Why is Female Labor Force Participation Declining in China? A Perspective from Urban Commuting*

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Abstract

Increased commuting time due to traffic congestion is a widespread problem faced by almost all major cities in the world. In addition to environmental pollution and personal health issues, it can also negatively impact the labor supply. Utilizing microdata from China's 1% population census data in 2015, we find that for every additional minute of commuting time, the probability of labor participation among married women decreases by an average of 0.50 percentage points. The variation in commuting time can explain 41.1% of the difference in labor participation rates of married women across cities in our sample. Our study also sheds light on the puzzle of declining female labor participation in China in the past decade, particularly in the context of the nation's rapid urban expansion and escalating commuting time.

Keywords: Commuting Duration; Female Labor Participation; Potential Urban Form; 2SLS Estimation

JEL Classification: R14, R41, R58, J16, J22, O18

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1 Introduction

Since establishing the market economy in 1992, China has undergone a rapid urbanization process, with the urbanization rate increasing from 26.4% in 1990 to 63.9% in 2020 — a 1.25 percentage points annual increase on average. During the same period, the urban population surged from 302 million to 902 million, with an annual growth rate of 3.7%. While the urban expansion has brought positive social and economic impacts such as scale effects and higher productivity (Duranton et al., 2015), it also brings negative impacts such as severe traffic congestion and longer commuting time (Newman and Kenworthy, 1999; Blau and Kahn, 2000; Harari, 2020). For example, in Beijing main urban area, the average one-way commuting time for office workers increased from 45 minutes in 2010 to 51 minutes in 2021. Other major cities with populations over 10 million also experienced increases of a similar scale: Chengdu by 8 minutes, Wuhan and Zhengzhou by 7 minutes, and Xi'an and Hefei by 6 minutes. In addition to personal health losses (Currie and Walker, 2011; Simeonova et al., 2021) and environmental pollution (Chen et al., 2021), excessive commuting time can lead to worker fatigue, reducing work efficiency and working hours (Gutiérrez-i Puigarnau and van Ommeren, 2015; Carta and De Philippis, 2018).

In this paper, we examine how the average commuting time affects female labor participation in China's urban areas. Our study is motivated by the observation that the labor participation rate of Chinese women (aged fifteen and above) has experienced a substantial decline, dropping from 73% in 1990 to 64% in 2010, and subsequently to 60% in 2020. As the average education level for Chinese women continues to increase, the withdrawal of a large number of well-educated women from the labor market represents a tremendous waste of human capital. Meanwhile, China is also experiencing a rapid population aging. By the end of 2022, the proportion of the elderly population aged 65 has reached 14.9%, doubling its level from 7.0% in 2000. Under this trend of deepening population aging, the decline of female labor participation draws even more attention and raises the long-standing question that has not yet been satisfactorily answered in the literature (Hare, 2016): what causes the continuous decline in female labor participation in China? Using a unique individual-level data set matched by China's 2015 mini-census and corresponding urban geographic information, this paper contributes a novel discussion to this question from the perspective of urban commuting time.

Using the exogenous variation in the potential urban form that we constructed for China's urban areas (county level), we find that when the average commuting time increases by one minute, the probability of labor participation among married women decreases by 0.50 percentage points on average. Across different counties in our sample, the range between the longest and shortest average commuting duration is 48.1 minutes, which suggests 24.0 percentage points difference in labor participation given everything else equal. This counts for more than 40% of the 59.8 percentage points range of married women's labor participation rate across different counties. Furthermore, based on our estimates, a 4.7-minute increase in commuting time accounts for a decrease of 2.35 percentage points in married women's labor participation rate, which is more than 40% of the total 5 percentage points decrease between 2008 and 2020. These effects are significant both economically and statistically.

Our paper contributes to the literature that estimates the impact of urban commuting time on labor supply. Existing studies have not reached a consensus. For example, Cogan (1980) hypothesizes that longer commuting time would negatively affect working hours, but the data did not support this conclusion. In contrast, some studies have found that longer commuting time increase individuals' weekly working hours (Gutiérrez-i Puigarnau and van Ommeren, 2015; Gimenez-Nadal et al., 2018). There are papers which particularly focus on female labor supply. Black et al. (2014) estimate the effect of commuting time on wives' labor supply using data from 50 major cities in the United States, finding that an increase in commuting time leads to wives withdrawing from the labor market. Kawabata and Abe (2018) assess the impact of commuting time on female labor participation and workspace distribution patterns based on data from urban Tokyo, Japan. Their results indicate a significant negative effect of commuting time on the labor participation of married women with children, but the impact is not significant for unmarried women or married women without children. In contrast to the aforementioned studies, our paper does not rely on panel data, and we focus on the key explanatory variable of the average urban commuting time at the county level. As we will discuss in greater detail in the main text, this choice links directly to our identification strategy and policy discussions.

To the best of our knowledge, our paper is the first to rigorously examine the effect of commuting time on female labor participation in emerging developing economies from an empirical standpoint with large-sample microdata. While we focus on China, our result can be a useful reference for other emerging developing countries such as India, Indonesia, and Vietnam because they are also undergoing rapid urbanization. With the expansion of cities, these developing countries' major cities are also facing increasingly severe traffic congestion issues. These countries also share similar characteristics to China, such as male dominance in the labor market and having the need to improve a low female labor force participation rate. Empirically quantifying the causal impact of commuting duration on Chinese women's labor participation helps the understanding of the significance of improving urban commuting in these developing countries.

Our paper contributes to the study of Chinese females' status in the labor market. It provides an explanation of the continual decline of female labor participation rates over the past few decades from a novel perspective of commuting time. In the last 60 years, the United States, the European Union, Japan, and South Korea have all experienced a continuous rise in female labor participation rates, prompting numerous scholars to conduct empirical research on female labor participation. Some scholars have argued the relationship between fertility rates and female labor participation, positing that a decline in fertility rates is one of the essential reasons for the increase in female labor supply and promoting economic growth (Angrist and Evans, 1996; Bloom et al., 2009).[1] Unlike the world's major developed countries, China, as the largest developing country, has experienced a significant decline in its total fertility rate over the past 30 years, from 2.5 in 1990 to 1.3 in 2020. Yet, the labor participation rate of Chinese women aged 15 and above has continuously decreased. Fertility behavior is unlikely the main reason for the decline in the labor participation rate of Chinese women. Our research shows that an increase in urban commuting time has a significant negative impact on female labor participation, and it explains the variations in female labor participation rate across regions and time.

Our paper also contributes to the studies of China's urban development by providing a reliable identification strategy for the impact of commuting time on labor supply. It is well understood that OLS estimators are likely biased in this context for various reasons. For example, commuting time can be mismeasured, causing attenuation bias if the measurement error is classical. There are unobserved confounders at the individual level that affect both labor participation and commuting time. A more capable female is more likely to work and can afford to live in better locations, inducing omitted variable bias if these factors are ignored. The endogeneity issues

[1] To date, numerous scholars have researched the impact of paid maternity leave, childbirth, husband's wages, and changes in working hours on female labor participation or supply (Angrist and Evans, 1996; Cruces and Galiani, 2007; Stancanelli and Soest, 2012; Liu et al., 2022). However, only a few studies have considered the impact of commuting time on female labor supply.

can also rise at the city level. For example, unobserved factors such as the local government's governance ability can confound the actual urban form and labour participation rate. Ignoring the sorting of individuals across cities also leads to a downward bias in OLS estimates. In this paper, we take advantage of China's fast urbanization process since 2000, a feature we do not observe in most developed countries. Thus, our identification strategy is significantly different and complements the existing research focuses on developed countries.[2] Specifically, based on the nighttime light remote sensing data, we are able to calculate the *potential urban footprint* in the year 2015 for each county-level urban area following the method of Harari (2020). Using the form of the *potential urban footprint*, we further calculate correspondingly compactness indices as our instrumental variables for commuting time. As argued in Harari (2020), the *potential urban footprint* (hence the compactness indices) tends to be orthogonal to the selection effects in the urbanization process and, therefore, can serve as a valid IV. We also conducted a series of tests on the validity of these instruments; the results show that the validity is not rejected.

The rest of the article is organized as follows. Section 2 introduces some basic facts about commuting and labor participation of Chinese women and the data and variables used. Section 3 introduces the identification strategy. We report empirical results in Section 4 and analyze the heterogenous effect in Section 5. Section 6 concludes the paper.

2 Data

2.1 Data Sources and Definition

We primarily focus on the labor supply of married women in China. The reason for selecting married women as the research subject is that this group contributes most to the substantial changes observed in female labor participation over the past few decades (Juhn and Potter, 2006). We draw our primary data from China's 1% population census data in 2015 (also known as the 2015 Mini Census). This data encompasses the entire nation, with county-level cities as subpopulations, and it employs the stratified, two-stage, probability proportional, and cluster sampling methods. It surveys the registered permanent population in 31 provinces, directly governed municipalities, and autonomous regions, covering 21.31 million people, or 1.55% of

[2] For example, Gutiérrez-i Puigarnau and van Ommeren (2015) and Carta and De Philippis (2018) utilize the employer-driven changes in commuting distance to identify the causal impact, as we will discuss in more detail in Section 2.

the total population. The data used in this article further systematizes the sampled data, representing 1.5‰ of the total population, or 2.003 million individuals. Only samples with husbands aged 20-60 and wives aged 20-50 are retained,[3] excluding wives who are students. The county-level variables used in the paper mainly come from the CEIC China Economic Database. In the later empirical strategy section, we will detail the construction process of the instrumental variable and the specific sources of related data.

2.1.1 Dependent Variable.

The dependent variable of interest is women's labor participation (*Flp*). The 2015 Mini Census data provides a survey of individual work status, specifically divided into three categories: working, in job training or seeking work, and not working. Following the current mainstream literature (Chen and Ge, 2018; He and Zhu, 2016), we define the first two categories as participating in the labor market, with the variable Flp valued at 1, and the third category as not in the labor market, with *Flp* valued at 0.

2.1.2 Core Explanatory Variable.

The 2015 Mini Census data provides a survey on individual commuting conditions, asking about the time required for individuals to travel to work. This is the only large-scale individual-level commuting duration survey data available in China's population census data over the years. The core explanatory variable of this article is the average commuting time of all individuals in the county where a married woman resides (*commut*).

2.1.3 Control Variables.

The 2015 Census contains detailed individual characteristics for both husbands and wives, such as the ages, years of education, the wife's ethnic group (Han Chinese valued at 1 and other ethnicities at 0), the wife's household registration (rural area valued at 1 and non-rural at 0), the number of children in the family (Childnum), whether the residence is rented (Renthouse, equals to 1 with rented home), and whether the husband participates in work (Flp_hus, with participation valued at 1 and otherwise at 0).

[3] In China, the statutory retirement age is 50 for females and 60 for males.

2.1.4 Instrumental Variable.

In existing literature, one popular identification strategy is to use natural experiments such as changes in commuting distance due to company address changes (Zax and Kain, 1996; Gutiérrez-i Puigarnau and van Ommeren, 2015; Carta and De Philippis, 2018). We do not use company address changes as the instrumental variable for commuting time because our core explanatory variable is commuting time, not distance. In addition, our data set is cross-sectional data, and it does not contain information about the address change of companies. Instead, we rely on the variation in the geographic shape of urban areas. We first use the nighttime light remote sensing data from the Defense Meteorological Satellite Program (DMSP) of the United States Department of Defense and the Suomi NPP (a new generation of Earth observation satellite launched in 2011) and calculate the *potential urban footprint* defined in Harari (2020). Next, using the *potential urban footprint*, we construct two compactness indices (see Angel et al., 2005), namely the standardized Cohesion index (Ncohension) and standardized Range index (Nrange), as our instrumental variable. A less compact urban form often leads to longer commuting time. Therefore, these indices satisfy the relevance condition for instrumental variables. On the other hand, the potential urban footprint depends on historical and geographical conditions, is less likely to be correlated with current policy choices on urban planning, and therefore meets the exogeneity condition. Please see more discussions in Section 3.

2.2 Descriptive Analysis

Table 1 reports the descriptive statistics of the variables. The overall labor participation rate of Chinese women in our sample is about 72.1%. Women whose average commuting time at the prefecture-level city is less than 35 minutes have a notably higher labor participation rate than those with commuting time exceeding 35 minutes, indicating a negative correlation between urban commuting time and female labor participation. Areas with longer commuting time have a higher probability of families renting homes. In addition, the average age of husbands is about 3 years older than that of wives, with an average of approximately 0.4 more years of education. In the sample, the proportion of wives who are Han Chinese is 95.6%, those with rural household registration account for 62.2%, the average number of children borne by women is 1.54, and 11.3% of families choose to rent their homes. Lastly, we find that the labor participation rate of matched husbands is 89.7%, which is about 18 percentage points higher than the average level of wives.

Table 1: Descriptive Statistics

	All *N=135780*		*Commute_ave>=35* *N=69821*		*Commute_ave<35* *N=65959*		*Difference*
	(1)		(2)		(3)		(3)-(2)
Variables	mean	S.D.	mean	S.D.	mean	S.D.	
Flp	0.721	0.449	0.690	0.462	0.753	0.431	0.063***
Commute/100	0.378	0.102	0.453	0.090	0.300	0.033	-0.153***
Age	40.182	7.248	39.899	7.244	40.480	7.240	0.581***
Age_hus	43.525	8.775	43.270	8.833	43.794	8.704	0.524***
School	9.548	3.167	9.971	3.366	9.102	2.877	-0.869***
School_hus	9.936	2.984	10.322	3.189	9.527	2.691	-0.795***
Han Chinese	0.956	0.205	0.950	0.217	0.962	0.191	-0.012***
Rural	0.622	0.485	0.536	0.499	0.713	0.452	0.177***
Childnum	1.539	0.789	1.481	0.801	1.600	0.772	0.119***
Rent	0.113	0.316	0.130	0.336	0.095	0.293	-0.035***
Flp_hus	0.897	0.304	0.877	0.328	0.918	0.274	0.041***
Ncohesion	1.119	0.226	1.141	0.273	1.096	0.158	-0.045***
Nrange	1.247	0.185	1.278	0.209	1.215	0.150	-0.063***
Nproximity	1.067	0.088	1.078	0.103	1.055	0.067	-0.023***
Nspin	1.176	0.255	1.209	0.304	1.141	0.182	-0.068***

Figure 1 plots the average commuting time and the average labor participation rate of women in different prefecture-level cities. It can be seen that there is a very large difference in the average commuting time across different cities. The longest average commuting time is in the suburban counties of Beijing, at 70.7 minutes, while the shortest is in Suizhou City, Hubei Province, at only 22.6 minutes, with a difference of 48.1 minutes between these two. There is also a very large difference in female labor participation rates in different cities. The labor participation rate in Shigatse, Tibet, reaches 93.0%, while in Baoshan, Yunnan Province, reaches 92.4%, while in Suozhou City, Shanxi Province, the average labor participation rate for women is only 34.1%, a difference of 58.3 percentage points. Overall, there is a negative correlation between urban commuting and female labor participation rates, with a simple correlation coefficient of -0.13.

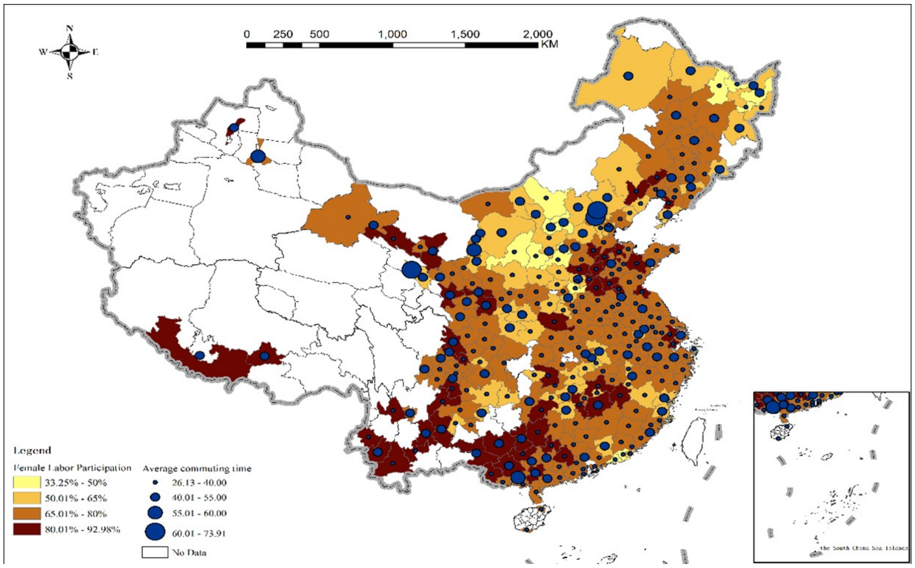

Figure 1: Urban average commuting time and female labor participation rate of Chinese prefecture cities in 2015

3 Empirical Strategy

We estimate the impact of average commuting time on females' labor participation based on the following regression equation:

$$Flp_{ic} = \beta_1 commut_{ic} + \beta_2 X_{ic} + p_i + \varepsilon_{ic} \tag{3.1}$$

Here, Flp_{ic} is the labor participation status of women i in county c, valued at 1 if she participates in the labor market and 0 if she exits the labor market. $commut_{ic}$ is the average urban commuting time in the county c where woman i resides divided by 100 (for a better presentation of the results). X_{ic} are other control variables affecting her labor participation, p_i represent the province in which i lives in, and ε_{ic} is the error term. Here, β_1 reflects the impact of average commuting duration on wives' labor participation.

The main challenge in estimating β_1 is the endogeneity of $commut_{ic}$. The average commuting time in the city c observed at a specific point in time is determined by exogenous geographic factors and endogenous factors such as the city's governance policy choices. A city with stronger governance ability can deliver better urban traffic planning and other economic policies, affecting both commuting time and labor participation rate. Individual sorting across cities can also bias the OLS estimates. Costa and Kahn (2000) show that high-power couples tend to sort into larger cities to solve co-located work problems.[4] Since commute times tend to be longer in large cities, OLS generally underestimate the commuting effect when sorting is present (Farré et al., 2023). To address estimation bias caused by endogeneity issues, we use the instrumental variable approach that explores the exogenous variation of geographic shapes across different urban areas. Specifically, we construct the compactness indices of the potential urban footprint of the main economic activity area in the county as instrumental variables. On the one hand, urban compactness is relevant to commuting time. Since 1990, China has undergone rapid urbanization characterized primarily by the rapid expansion of urban land area Wang et al. (2020). "Urban sprawl" leads to changes in the spatial form of urban agglomerations, leading to increasingly "non-compact" urban forms (Angel et al., 2010). The non-compact urban form can create a series of difficulties in providing public goods and services, resulting in higher commuting costs and limited transportation choices Bento et al. (2005). On the other hand, as argued in Harari (2020), the potential urban footprint measure explores the exogenous topographic obstacles along the urban area's expansion path and is likely to be orthogonal to the unobserved confounders such as urban planning policy. Our IVs also share a similar spirit as those that have been used in urban economics. For example, Baum-Snow (2007) uses the planned portions of the interstate highway system as the instrumental variable for the total number of highways built. In the remaining part of this section, we will discuss how we construct these variables in greater detail and discuss the sorting issue in Sections 4.3 and 4.4.

3.1 Measurement of Urban Form

The development of remote sensing technology and the availability of nighttime light remote sensing data have made it possible to measure the shapes of build-up urban polygons more precisely (see studies in Angel et al., 2005; Cao et al., 2019; Chen et al., 2019). In this paper, we also rely on the nighttime light remote sensing data, which comes from two sources. The first is from the Defense Meteorological Satellite Program (DMSP) of the United States Department of Defense, which provides DMPS-OLS data with a sensor spatial resolution of 3000 meters. The generated nighttime light remote sensing products typically have a spatial resolution of 1000 meters, covering the period from 1992 to 2013. The second source is Suomi NPP, a new generation of Earth observation satellite launched in 2011. This satellite carries a Visible

[4] Costa and Kahn (2000) defines high-powered couples as couples in which both husband and wife have earned a college degree.

Infrared Imaging Radiometer Suite (VIIRS), which can acquire new nighttime light remote sensing images (Day/Night Band, DNB wavelength). The spatial resolution of NPP-DNB has been improved to 750 meters, and the generated nighttime light remote sensing products usually have a spatial resolution of 500 meters, covering from 2012 to the present. Due to issues such as lack of radiometric calibration and light spillage, nighttime light remote sensing data requires preprocessing (Letu et al., 2010; Levin et al., 2020). We adopt the processing method of Chen et al. (2021), where the calibrated long-term series data show good pixel consistency.

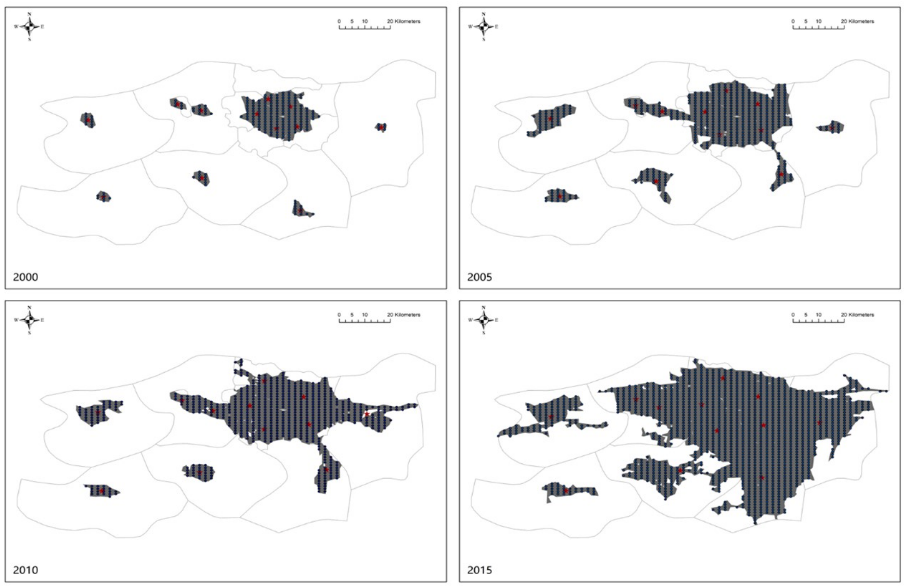

Figure 2: Urban Form Changes in Zhengzhou City from 2000 to 2015

We illustrate the evolution of urban form using the prefecture of Zhengzhou as an example. Specifically, Figure 2 displays built-up areas of eleven counties (including county-level cities) in Zhengzhou in 2000, 2005, 2010, and 2015, where the pentagrams represent the physical centers of each district. As we can observe from the figure, there has been a fast expansion of the build-up areas, which is consistent with the data published in statistical yearbooks. For instance, in 2000, Zhengzhou City had an urban area of 1,287 square kilometres and a total population of 6,659,000; by 2015, the urban area had increased to 2,220 square kilometres, and the urban population had reached 10,692,000. Furthermore, the form of the build-up areas and corresponding compactness indices (formally defined in Section 3.3) for different counties also demonstrate significant cross-sectional variations.

3.2 Potential Urban Form

The observed urban form itself results from economic, social, and balanced urban development, so we cannot directly use it to construct instrumental variables for commuting time. Following Harari (2020), we use the potential urban form instead. The basic idea is that during urban expansion, exogenous topographical obstacles can lead to changes in urban form, significantly impacting the construction of transportation infrastructure in counties and affecting people's commuting duration. We first demarcate the largest contiguous area of developable land within each county and refer to it as the "potential maximum developable range". Then, based on the predicted population data of the county and the baseline population density, the potential area of the county-level city during the sample period is predicted,[5] and the radius of the equivalent area circle for this potential area is estimated. Next, the *potential urban footprint* is determined as the intersection of the "potential maximum developable range" and the circle with the predicted radius. Finally, various compactness indices are calculated as instrumental variables, as detailed in Section 3.3. The following algorithm itemizes the steps.

Algorithm 3.1 *Consider following steps:*

1. *Using population census data from 1982 and 1990, calculate the average annual population growth rate for each county and use this rate for trend extrapolation to obtain mechanically grown data* $\widehat{pop_{c,t}}$*;*

2. *Identify the largest area of developable land within the radius of the county-level city (excluding water bodies, excluding areas with a slope of more than 15°), to determine the "potential maximum developable range" of the county;*

3. *Starting from the year 2000 county boundaries, predict the potential footprint of the county-level city in 2015, completed in three steps:*

   (a) *Predict the potential area of the county-level city in 2015.*[6]

$$\log(area_{c,2015}) = \alpha \log(\widehat{pop}_{c,2015}) + \beta \log\left(\frac{pop_{c,2000}}{area_{c,2000}}\right) + f_p + \varepsilon_{c,t}$$

[5] Using predicted growth is crucial because endogenous factors could influence actual growth.

[6] It is important to note that in the regression prediction of county-level area, we included the fixed effect f_p at the prefecture-level rather than county-level. This is because using county-level fixed effects could lead to overfitting. With the prefecture-level fixed effect, the R^2 is 73%.

(b) Calculate the predicted radius under the equivalent area circle and use $\hat{r}_{c,t}$ to demarcate the predicted boundaries of the county-level city and outline the shape of the county-level city.

$$\hat{r}_{c,t} = \sqrt{\frac{\widehat{area}_{c,2015}}{\pi}}$$

(c) The potential urban footprint $\tilde{S}_{c,t}$ is the intersection of the circle with radius $\hat{r}_{c,t}$ and the "potential maximum developable range" from Step 2. Figure 3 shows the estimation process of the potential urban form.

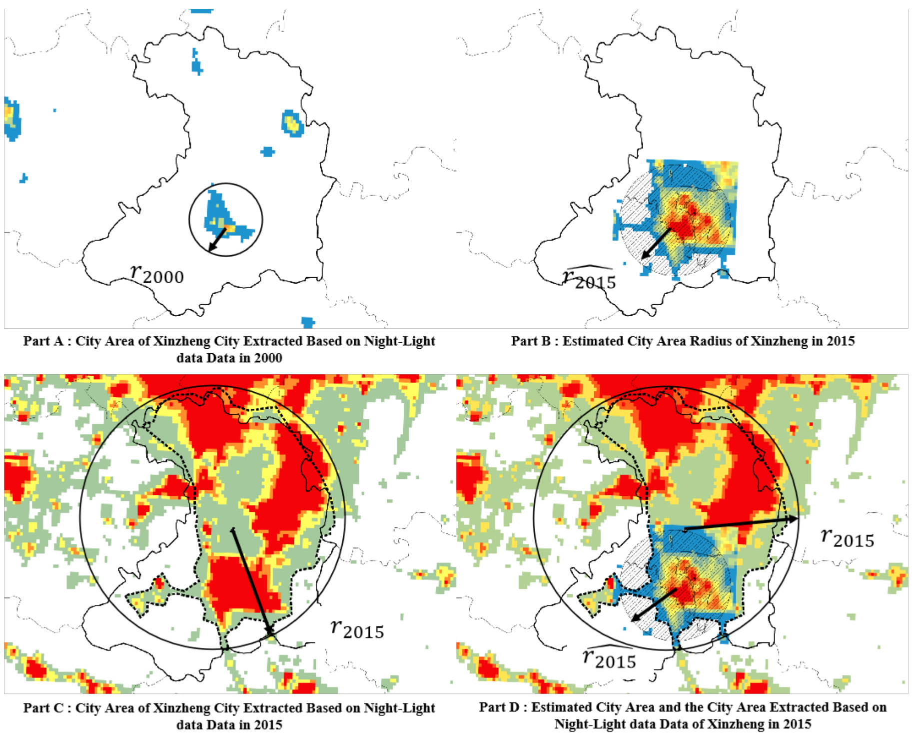

Figure 3: Potential city shape estimation

3.3 Potential Urban Compactness Index

The concept of "compactness" of an urban area originates from urban planning and landscape ecology. In this paper, we use the compactness indices proposed in Angel et al. (2010) to measure the urban form for each county in 2015. Specifically, we focus on the Cohesion index and Range index.[7] To calculate the Cohesion index, we first create a grid of 20,000 points

[7] Angel et al. (2010) proposed four types of urban form indices, in addition to the Cohesion index and Range index used in this paper, which also includes the Proximity index and Spin index. Table 1 reports the descriptive

evenly distributed in a grid pattern throughout the urban polygon. Then, independently for each replication $k = 1, 2, \cdots 30$, we randomly draw 1,000 points from this grid and calculate the average distance among all pairs for each replication, and further average them across 30 replications:

$$\text{Cohesion} = \frac{1}{30}\sum_{k=1}^{30}\text{Cohesion}_k, \quad \text{Cohesion}_k = \frac{1}{n}\sum_{i=1}^{n} d_{i,k}$$

where $d_{i,k}$ is distance between the i-th pair drawn in the k-th replication and $n = 999 \times 500$ is the total number of pairs for each replication. Figure 4 illustrates the calculation for one replication. To separate the potential urban scale from geometric effects, as in Harari (2020), we normalize it by the Cohesion index of "Equivalent Area Circle" (EAC), which is a circle with an area equal to that of the targeted polygon.

$$\text{normalized Cohesion(nCohesion)} = \frac{\text{Cohesin}}{\text{Cohesion}_{EAC}}$$
$$\text{Cohesion}_{EAC} = 0.9054 \times \text{radius}_{EAC}$$

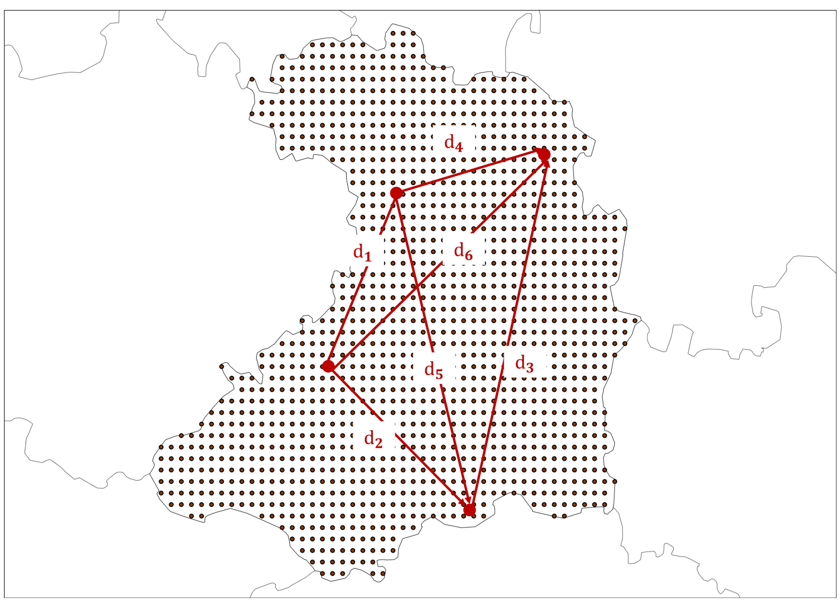

Figure 4: Example of Cohesion Index

The second is the Range index, which captures the maximum distance between two points randomly selected from the shape's perimeter, representing the possible longest distance between two points within the urban polygon. Again, we replicated it for 30 and normalized the range

statistics of these two indices, and Appendix Table 6 uses these two potential indices for robustness testing.

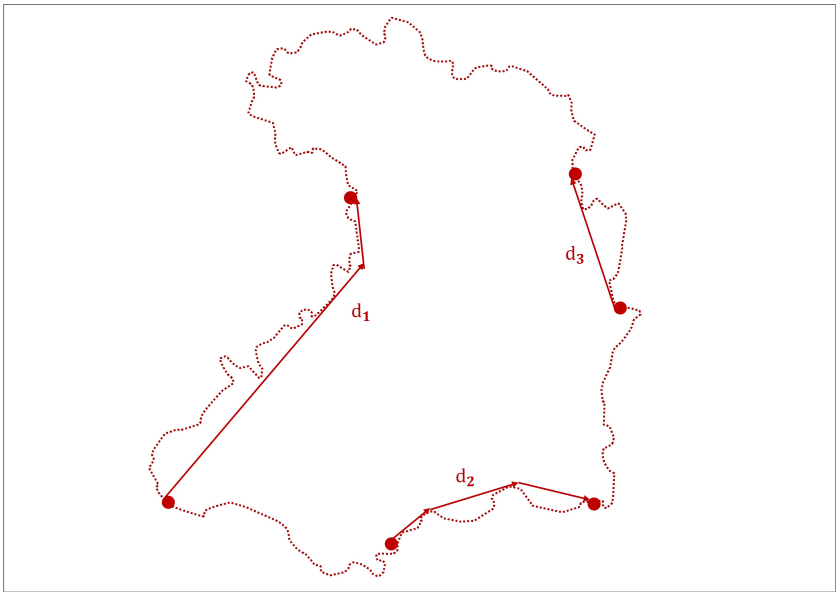

Figure 5: Example of Range Index

index using the EAC.

$$\text{Range} = \frac{1}{30}\sum_{k=1}^{30}\text{Range}_k, \quad \text{Range}_k = \max(d_{1,k}, d_{2,k}, \ldots, d_{n,k})$$

$$\text{normalized Range}\,(nRange) = \frac{\text{Range}}{\text{Range}_{EAC}}$$

Both the Cohesion index and the Range index are inverse indicators of urban compactness. A larger value of these indices implies a less compact urban form. When other conditions are equal, a less compact city means longer distances between two points within the city, and thus, longer commuting time. Table A.1 in the Appendix lists the compactness indices calculated from the potential urban forms of various counties in Zhengzhou, as well as the average commuting time. We find a strong positive correlation between the normalized indices and commuting duration. With these indices as IVs, the first stage estimation equation is given by

$$\text{commut}_{ic} = \alpha_1 N\tilde{S}_{ic} + \alpha_2 X_{ic} + p_i + \varepsilon_{ic}, \tag{3.2}$$

where $N\tilde{S}_{ic}$ is the normalized compactness indices based on the potential urban form of the county-level area c where individual i resides.

4 Empirical Results

4.1 Baseline Results

We first report the OLS estimates of the linear probability model as a baseline reference.[8] From Table 2, we can see that commuting time significantly negatively impacts women's labor participation. The same conclusion holds with or without including other controls and provincial or prefecture-level dummy variables. A one-minute increase in the average commuting time in a city will lead to a decrease in women's labor participation rate of about 0.25 percentage points (see columns 3 and 4). The estimated results of other control variables also conform to economic expectations, for example, women's own age has an inverted U-shaped impact on their labor participation, which is consistent with the life-cycle theory expectations. Women's years of education have a positive impact on their own labor participation, while the husband's years of education have a negative impact on the wife's labor participation.

4.2 IV Regression

Introducing a set of control variables to the model does not resolve the potential problems of omitted variables and simultaneity selection, as we discussed before. We then use the compactness indices constructed in Section 3 as IVs and perform a 2SLS estimation. Table A.2 in the appendix reports the first-stage regression results. Using either the normalized cohesion index or range index, we find that a less compact urban area is associated with longer commuting duration, and both are significant at the 1% level. This result is also consistent with Harari (2020). The first-stage results show that each kilometer increase in the normalized potential cohesion index or range index will increase the average commuting duration in the city by 5.1 minutes or 8.4 minutes, respectively.

Table 3 reports the main regression results of this paper. Columns 1 and 2 use the Cohesion index as the instrumental variable, columns 3 and 4 use the Range index, and columns 5 and 6 include both the Cohesion index and Range index as instrumental variables. Under different instrumental variable settings, the county average commuting duration has a significant negative impact on female labor participation. The results of the 2SLS estimation using all control

[8]We also estimate the IV-Probit model, and the results are qualitatively similar. For exposition purposes, we only report the results of the linear probability model in the main text. The results for IV-Probit model is discussed in the robustness analysis (Section 4.4).

Table 2: The Impact of Commuting Duration on FLP: OLS

	(1)	(2)	(3)	(4)
Commute/100	-0.346***	-0.388***	-0.264***	-0.254***
	(0.032)	(0.034)	(0.029)	(0.028)
Age		0.052***	0.056***	0.056***
		(0.002)	(0.002)	(0.002)
(Age/10)^2		-0.065***	-0.069***	-0.069***
		(0.003)	(0.003)	(0.003)
Age_hus		0.003***	-0.003**	-0.003**
		(0.001)	(0.001)	(0.001)
(Age_hus/10)^2		-0.004***	0.005***	0.005***
		(0.001)	(0.001)	(0.001)
School		0.016***	0.022***	0.022***
		(0.001)	(0.001)	(0.001)
School_hus		-0.008***	-0.005***	-0.006***
		(0.001)	(0.001)	(0.001)
Other controls	No	No	Yes	Yes
Fe	No	Province	Province	Prefecture
Observations	135780	135780	135780	135780
R-squared	0.024	0.040	0.093	0.113

Notes: Other control variables include ethnicity, whether the household registration is rural, number of children, and whether the housing is rented. Robust standard errors clustered at the county level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

variables and two instrumental variables (column 6) indicate that every additional minute of commuting time decreases the probability of the female's labor participation by about 0.38 percentage points. In our data set, the maximum difference in commuting duration among different prefectures is 48.1 minutes, corresponding to a 24.0 percentage points difference in the female labor participation rate (given the linear functional form). In our data set, the maximum difference in female labor participation rates among prefectures is 58.3 percentage points, so the difference due to commuting duration can explain up to 41.1% of the regional difference in female labor participation. This result is consistent with the conclusion drawn by Black et al. (2014) using data from major U.S. cities.

Our result can also partly explain why China's female labor participation rate tends to decline. Since entering the 21st century, China's urban area has been expanding continuously, with a large influx of labor into big cities, coupled with the rising number of privately-owned cars, leading to an increase in commuting duration in major Chinese cities. In China, the primary economic source often comes from the husband. When the city expands and traffic congestion increases commuting duration, more family caregiving responsibilities tend to fall on the wife, thereby reducing female labor participation. According to the data we collected from 39 major cities in China, the average city commuting time increased from 30.5 minutes to 35.2 minutes from 2008 to 2020, an increase of 4.7 minutes. Based on the estimation results in Table 3, this means that the increase in urban commuting duration causes a 2.35 percentage point decrease in female labor participation in these cities, which counts for more than 40% of the change over this period.[9]

Table 3: The Impact of Commuting Duration on FLP: 2SLS

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Commute/100	-0.819***	-0.581**	-0.761***	-0.460**	-0.776***	-0.498***
	(0.288)	(0.296)	(0.182)	(0.187)	(0.178)	(0.186)
Age		0.056***		0.056***		0.056***
		(0.002)		(0.002)		(0.002)
(Age/10)^2		-0.069***		-0.069***		-0.069***
		(0.003)		(0.003)		(0.003)
Age_hus		-0.003***		-0.003***		-0.003***
		(0.001)		(0.001)		(0.001)
(Age_hus/10)^2		0.005***		0.005***		0.005***
		(0.001)		(0.001)		(0.001)
School		0.023***		0.023***		0.023***
		(0.001)		(0.001)		(0.001)
School_hus		-0.005***		-0.005***		-0.005***
		(0.001)		(0.001)		(0.001)
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistics	11.8	10.6	57.1	42.2	30.8	23.2
Hansen J statistics (P-value)					0.828	0.660
Observations	135,780	135,780	135,780	135,780	135,780	135,780

Notes: Other control variables include ethnicity, whether the household registration is rural, the number of children, and whether the housing is rented. Robust standard errors clustered at the county level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Validity of IV

In this section, we further discuss the quality of the IVs. As shown in Table 3, when using both indices simultaneously, the Hansen J statistic is not significant at the 10% level, indicating that the hypothesis of the exogeneity of the two instrumental variables cannot be rejected. In

[9] According to the International Labor Organization's calculations, China's female labor force participation rate has declined by 5 percentage points from 65% in 2008 to 60% in 2020, implying that the increase in commuting hours has contributed 47.0% to the decline in women's labor force participation rate.

addition, the first-stage F-statistics are all above 10. According to the rule of thumb proposed by Staiger and Stock (1997), they are not weak instrumental variables.

The validity of the instrumental variable also requires the exclusion restriction, meaning that instrumental variables can only affect the dependent variable through its impact on commuting time, not directly or through other variables. In the empirical context of our study, the urban form could affect female labor force participation through other channels, which we will examine below.

First, couples in which both partners work are also likely to work in places with more compact urban formations and shorter commutes. This sorting motivation is a potential threat to the causal identification in this paper. To verify the validity of the instrumental variable exclusion restriction, we follow Altonji et al. (2005) and test sorting based on observable characteristics. We restrict the sample to those who have moved across counties in the last 5 years. The test examines whether individual characteristics that matter for labor supply are associated with potential urban form. Table A.3 reports the results of the test, with columns 1 and 2 being the probability of a woman and her spouse earning a college degree, and column 3 being the probability of being a high-powered couple, and column 4 the number of children born. The results show that potential urban form is not correlated with any of these observable personal characteristics, supporting the validity of our identification strategy.

Second, the urban form may affect the incentive to work through housing prices. However, the effects can be mixed. A compact urban area may increase the housing price because of the agglomeration effect, but it can also negatively affect the housing price if the area is too crowded. Meanwhile, higher housing prices can either increase the incentive to work (because of higher living costs) or decrease it (because of the wealth effect). We estimated the impact of potential urban form on average housing prices, with the results listed in columns 1 and 2 of Table A.5. The empirical results show that after controlling for total investment scale and population size, whether measured by the Cohesion index or Range index, the impact of potential urban form on housing prices is not statistically significant. This excludes the channel of urban form affecting female labor force participation through housing prices.

Third, another possible channel is through the local economic development level (measured in GDP). Studies have shown that economic development and improved household economic conditions can have a positive impact on female labor participation (Lahoti and Swaminathan, 2016; Mehrotra and Parida, 2017). The potential urban form may also affect female labor participation rates by improving economic development. Columns 3 and 4 of Table A.5 report the estimation results of regressing GDP on compactness indices. We find that after controlling for total investment scale and population size, urban form has no significant impact on GDP. As a further robustness check, we also use the nighttime light index as a proxy of GDP and obtain the same result.[10]

To conclude the above discussions, we combine the zero-first-stage test proposed by Bound and Jaeger (2000), and the method proposed by Conley et al. (2012), constructing a simplified model that includes the instrumental variable, and then estimating the related parameters. Specifically, we consider the following regression:

$$Flp_{ic} = \beta_1 \widehat{commut}_{ic} + \beta_2 X_{ic} + \gamma N\widetilde{S}_{ic} + p_i + \varepsilon_{ic}, \tag{4.1}$$

where $\widehat{commut}_{ic}$ is the commuting duration predicted by Equation (3.2). We focus on γ – the coefficient of the IV. Conley et al. (2012) argue that if γ is close to 0, the instrumental variable is "almost exogenous". Table A.6 presents the parameter estimation results of Equation (4.1). Since the null hypothesis of $\gamma = 0$ can not be rejected at 10% level, the empirical evidence supports our instrumental variable to be at least "almost exogenous". In summary, we find that the potential urban form as an instrumental variable for commuting time is appropriate. Although we cannot completely rule out that urban form affects female labor force participation through other pathways, we believe the impact of the other pathways is unlikely significant.

4.4 Robustness Analysis

4.4.1 Control function approach

Since the dependent variable is binary, another way to estimate the causal impact is the control function method proposed by Heckman (1979) and Rivers and Vuong (1988). Specifically, we first estimate the residuals based on Equation (2) and then introduce the estimated residuals as a control variable into Equation (1). Since the factors causing endogeneity have already been controlled, we then estimate the Probit model to obtain consistent estimates of the parameters.

[10] The nighttime light index has been used in the mainstream literature as a proxy for GDP (Henderson et al., 2012; Hodler and Raschky, 2014; Alesina et al., 2016; Chodorow-Reich et al., 2020).

Table 4 shows the marginal effects of urban commuting duration on female labor participation. Column (1) uses the potential Cohesion index as the instrumental variable to estimate the residuals in the first stage, column (2) uses the potential Range index as the instrumental variable, and column (3) uses both types of indices as instrumental variables. The estimation results based on the IV-Probit model are qualitatively consistent with the linear model.

Table 4: Robustness Test Based on the Control Function Method

Variables	(1)	(2)	(3)
Commute/100	-0.608**	-0.503***	-0.538***
	(0.252)	(0.190)	(0.182)
Resid	0.336	0.231	0.269
	0.255	0.195	0.188
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
Observation	135,780	135,780	135,780

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.4.2 Other compactness indices

Angel et al. (2010) proposed four types of urban form indices, including the previously mentioned Cohesion index and Range index, as well as the Proximity index and Spin index. We also calculated these two types of potential urban form indices and used them as instrumental variables for urban commuting to test the robustness of the previous estimation results. **??** lists the estimation results, which are qualitatively similar to our baseline model.

4.4.3 Road condition

Urban transportation infrastructure networks can have a significant effect on urban form (Baum-Snow et al., 2017), and hence the commuting time. On the other hand, if a city has a developed road network and good traffic conditions, it can also improve employment. Ignoring this variable might lead to inaccurate estimation results. To address this issue, we introduced road network density as a control variable and re-estimated the impact of commuting on female labor force participation. The results in Table 5 show that an increase in road density increases women's labor participation. However, even after introducing urban road network density as a control variable, we still find a significant negative causal impact of urban commuting on female labor force participation. The size of the parameter estimation does not change significantly after introducing road network density, indicating that our estimation results are very robust.

Table 5: The Impact of Controlling Road Density

	(1)	(2)	(3)
Dep. Var	Flp	Flp	Flp
Commute/100	-0.669*	-0.673**	-0.671**
	(0.353)	(0.293)	(0.273)
Roaddesity	0.010	0.010*	0.010**
	(0.006)	(0.005)	(0.005)
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
First stage F statistics	9.32	18.48	11.51
Hansen J statistics (P-value)			0.627
Observation	134,302	134,302	134,302

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.4.4 Economic development

Table 6 lists the 2SLS estimation results after controlling for the level of economic development (Nighttime light as proxy). Although there is a positive correlation between economically developed areas and women's labor participation, the negative impact of urban commuting on women's labor participation does not change after introducing the level of economic development. Therefore, we can exclude the impact of potential urban form on local economic development, thereby affecting female labor participation.

4.4.5 Wage Differences

In spatial equilibrium, a person's ability to tolerate a longer commute often requires a higher wage income to compensate, which means that in cross-city comparisons, those places with longer commutes tend to have higher productivity and wages. And within a city means greater variability in productivity and wages. It also means that wage differentials can have simultaneous effects on urban commuting and labor force participation. In order to control for the effect of wage differentials, we compute the coefficient of dispersion of average monthly individual income in the location city and the gender wage gap between men and women based on the 2005 1% population sample microdata, which are introduced as control variables in the empirical

Table 6: The Impact of Controlling for Economic Development Level

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Commute/100	-1.545***	-1.028**	-1.151**	-0.845*	-1.309***	-0.911**
	(0.573)	(0.482)	(0.492)	(0.453)	(0.436)	(0.391)
Age		0.057***		0.057***		0.057***
		(0.002)		(0.002)		(0.002)
(Age/10)^2		-0.070***		-0.070***		-0.070***
		(0.003)		(0.003)		(0.003)
Age_hus		-0.003**		-0.003**		-0.003**
		(0.001)		(0.001)		(0.001)
(Age_hus/10)^2		0.005***		0.005***		0.005***
		(0.001)		(0.001)		(0.001)
School		0.023***		0.022***		0.022***
		(0.001)		(0.001)		(0.001)
School_hus		-0.005***		-0.005***		-0.005***
		(0.001)		(0.001)		(0.001)
Light	0.007**	0.005**	0.005*	0.004*	0.006**	0.004**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistics	10.1	8.7	8.1	7.6	7.1	6.4
Hansen J statistics (P-value)					0.498	0.721
Observations	132,762	132,762	132,762	132,762	132,762	132,762

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

equations, respectively. Table 7 reports the 2SLS estimation results after the introduction of these two types of control variables, and we again find a negative effect of commuting hours on female labor participation, and the estimated coefficients are very close to the benchmark results.

4.4.6 Sorting Effects

Finally, to further examine the potential threat of sorting on our results, we exclude samples in which cross-county migration occurs within five years of the sample and conduct 2SLS estimation based on samples in which no migration occurs. We find that the estimation results after excluding the cross-county sample remain consistent with the baseline results, again suggesting that the sorting issue does not have a substantial impact on your empirical results in this paper. Of course, based on our sample, the very low share of the sample with cross-county migration in the last 5 years, 7.6%, is tied to China's strict household registration system and large migration

Table 7: Controling the Impact of Wage Differences

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Flp	Flp	Flp	Flp	Flp	Flp
Commute/100	-0.502*	-0.386**	-0.422**	-0.606**	-0.545***	-0.564***
	(0.304)	(0.196)	(0.196)	0.292	0.184	0.183
Wage difference	-0.268***	-0.286***	-0.280***			
	(0.060)	(0.046)	(0.046)			
Gender wage gap				-0.145***	-0.146***	-0.146***
				(0.013)	(0.013)	(0.013)
Ccontrols	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistics	10.82	42.02	23.19	10.74	43.26	23.77
Hansen J statistics (P-value)			0.693			0.825
Observation	135,780	135,780	135,780	135,780	135,780	135,780

Notes: Wage differences are measured by the coefficient of dispersion of the monthly wage level of non-student students aged 16-59 in each prefecture, and Gender wage gap is measured by the ratio of the average wage of men and women aged 15-69 in each prefecture, with the original data coming from the micro data of the 2005 1% Population Sample Survey; the instrumental variables in columns 1 and 4 are Ncohension, the instrumental variable in columns 2 and 5 is Nrange, and columns 3 and 6 introduce both types of instrumental variables. Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

costs. Thus sorting is not a serious issue that can have an impact on the results of this paper in the Chinese context.

Table 8: Excluding the Effects of Sorting

	(1)	(2)	(3)
Dep. Var	Flp	Flp	Flp
Commute/100	-0.668**	-0.492**	-0.547***
	(0.327)	(0.202)	(0.204)
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
First stage F statistics	9.34	38.09	20.87
Hansen J statistics (P-value)			0.551
Observation	125,395	125,395	125,395

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5 Heterogeneity

5.1 Education

Previous literature has theoretically and empirically demonstrated that if the wife's income constitutes a smaller proportion of a household, the negative impact of urban commuting on her labor participation is greater (Black et al., 2014; Carta and De Philippis, 2018). Since income largely depends on educational level, the higher the wife's education level, the higher her work income. Therefore, we expect to observe a small magnitude of the causal effect for women with higher education levels. This is supported by the first two columns Table 9. For married women with higher education, each additional minute of urban commuting time decreases the labor participation rate by 0.35 percentage points, compared to 0.57 percentage points for wives without higher education. The opportunity cost of exiting the labor market is higher for women with higher education levels. Therefore, they tend to "tolerate" longer commuting duration more than those with lower education levels.

Table 9: Heterogeneity Tests for Education Level and Age of Children

Variables	1	(2)	3	4	5
	College above	Below college	Kids' age below 6	Kids' age above 6	Have no kids
Commute/100	-0.348**	-0.574***	-0.582**	-0.486**	-0.281
	(0.136)	(0.210)	(0.241)	(0.201)	(0.307)
Ccontrols	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes
First stage F statistics	32.35	20.65	23.43	20.68	21.08
Hansen J statistics (P-value)	0.960	0.490	0.601	0.620	0.550
Observations	6991	128789	35668	93964	8704

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Fertility

When there are infants or young children requiring care in the family, the role of women in the family work significantly increases. The negative impact of longer commuting duration on married women's labor participation will be more pronounced. Column 3 of Table 9 shows that for each additional minute of commuting, the labor participation rate of married women decreases by 0.58 percentage points if they have children aged 6 or under. On the other hand, Column 4 shows that the impact is negative and significant for women with children aged 6 or below, and such an effect is relatively smaller (from -0.58 to -0.49) for women with children above 6. While for childless households, on the other hand, the effect of increased commuting hours on female labor force participation does not pass the significance test. Our result is similar to Black et al. (2014), who used state-level data in the United States and found that commuting time had a more significant negative impact on the labor participation of married women with young children.

5.3 Regional Heterogeneity

Since China's market reforms, the eastern coast regions and big cities have aggregated more and better-quality education, healthcare, cultural, and entertainment resources, and in general, have a more open culture. Therefore, the eastern coastal regions have attracted workers from inland provinces or rural areas. Consequently, eastern coastal regions and big cities tend to be over-populated and have issues such as traffic congestion. In our sample, women living in 70 major cities have an average commuting duration of 41.5 minutes, compared to 37.0 minutes for women residing in non-major cities, a statistically significant difference of 4.5 minutes at the 1% significant level.

Based on our data, we divided the sample's residential locations into eastern coastal vs. inland provinces, as well as big cities vs. small cities. We estimated the impact of urban commuting on female labor participation in coastal and inland, big and small cities, respectively. Table 10 presents the parameter estimation results for each subsample. We find that in economically more developed coastal provinces, urban commuting has a significant negative impact on female labor participation, while in inland areas, the impact of urban commuting is not significant. Additionally, urban commuting has a significant negative impact on female labor participation in the 70 major cities, but the impact in other smaller cities is not significant. This result matches with stylized cultural facts that in big or eastern coast cities, the lifestyle is more intense, and people have more anxiety.

Table 10: Heterogeneity by Region and City Size

Variables	(1)	(2)	(3)	(4)
	Coastal	Inland	Big city	Non-big city
Commute/100	-0.936***	-0.077	-0.493**	-0.807
	(0.354)	(0.193)	(0.167)	(0.527)
Ccontrols	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes
First stage F statistics	10.14	19.87	26.05	4.30
Hansen J statistics (P-value)	0.177	0.127	0.912	0.688
Observations	58749	77031	43516	92264

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.4 Availability of Subway

A city's transportation infrastructure can significantly affect urban commuting and employment choices. The subway system, on the one hand, can alleviate surface traffic pressure to a certain extent; on the other hand, it provides commuters with an additional transportation option. Because subway transportation is more predictable, we believe that the availability of a subway system can significantly alleviate the anxiety caused by commuting for city workers, thereby reducing the impact of commuting duration on the labor participation of married women.

We divided our samples into those with and without subways and respectively estimated the impact of commuting duration on married women's labor participation. We found that in cities with subways, the impact of urban commuting on the labor participation of married women is not statistically significant. In contrast, in cities without subways, the impact is significantly negative. This conclusion is more pronounced in the sample of large cities because constructing subways in Chinese cities is conditional—only: cities with a large economic volume, strong financial strength, and certain population size can build subways. In 2015, only 24 cities in China had opened subways, and among these, 18 were major cities, indicating that the opening of subways mainly affects the labor participation of married women in large cities. As seen in column 4 of Table 11, in large cities without subways, the impact of urban commuting on the labor participation of married women is numerically and statistically higher than in the overall sample. The estimation results in Table 11 suggest that when a city opens a subway, the negative impact of urban commuting on the labor participation of married women becomes insignificant, implying that the adverse effects of commuting duration on married women's labor participation can be greatly mitigated by enriching the mode of transportation.

Table 11: Subway Availability

Variables	(1)	(2)	(3)	(4)
	All samples		Big city samples	
	Open subways	No subway	Open subways	No subway
Commute/100	-0.093	-0.89**	-0.039	-1.186***
	(0.119)	(0.368)	(0.133)	(0.377)
Ccontrols	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes
First stage F statistics	23.88	9.07	17.73	6.84
Hansen J statistics (P-value)	0.981	0.776	0.807	0.679
Observations	19529	116251	16751	26765

Notes: City metro information data is from website www.guangjuntong.com. Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

Using microdata from China's 1% Population Census data in 2015, this paper empirically analyzes the impact of commuting duration on female labor participation in China. Using the exogenous variation in the potential urban footprint as the identification source, we find that urban commuting duration substantially impacts the labor participation of married women, with each additional minute of commuting reducing the probability of labor participation by an average of 0.5 percentage points. The difference in commuting duration between cities can explain 41.1% of the variation in labor participation rates of married women in cities. The increased commuting time over past decades can also explain a significant portion of the decrease in women's labor participation.

Heterogeneity analysis results show that the higher the woman's education level, the lower the negative impact of urban commuting duration on her labor participation; when there are children aged 6 and below in the family, the negative impact of urban commuting duration on the labor participation rate of married women is greater. This research finding is consistent with some empirical studies based on data from developed countries (Black et al., 2014; Carta and De Philippis, 2018). In addition, we also find that in China's coastal areas and large and medium-sized cities, urban commuting has a significant negative impact on female labor participation, while in inland areas and smaller cities, the impact of urban commuting on female labor participation is not significant.

Finally, we find that in large cities where subways have been opened, the impact of urban commuting on female labor participation is no longer significant, while in cities without subways (including large cities), commuting has a significant negative impact on female labor participation.

This research has explicit policy implications. Over the past 30 years, as China has experienced rapid urbanization, the urban population has grown rapidly, making some large cities increasingly congested. Traffic congestion has become one of the significant reasons for the decline in female labor force participation, as commuting durations in many large cities continue to increase. Against the backdrop of an aging population, improving female labor participation is of great significance. Moreover, with the continuous increase in the average years of education among Chinese women, it would be a considerable waste of human capital if many women exit the labor market. This implies that reducing urban commuting duration is of significant policy importance to increase female labor participation. In addition, empirical research in this paper finds that in some traffic-congested large cities, opening subways can significantly reduce the negative impact of commuting duration on female labor participation, indicating that providing more commuting options and reducing the uncertainty of individual commuting duration can also reduce the negative impact of commuting duration on female labor participation, achieving the goal of increasing female labor participation.

Appendix

Table A.1: Urban Form, Potential Urban Form, and Commuting Duration in Various Districts and Counties of Zhengzhou

County	Cohesion Index (KM) S	Cohesion Index (KM) $\widetilde{S}$	Cohesion Index (KM) N$\widetilde{S}$	Range index (KM) S	Range index (KM) $\widetilde{S}$	Range index (KM) N$\widetilde{S}$	commuting time minutes
Zhongyuan District	8.25	2.040	2.650	22.28	19.940	1.166	60.39
Erqi District	8.10	6.161	1.093	21.15	15.383	1.235	42.17
Guancheng Hui District	8.61	1.673	1.120	24.13	18.527	1.263	46.74
Jinshui District	9.82	3.070	1.504	27.77	21.662	1.828	46.25
Shangjie District	3.78	3.820	1.103	10.69	10.804	1.412	35.75
Huiji District	10.76	1.996	1.144	34.90	13.297	1.772	54.37
Zhongmu County	16.36	5.334	1.071	50.89	15.129	1.375	27.44
Gongyi city	11.98	7.878	1.010	43.72	19.193	1.114	40.41
Xingyang City	14.03	7.614	1.053	41.48	19.145	1.198	33.10
Xinmi City	16.26	8.125	1.008	47.25	19.585	1.100	39.75
Xinzheng City	14.95	5.564	1.133	38.93	18.920	1.389	32.43
Dengfeng City	7.31	1.255	1.324	22.48	17.163	1.194	31.27

Notes: S and $\widetilde{S}$ are indices based on the actual urban form and the potential urban form, respectively. $N\widetilde{S}$ is the normalized version of $\widetilde{S}$.

Table A.2: First Stage Results: The Impact of Potential Urban Form on Commuting Duration

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Commute	Commute	Commute	Commute	Commute	Commute
Ncohesion	0.058***	0.051***			0.032**	0.031**
	(0.016)	(0.015)			(0.016)	(0.016)
Nrange			0.101***	0.084***	0.086***	0.069***
			(0.013)	(0.013)	(0.015)	(0.015)
Age		0.002***		0.002***		0.002***
		(0.000)		(0.000)		(0.000)
(Age/10)^2		-0.002***		-0.002***		-0.002***
		(0.001)		(0.001)		(0.001)
Age_husband		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
(Age_hus/10)^2		0.001		0.000		0.000
		(0.000)		(0.000)		(0.000)
School		0.002***		0.002***		0.002***
		(0.000)		(0.000)		(0.000)
School_hus		0.002***		0.002***		0.002***
		(0.000)		(0.000)		(0.000)
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135780	135780	135780	135780	135780	135780
R-squared	0.239	0.272	0.253	0.279	0.257	0.283

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Urban Form and Individual Characteristics of Migrants -OLS

	(1)	(2)	(3)	(3)
Dep. Var	College-wives	College-husbands	Power couple	Kid number
Ncohesion	-0.013	0.000	-0.022*	-0.055
	(0.014)	(0.016)	(0.013)	(0.045)
Nrange	-0.005	0.023	-0.010	-0.048
	(0.016)	(0.015)	(0.014)	(0.048)
Controls	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes
Observations	10385	10385	10385	10385

Notes: The sample includes married women aged between 16-50 and men aged between 16-60 years old who changed the residence of county in the last 5 years. The independent variable in column (1) is the probability of having college degree for wives, in column (2) is the probability of having college degree for husbands, in column (3) is the probability of being a power couple and in column (4) is the number of children. All regressions include the control variables at the individual level (age, schooling years, and hukou race dummies for both wives and husbands), and regional dummies. Robust standard errors clustered at county level in parentheses. Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sources: The 2015 1% Population Sample Survey Microdata.

Table A.4: Descriptive Statistics of County-Level Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
GDP 1 billion Yuan RMB	1927	18.210	24.073	0.232	310.000
House price 1 hundred Yuan RMB	888	70.981	64.686	17.850	727.820
Nighttime light index	2253	2.58	6.26	0.00	67.78
Ncohesion	2089	1.107	0.205	0.996	5.486
Nrange	2089	1.244	0.193	1.033	2.722
Ncohesion_10	2362	1.180	0.151	1.010	2.514
Nrange_10	2361	1.632	0.284	1.172	3.711
Road density (Kilometers/square kilometer)	2761	0.627	1.415	0.001	23.682
Population (10 thousand)	2424	50.243	37.738	1.000	547.490
Investment (1 billion Yuan RMB)	1927	15.166	14.846	0.194	120.000

Table A.5: The impact of city shape on housing price and GDP

	(1)	(2)	(3)	(4)
VARIABLES	houseprice	houseprice	gdp	gdp
Ncohesion	3.635		-1.621	
	(2.817)		(1.707)	
Nrange		5.797		2.043
		(8.906)		(1.442)
Invest	0.381***	0.385***	1.251***	1.251***
	(0.115)	(0.115)	(0.111)	(0.110)
Population	0.013	0.015	0.034	0.035*
	(0.039)	(0.040)	(0.021)	(0.020)
Observations	296	296	1,435	1,435
R-squared	0.512	0.511	0.789	0.789

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.6: Simplified Form After Introducing Instrumental Variables

	(1)	(2)	(3)
Dep. Var	Flp	Flp	Flp
Commute/100	-0.298**	-0.305**	-0.300**
	(0.139)	(0.135)	(0.137)
Ncohesion	-0.014		-0.012
	(0.014)		(0.014)
Nrange		-0.013	-0.008
		(0.019)	(0.018)
Controls	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
Observations	135,780	135,780	135,780
R-squared	0.090	0.090	0.090

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.7: Robustness Test Based on the Control Function Method

Variables	(1)	(2)	(3)
Commute/100	-0.559**	-0.343*	-0.414**
	(0.247	(0.190)	(0.185)
Resid	0.299	0.080	0.154
	0.251	0.195	0.191
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
Observation	135576	135576	135576

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Robust test using other potential city shape index as IV

Variables	(1)	(2)	(3)	(4)
Commute/100	-0.890***	-0.606**	-0.812***	-0.532**
	(0.235)	(0.236)	(0.224)	(0.224)
Age		0.056***		0.056***
		(0.002)		(0.002)
(Age/10)^2		-0.069***		-0.069***
		(0.003)		(0.003)
Age_hus		-0.003***		-0.003***
		(0.001)		(0.001)
(Age_hus/10)^2		0.005***		0.005***
		(0.001)		(0.001)
School		0.023***		0.023***
		(0.001)		(0.001)
School_hus		-0.005***		-0.005***
		(0.001)		(0.001)
Other controls	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes
First stage F statistics	31.8	25.5	28.2	23.6
Observations	135,780	135,780	135,780	135,780

Notes:Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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