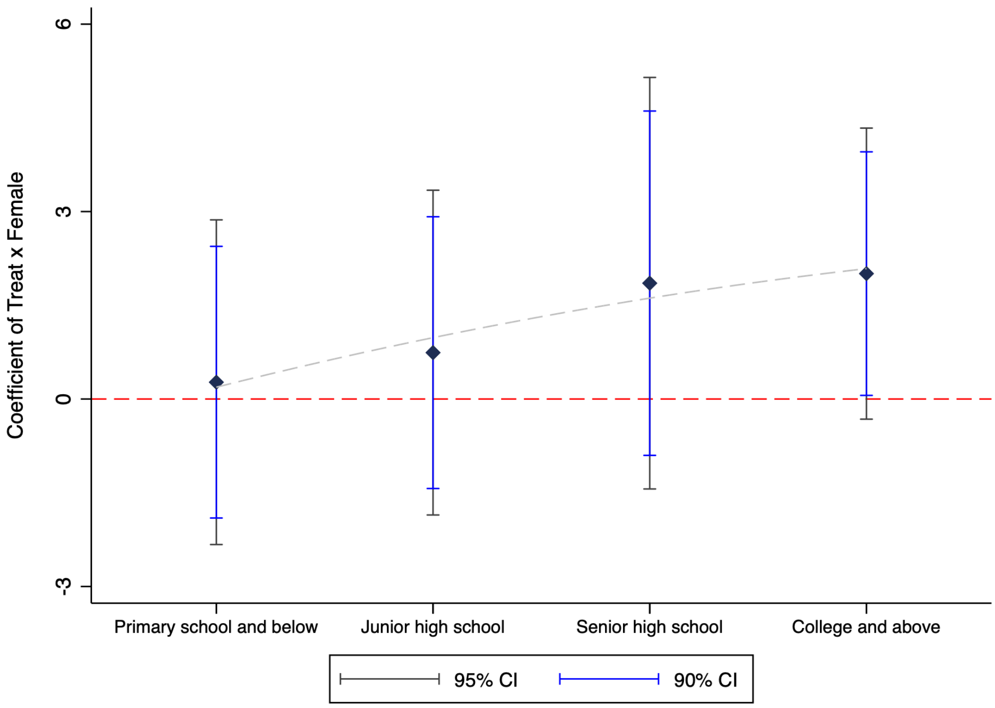


Figure 7: Effects of Eleme on the Labor Supply by Education

Notes: This figure shows the estimates of coefficient $\beta_{g,2}$ from equation (4). The dependent variable is the number of market hours per week conditional on non-farm employment. Each diamond point represents the coefficient of the interaction between treatment status and the female indicator within each specific education group. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

Table 1: Summary Statistics

	Mean	**S.D.**	**Min**	**Max**	**Obs.**
Housework					
Mean imputed housework	1.997	1.767	0	10	32013
Weighted mean imputed housework	1.959	1.768	0	10	32006
Daily housework	2.061	1.900	0	10	18537
Housework on weekdays	1.707	1.640	0	9	13476
Housework on weekends	2.110	1.740	0	9	13476
Eleme Entry					
Treat	0.554	0.497	0	1	32013
Individual Demography					
Age	41.031	11.384	16	59	32013
Male	0.487	0.500	0	1	32013
Socioeconomic Status					
Married	0.857	0.350	0	1	32013
Urban	0.259	0.438	0	1	32013
Primary school and below	0.414	0.493	0	1	32013
Junior high school	0.328	0.469	0	1	32013
Senior high school	0.159	0.365	0	1	32013
College and above	0.100	0.300	0	1	32013
Employed	0.812	0.391	0	1	32013
Internet usage	0.409	0.492	0	1	32013
City-level Covariates					
ln(GDP)	5.171	1.051	3.26	7.60	32013
Service industry percentage	43.760	9.290	18.44	79.10	32013
ln(Population)	8.433	0.628	6.88	10.43	32013

Notes: This table shows the descriptive statistics of our main variables, including the mean, standard deviation, minimum, maximum, and observations. For a detailed description of these variables, see Appendix Table A1.

Table 2: Baseline Results: Housework

Dependent Variable: Housework	(1)	(2)	(3)	(4)	(5)
Treat	-0.202***	-0.198***	-0.197***	-0.182**	-0.165**
	(0.072)	(0.072)	(0.075)	(0.074)	(0.075)
Individual demographic controls	YES	YES	YES	YES	YES
Individual SES controls		YES	YES	YES	YES
City controls			YES	YES	YES
City FE	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	
Province linear trends				YES	
Province $\times$ Wave FE					YES
Observations	32012	32012	32012	32011	32010
R^2	0.241	0.254	0.254	0.255	0.257
Num of clusters	112	112	112	112	112
Mean of DepVar	1.997	1.997	1.997	1.997	1.997

Notes: This table explores the effect of the introduction of Eleme in a city on time spent on housework. In all columns, the dependent variable is the mean imputed housework hours per day. Our individual demographic controls consist of age, age squared, and gender. The individual socioeconomic status (SES) controls include hukou status (urban or rural), marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table 3: Heterogenous Time Trends

	(1)	(2)	(3)	(4)	(5)
Panel A: Housework					
Treat	-0.160**	-0.194**	-0.185**	-0.205***	-0.190**
	(0.076)	(0.075)	(0.074)	(0.074)	(0.074)
Panel B: Weighted Housework					
Treat	-0.160**	-0.196**	-0.186**	-0.206***	-0.191**
	(0.077)	(0.076)	(0.075)	(0.075)	(0.075)
City FE	YES	YES	YES	YES	YES
Expansion Group × Wave FE	YES				
Baseline Housework × Wave FE		YES			
Baseline Catering Firm × Wave FE			YES		
Baseline Catering Sales Ratio × Wave FE				YES	
Baseline Catering Employment Ratio × Wave FE					YES
Controls	YES	YES	YES	YES	YES
Observations	32012	32012	29380	29380	29380
R^2	0.255	0.254	0.245	0.245	0.244

Notes: The dependent variables in Panel A and Panel B of this table are the mean imputed housework hours per day and the weighted mean imputed housework hours per day, respectively. Baseline housework is calculated as the average housework hours in each city in the 2010 wave. Baseline catering firm, baseline catering sales ratio, and baseline catering employment ratio are calculated as the city-level number of firms, the ratio of sales to GDP, and the employment ratio of the accommodation and catering industry in 2010. The data on the accommodation and catering industry of each city are from the China Statistical Yearbooks for Regional Economy. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table 4: Restricting to Expansion Groups 2 & 3

Dependent Variables:	Housework		Weighted Housework	
	(1)	(2)	(3)	(4)
Treat	-0.166**	-0.166*	-0.164**	-0.164*
	(0.077)	(0.069)	(0.077)	(0.067)
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	22543	22543	22539	22539
R^2	0.256	0.256	0.257	0.257
Num of clusters	85	4	85	4

Notes: The dependent variables are the mean imputed housework hours and weighted mean imputed housework hours in columns (1)-(2) and columns (3)-(4), respectively. We restrict the sample to the second and third expansion groups, which include cities that were covered by Eleme between 2014 and 2015. We also restrict the regression within a shorter time window (i.e. from the 3rd quarter of 2014 to the 3rd quarter of 2016), which is more focused and concentrated. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. Standard errors in columns (1) and (3) are clustered at the city level, while those in columns (2) and (4) are clustered at the expansion group by wave level, and reported in parentheses. * denotes for significance at 10%, ** at 5% and *** at 1%.

Table 5: Heterogeneity by Family Size

Dependent Variable: Housework	Small Family		Large Family	
	(1)	(2)	(3)	(4)
Treat	-0.189**	-0.172*	-0.401*	-0.281
	(0.077)	(0.088)	(0.218)	(0.225)
Treat × Female		-0.036		-0.243*
		(0.060)		(0.126)
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	26411	26411	5595	5595
R^2	0.247	0.247	0.309	0.310

Notes: The dependent variable is the mean imputed housework hours per day in all columns. We categorize households into two groups by comparing the number of people who eat at home with six (i.e., the 75th percentile). The number of people who eat at home in a small family is six or fewer, while in a large family is more than six. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table 6: Heterogeneity by Family Structure

Dependent Variable: Housework	(1)	(2)	(3)	(4)
Treat	-0.166	-0.298*	-0.435***	-0.466
	(0.108)	(0.165)	(0.127)	(0.356)
With coresident elderly above 65		YES	YES	YES
With coresident children under 18			YES	
With coresident children under 7				YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	15144	2389	3000	327
R^2	0.277	0.269	0.238	0.431

Notes: The dependent variable is the mean imputed housework hours per day in all columns. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table 7: Effects on Leisure and Well-being

Dependent Variables:	Sleep Hours		Weighted Sleep Hours		Health		Life Satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat	0.078	0.047	0.081	0.057	0.066*	0.055	0.001	-0.009
	(0.062)	(0.061)	(0.062)	(0.062)	(0.035)	(0.034)	(0.036)	(0.036)
Treat × Female		0.063**		0.052*		0.022**		0.020*
		(0.031)		(0.030)		(0.011)		(0.011)
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	31923	31923	31912	31912	32010	32010	31998	31998
R^2	0.071	0.071	0.064	0.064	0.194	0.195	0.056	0.056
Mean of DepVar	7.940	7.940	7.834	7.834	0.419	0.419	0.554	0.554

Notes: The dependent variables are the sleep hours in columns (1)-(2), weighted sleep hours in columns (3)-(4), good self-reported health indicator in columns (5)-(6), and life satisfaction indicator in columns (7)-(8). Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Appendix

Figures

Figure A1: Eleme Homepage as of May 2014

Notes: This figure shows a snapshot of the homepage of Eleme as of May 7th, 2014 recovered via the Wayback Machine. The snapshot displays a list of cities that had access to Eleme's services by that date.

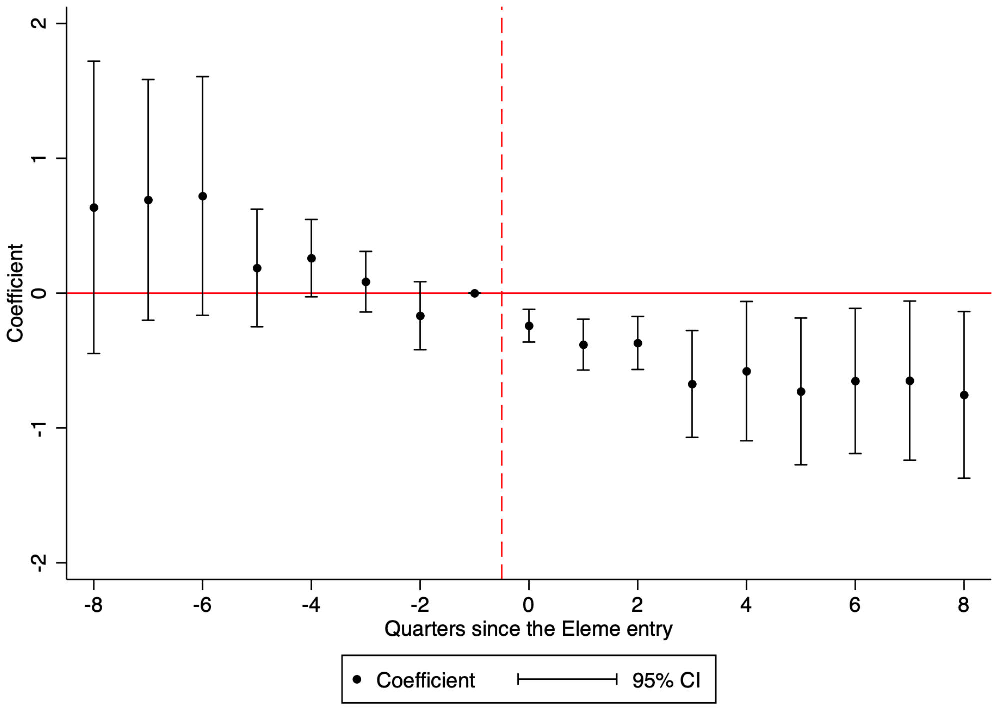
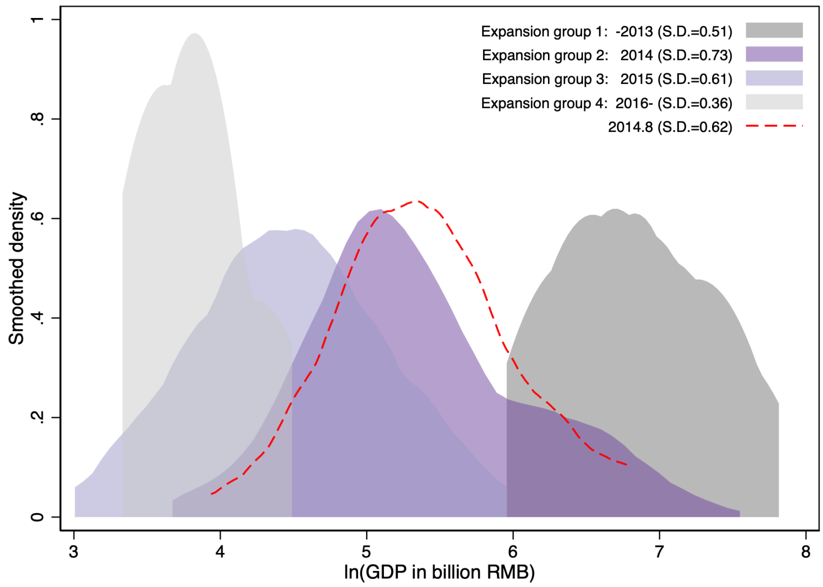
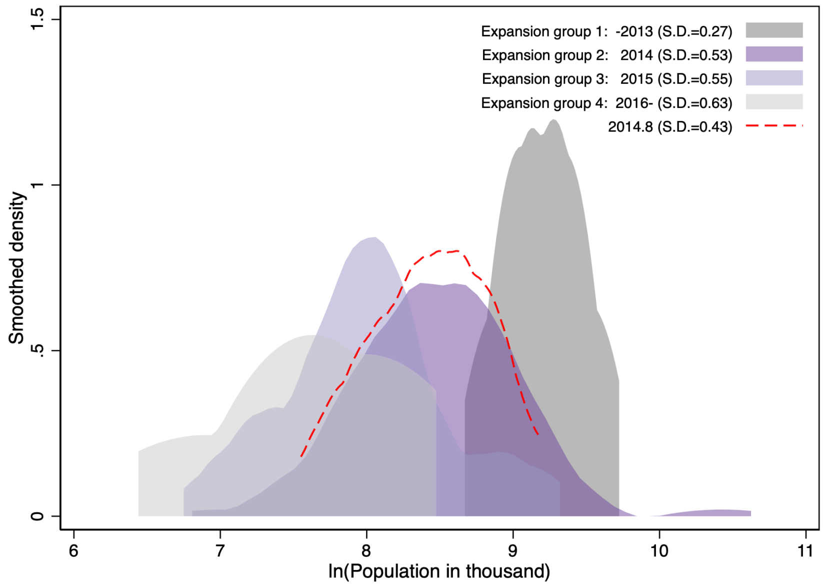


Figure A2: Effects of Eleme on the Time Spent on Weighted Housework

Notes: This figure shows the event study estimates based on equation (3). The dependent variable is the weighted mean imputed housework hours per day. The bars represent 95% confidence intervals. Standard errors are clustered at the city level.



(a) GDP



(b) Population

Figure A3: City Characteristics by Expansion Groups

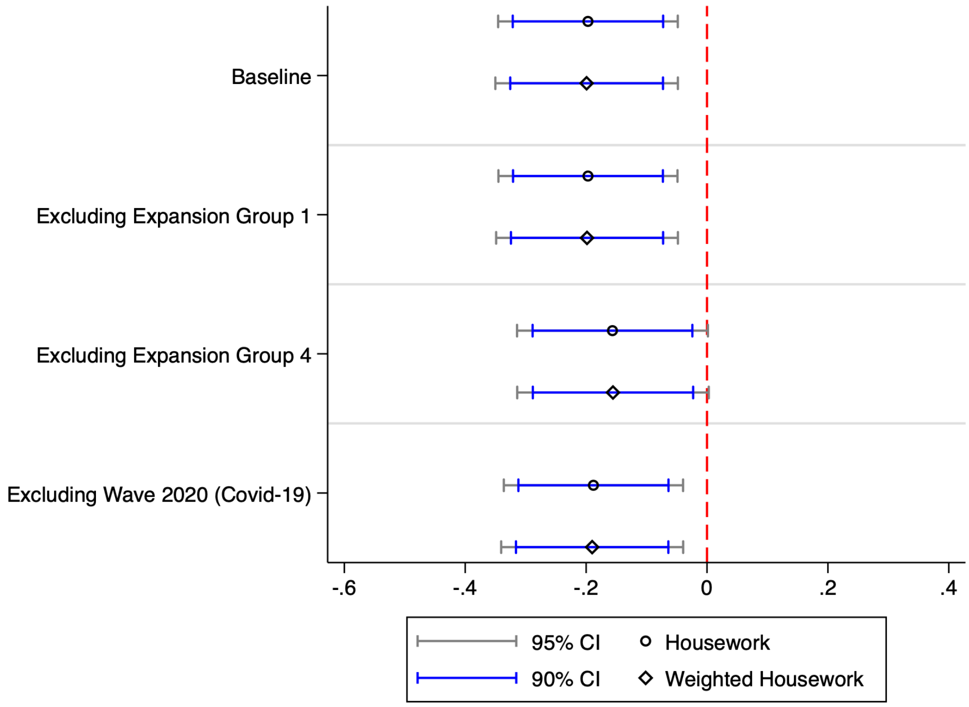


Figure A4: Sample Modification

Notes: This figure shows the estimates based on the equation (1) with various choices of sample. The outcome variables are the mean imputed housework hours, represented by hollow circles, and weighted mean imputed housework hours, represented by hollow diamonds. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

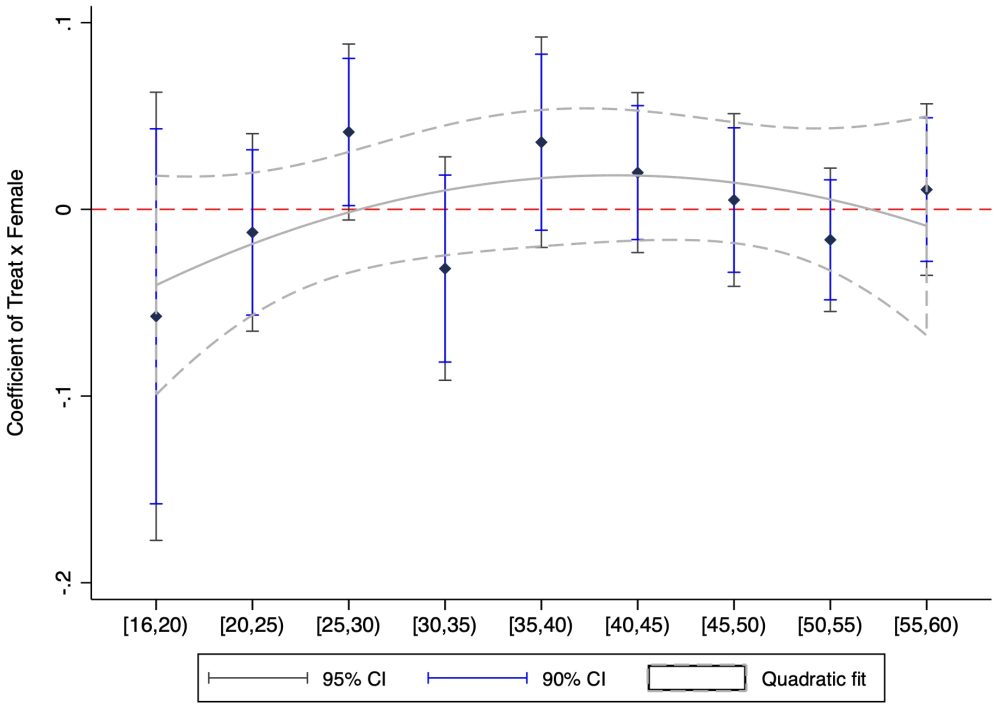


Figure A5: Effects of Eleme on the Extensive Margin of Labor Supply by Age

Notes: This figure shows the estimates of coefficient $\beta_{g,2}$ from equation (4). The dependent variable is the non-farm employment indicator. Each diamond point represents the coefficient of the interaction between treatment status and the female indicator within each specific age group. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

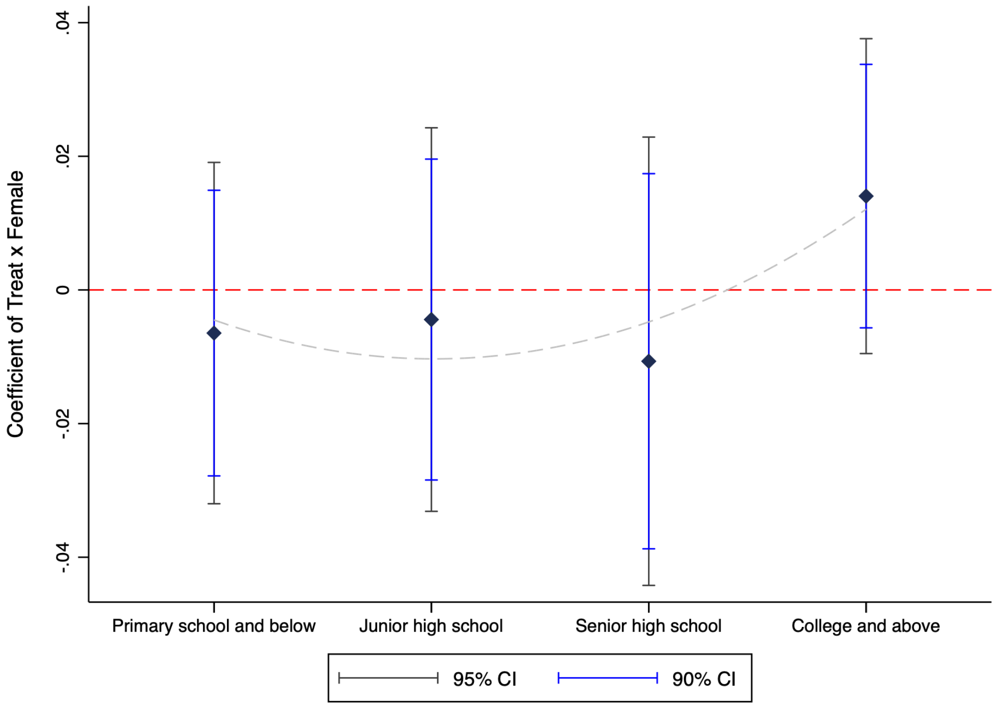


Figure A6: Effects of Eleme on the Extensive Margin of Labor Supply by Education

Notes: This figure shows the estimates of coefficient $\beta_{g,2}$ from equation (4). The dependent variable is the non-farm employment indicator. Each diamond point represents the coefficient of the interaction between treatment status and the female indicator within each specific education group. The blue and gray bars represent 90% and 95% confidence intervals, respectively. Standard errors are clustered at the city level.

Tables

Table A1: Variable Description

Variable	Description
Housework	Mean imputed housework hours per day
Weighted housework	Weighted mean imputed housework hours per day
Treat	Equals to one if Eleme was available in the respondent's city in the quarter and year that he/she took the survey
Age	The respondent's age
Male	Equals to one if the respondent is a male
Married	Equals to one if the respondent was married
Urban	Equals to one if the hukou status of the respondent is urban
Primary school and below	Equals to one if the highest education of the respondent is primary school and below
Junior high school	Equals to one if the highest education of the respondent is junior high school
Senior high school	Equals to one if the highest education of the respondent is senior high school
College and above	Equals to one if the highest education of the respondent is college and above
Employed	Equals to one if the respondent was employed at the survey time
Internet usage	Equals to one if the respondent used the internet at the survey time
ln(GDP)	The natural logarithm of GDP (billion RMB) in the city
Service industry percentage	Proportions of the service industry to GDP
ln(Population)	The natural logarithm of population (thousand person) in the city

Table A2: Baseline Results: Weighted Housework

Dependent Variable: Weighted Housework	(1)	(2)	(3)	(4)	(5)
Treat	-0.205***	-0.200***	-0.199**	-0.183**	-0.166**
	(0.072)	(0.073)	(0.076)	(0.075)	(0.076)
Individual demographic controls	YES	YES	YES	YES	YES
Individual SES controls		YES	YES	YES	YES
City controls			YES	YES	YES
City FE	YES	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES	
Province linear trends				YES	
Province × Wave FE					YES
Observations	32005	32005	32005	32004	32003
R^2	0.241	0.257	0.257	0.258	0.260
Num of clusters	112	112	112	112	112
Mean of DepVar	1.959	1.959	1.959	1.959	1.959

Notes: This table explores the effect of the introduction of Eleme in a city on time spent on housework. In all columns, the dependent variable is the weighted mean imputed housework hours. Our individual demographic controls consist of age, age squared, and gender. The individual SES controls include hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table A3: Baseline Results: Housework on Weekdays and Weekends

Dependent Variables	Housework on weekdays (1)	Housework on weekends (2)
Treat	-0.586***	-0.458***
	(0.148)	(0.086)
City FE	YES	YES
Wave FE	YES	YES
Controls	YES	YES
Observations	13473	13473
R^2	0.269	0.235
Mean of DepVar	1.707	2.110

Notes: The dependent variables are time used for housework on weekdays and weekends in columns (1) and (2), respectively. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table A4: Robustness: Alternative FEs

Dependent Variables:	Housework			Weighted Housework		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.272**	-0.290*	-0.395*	-0.277**	-0.275*	-0.364*
	(0.131)	(0.160)	(0.215)	(0.130)	(0.158)	(0.212)
Individual FE	YES	YES	YES	YES	YES	YES
Wave FE	YES	YES		YES	YES	
Survey-quarter FE		YES			YES	
Survey-year-by-quarter FE			YES			YES
Controls	YES	YES	YES	YES	YES	YES
Observations	19331	19331	19331	19321	19321	19321
R^2	0.685	0.685	0.686	0.686	0.686	0.686
Num of clusters	91	91	91	91	91	91
Mean of DepVar	2.164	2.164	2.164	2.123	2.123	2.123

Notes: The dependent variables are the mean imputed housework hours and weighted mean imputed housework hours in columns (1)-(3) and columns (4)-(6), respectively. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table A5: Robustness: Alternative Clustering Methods

Dependent Variables:	Housework		Weighted Housework	
	(1)	(2)	(3)	(4)
Treat	-0.198**	-0.198**	-0.200**	-0.200**
	(0.089)	(0.081)	(0.092)	(0.084)
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	32012	32012	32005	32005
R^2	0.254	0.254	0.257	0.257
Num of clusters	26	9	26	9

Notes: The dependent variables are the mean imputed housework hours and weighted mean imputed housework hours in columns (1)-(2) and columns (3)-(4), respectively. Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. Standard errors in columns (1) and (3) are clustered at the province level, while those in columns (2) and (4) are clustered at the expansion group by wave level, and all standard errors are reported in parentheses. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.

Table A6: Effects on Labor Market

Dependent Variables:	Non-farm Employment	Hours Conditional on Non-farm Work	Wages Conditional on Non-farm Work	
	(1)	(2)	(3)	(4)
Treat	0.055**	-1.178	0.375***	0.306***
	(0.026)	(1.163)	(0.078)	(0.081)
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
City linear trends				YES
Controls	YES	YES	YES	YES
Observations	27960	11671	14452	14452
R^2	0.415	0.099	0.172	0.183
Mean of DepVar	0.580	52.823	1.661	1.661

Notes: This table presents the average treatment effect of Eleme entry on the labor market outcomes. The dependent variables are the non-farm employment status in column (1), hours conditional on non-farm work in column (2), and wages conditional on non-farm work in columns (3)-(4). Our control variables consist of age, age squared, gender, hukou status, marital status, indicators for highest education (primary school and below, junior high school, senior high school, college and above), employment, and internet usage at the individual level, and GDP (in natural log), population (in natural log), and the share of the service industry at the city level. For a detailed description of the outcome, treatment, and control variables, see Appendix Table A1. * denotes for significance at 10%, ** at 5% and *** at 1%. Standard errors in parentheses are clustered at the city level.