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

Shenglong Liu† Xingyu Pan‡ Yuanyuan Wan§ Xiaoming Zhang¶ Shaojie Zhou‖

April 17, 2025

Abstract

The increase in commuting time due to traffic congestion is a widespread dilemma faced by most major cities worldwide. In addition to its impact on environmental pollution and personal health issues, it can 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 0.5 percentage points. The variation in commuting time can explain about 40% of the differences 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 over the past decade, specifically in the context of the nation's rapid urban expansion and escalating commuting time.

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

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

---

*We are grateful to the editor and two anonymous referees for valuable suggestions, which have significantly improved the paper. We also appreciate valuable comments from Nathaniel Baum-Snow, Weixing Cai, and Wei Zhang, and we thank Haoyang Xiong for his excellent data collection work. All errors are ours.

†Corresponding author. School of Public Policy and Management, Tsinghua University, China, 10084. Email: liushenglong@tsinghua.edu.cn. Shenglong Liu acknowledges the support of the National Natural Science Foundation of China #72073078.

‡School of Public Policy and Management, Tsinghua University. Email: xy-pan19@mails.tsinghua.edu.cn

§Department of Economics, University of Toronto, Email: yuanyuan.wan@utoronto.ca. Yuanyuan Wan acknowledges the support from the SSHRC Insight Grant #435-2024-0418.

¶School of Public Policy and Management, Tsinghua University. Email: zhangxm21@mails.tsinghua.edu.cn.

‖School of Public Policy and Management, Tsinghua University. Email: zhoushaojie@tsinghua.edu.cn. Shaojie Zhou acknowledges the support of the Tsinghua University Initiative Scientific Research Program # 2022THZWYY01.

1 Introduction

Once the market economy was established in 1992, China underwent 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 while the urban population surged from 302 million to 902 million, with an annual growth rate of 3.7%. Despite the urban expansion bringing positive social and economic impacts, such as scale effects and higher productivity (Duranton et al., 2015), it also results in severe traffic congestion and longer commuting time (Newman and Kenworthy, 1999; Blau and Kahn, 2000; Harari, 2020). To illustrate, in Beijing's 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 likewise 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 would lead to worker fatigue, which would inevitably affect work efficiency and work 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 motivation for this study derives from 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. This same group contributes most to the substantial changes observed in female labor participation over the past few decades in other countries like the US (Juhn and Potter, 2006). As the average education level for Chinese women continues to rise, the withdrawal of a substantial amount of well-educated women from the labor market represents a startling waste of human capital. Meanwhile, China is also experiencing rapid population aging. By the end of 2022, the proportion of the elderly population aged 65 reached 14.9%, doubling its level from 7.0% in 2000. In this trend of a steadily aging population, the decline of female labor participation draws considerable attention and raises the long-standing question that has not been adequately answered in the literature (Hare, 2016): what is causing 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 we constructed for China's urban areas (county level), we find that when the average daily commuting time (round trip) increases by one minute, the probability of labor participation among married women decreases by 0.5 percentage points on average. The range between the longest and shortest average commuting duration is 48.1 minutes across various counties in our sample, suggesting a 24.0 percentage points difference in labor participation, given everything else is equal. This accounts 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 five 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 yet reached a consensus. For example, Cogan (1980) hypothesizes that longer commuting time would negatively affect working hours; however, the data did not support this conclusion. In contrast, some studies have found that longer commuting time increases individuals' weekly working hours (Gutiérrez-i Puigarnau and van Ommeren, 2015; Gimenez-Nadal et al., 2018). Several papers focus primarily on female labor participation. Black et al. (2014) estimate the effect of commuting time on wives' labor supply using data from 50 major cities in the United States and discover 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. Unlike the aforementioned studies, our paper does not rely on panel data, and our key explanatory variable is the county-level average commuting time. This directive links directly to our identification strategy and policy discussions discussed in the main text in further detail.

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 as they are also undergoing rapid urbanization. Major cities in these developing countries are also facing climbing traffic congestion problems due to urban growth expansion. These countries also share similar characteristics to China, such as male dominance in the labor market and the quest to improve female labor force participation rate. Empirically quantifying the causal impact of commuting duration on Chinese women's labor participation helps to understand of the significance of improving urban commuting in these developing countries.

Our paper also adds discussions to the recently growing body of work that studies the effect of work-life balance consideration and women's home responsibilities on gender inequalities in the labor market. For example, women may have a stronger preference for shorter commutes, which has implications for their labor market outcomes (Petrongolo and Ronchi, 2020, Section 4). Based on a search model, Le Barbanchon et al. (2021) identify the indifference curves between wage and commute using French administrative data and find that the women's indifference curve is steeper. That is, women are more sensitive to the cost of commute. This explains why women are paid less than men but commute a shorter distance on average. In addition to our focus on women's labor participation, we also estimate the effect of commute on men's labor participation and find it is smaller than the magnitude of women's. While our paper focuses on an extensive margin, our conclusion is consistent with Le Barbanchon et al. (2021), who consider the intensive margin.

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 as one of the essential reasons for the increase in female labor supply and in promoting economic growth (Angrist and Evans, 1996; Bloom et al., 2009).[1] China, like other major developed countries, 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

[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., 2024). However, only a few studies have considered the impact of commuting time on female labor supply.

decreased. Fertility behavior is unlikely the main reason for the decline in the labor participation rate of Chinese women. Our research indicates a rise in urban commuting time has a significant negative impact on female labor participation, and it explains the variations in female labor participation rates across regions and time.

Identifying the causal effect of commuting time on labor force participation is challenging. For example, commuting time can be mismeasured, causing attenuation bias if the measurement error is classical. Unobserved confounders at the individual level can 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 can rise at the county level as well. For instance, unobserved factors, such as the local government's governance ability, may confound the actual urban form and labor participation rate. Moreover, ignoring the sorting of individuals across cities also leads to bias in OLS estimates.

We address the endogeneity by the instrumental variable approach. Specifically, we instrument the commuting time by compactness indices of the *potential* urban footprint, as proposed by Harari (2020). We avoid using the *actual* contemporaneous urban footprint, which may be correlated with the unobserved factors mentioned above. In contrast, the potential urban footprint is constructed based on geographic constraints that shape a counterfactual urban expansion over time. To be specific, it is defined as the intersection of two areas: (i) the largest contiguous developable land in the county (excluding natural barriers such as water bodies and steep terrain), and (ii) the counterfactual area the city would have occupied had it expanded uniformly in all directions, following a mechanical model of growth. Further construction details are provided in Section 2.2. This variable captures two sources of exogenous variation orthogonal to unobserved confounders: constraints imposed by geography and mechanically predicted urban growth patterns. Consequently, cities with similar expansion rates can exhibit markedly different urban shapes due to underlying geographic constraints—providing sufficient variation to identify the causal effects. Moreover, the shape of the potential urban footprint plausibly affects commuting time: all else equal, it is easier to commute in cities with a more "regular" shape (i.e., lower compactness indices). Empirically, we find that commuting time is significantly correlated with these compactness indices. Lastly, to validate the exclusion restriction, we conduct a series of robustness checks and find no evidence that the potential urban footprint directly influences labor force participation or operates through alternative channels.

Thus, 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. Our identification strategy is significantly different and complements the existing research. For example, Gutiérrez-i Puigarnau and van Ommeren (2015) and Carta and De Philippis (2018) utilize employer-driven changes in commuting distance to identify the causal impact in the UK and Germany, respectively. Our study shows that potential urban footprint can be a reliable instrument variable to consider when such data are available in the Chinese context.

We also study the heterogeneity of the causal impact of commuting time. We find that women with family-oriented obligations are more sensitive to commuting time, consistent with the discussions in Petrongolo and Ronchi (2020). The impact of commuting is lower for higher-educated women, which is reasonable because women with higher education, on average, have a better job perspective, and the opportunity cost of not working is higher. We also find that the impact of commuting time is much lower in cities with subways than in cities without. Hence, the negative effect of commuting time on women's labor participation can be greatly mitigated by enriching transportation infrastructures.

The rest of the paper is organized as follows. Section 2 introduces data and key variables. Section 3 presents the identification strategy. We report the main estimation results in Section 4 and conduct heterogeneity analysis in Section 5. Section 6 concludes the paper. Additional results and descriptive statistics are collected in the Appendix.

2 Data

In this section, we will discuss variables that we use for our main regressions and their sources. Our primary data source is China's 1% population census in 2015 (also known as the 2015 Mini Census). It contributes to our dependent variable, the key explanatory variable, and the control variables. We will discuss the construction of instrumental variables in Section 2.2.

2.1 Primary Data Source

China's 1% population Census dataset covers the entire nation, with county-level cities as sub-populations; 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 (1.55% of 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 (excluding wives who are students).[2] The county-level variables used in the paper primarily 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 taking value 1, and the third category as not in the labor market, with $Flp = 0$. The first row of Table 1 reports some summary statistics of Flp. The overall labor participation rate of Chinese women in our sample is 72.1%.

2.1.2 Core explanatory variable.

The second row of Table 1 reports the core explanatory variable of this article: the average commuting time (round trip) of all individuals in the county in which a married woman resides. Therefore, this variable takes the same values for individuals who live in the same county. The 2015 Mini Census data provides a survey on individual commuting conditions, concerned with the time required for individuals to travel to work and back home. This is the only large-scale individual-level commuting duration survey data available in China's population census data over the years. To better present the regression coefficients, we divide the actual minutes by 100 and denote it by *commute*. On average, the Chinese workers in our sample spend 37.8 minutes commuting every day.

To illustrate the association between Flp and *commute*, we divide the sample into two subsamples by 35 minutes (close to the median). We discover that the average labor participation

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

Table 1: Descriptive Statistics

	All		Commute≥35		Commute<35		Difference
Variables	mean (1)	S.D.	mean (2)	S.D.	mean (3)	S.D.	(3)-(2)
Flp	0.721	0.449	0.690	0.462	0.753	0.431	0.063***
Commute	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	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***
Sample size	135,780		69,821		65,959		

*** p<0.01, ** p<0.05, * p<0.1

rate is notably higher for cities with less commuting time, indicating a negative correlation between these two variables. We also split the sample by the 25% and 75% percentiles of *commute*, respectively. The results are qualitatively similar and collected in Table A.15 of the Appendix. Figure 1 plots the average commuting time and the average labor participation rate of women in prefecture-level cities. A large variation in the average commuting time across cities is observed. 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 the two. There is also a large difference in female labor participation rates in different cities. The labor participation rate in Baoshan, Yunnan, 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 commute and female labor participation rates, with a simple correlation coefficient of -0.13.

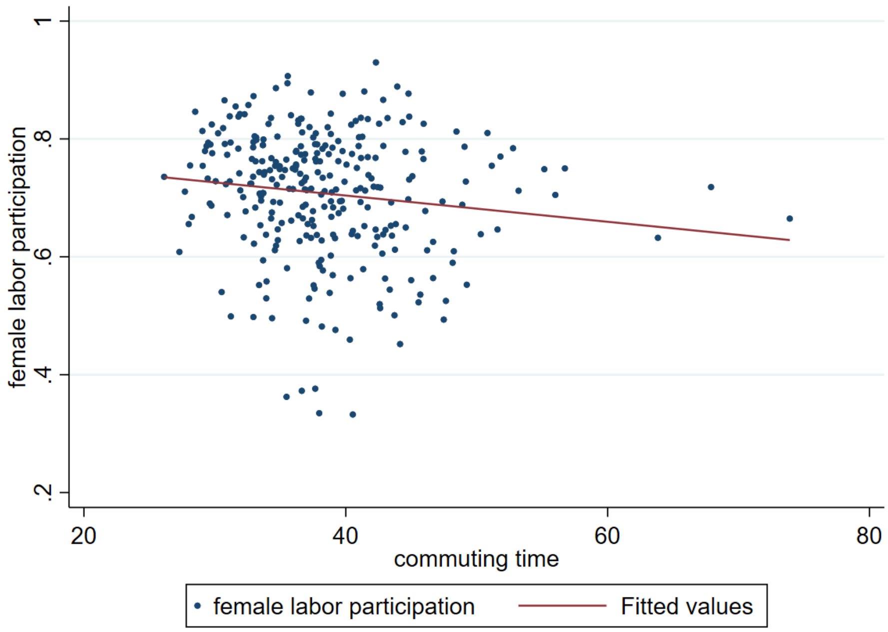


Figure 1: Average commuting time and female labor participation rate in Chinese cities in 2015

2.1.3 Demographic controls.

The 2015 Census also contains detailed individual characteristics for women and their husbands, such as women's age (denoted by *Age*), their husbands' age (*Age_hus*), years of education (*school*), education of their husbands (*school_hus*), women's ethnic group ($Han = 1$ if belongs to Han group), Hukou registration ($Rural = 1$ if registered in rural area), the number of children in the family (*Childnum*), whether the residence is rented ($Rent = 1$ if rented), and husbands' labor participates status ($Flp\_hus = 1$ if working, in job training or seeking work). Tables 1 and A.15 also report some descriptive statistics of these variables for the whole sample and subsamples.

2.2 Construction of Instrumental Variables

In this section, we follow the method proposed by Harari (2020) to construct our instrumental variables. In Section 2.2.1, we illustrate how to use nighttime light remote sensing data to draw the urban footprint. Next, in Section 2.2.2, we show how to use the mechanically predicted population growth and local geographical constraints to expand the actual urban footprint in 2000 to the potential urban footprint in 2015. Finally, we calculate the standardized Cohesion index ($Ncohension$) and standardized Range index ($Nrange$) of the potential urban footprint in 2015 as our instrumental variables (Section 2.2.3). We will discuss the validity of IVs in Section 3.

2.2.1 Nighttime light data and measurement of urban area

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 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 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 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 reveals good pixel consistency.

We illustrate the evolution of urban form using the prefecture of Zhengzhou as an example. Specifically, Figure 2 displays the built-up areas of eleven counties (including county-level cities) in Zhengzhou in 2000, 2005, 2010, and 2015. From the figure, we observe 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 a built-up area of 1,287 square kilometers and a total population of 6,659,000; by 2015, the built-up area had increased to 2,220 square kilometers, and the urban population had reached 10,692,000.

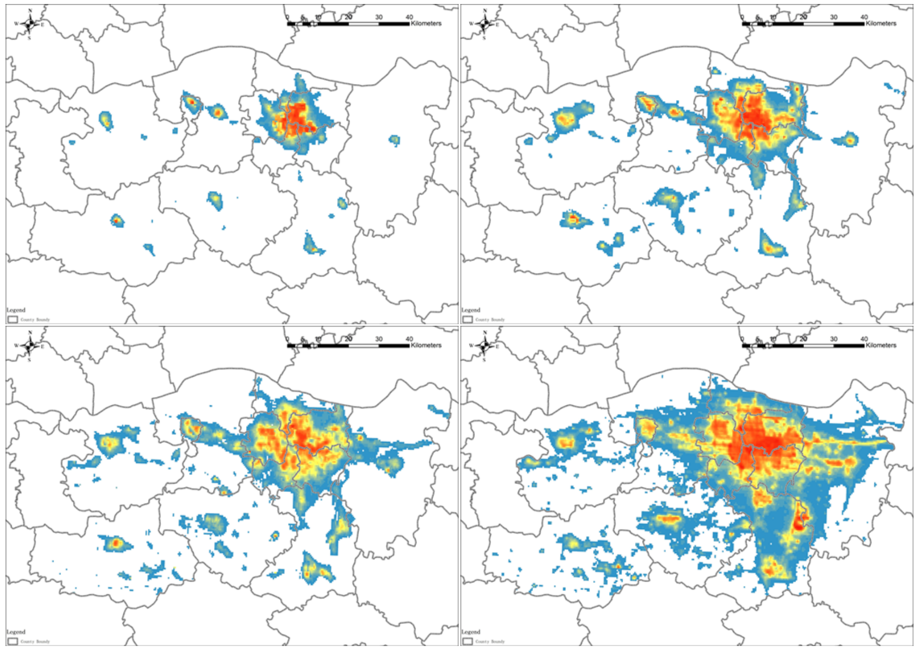


Figure 2: Urban Footprint Changes in Zhengzhou from 2000 to 2015

2.2.2 Potential urban footprint

As we will discuss in more detail in Section 3, the observed actual urban form itself results from economic, social, and balanced urban development and is subject to endogeneity concerns. 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". We follow the standard practice and use two criteria here: excluding water bodies and excluding areas with a slope of more than 15°. We identify terrains with steep slopes using the high-resolution global DEM data (SRTM/ASTER with a spatial resolution ranging from approximately 30 to 90 meters). Water bodies, including rivers, lakes, reservoirs, and wetlands, are extracted from China's Fundamental Geographic Information Database. Second, based on the predicted population data of the county and the baseline population density, the potential size of the county during the sample period is mechanically predicted,[3] and the radius of the equivalent area circle for this potential area is

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

estimated. It represents the area the county would have occupied if it expanded uniformly in all directions at a mechanical rate. Third, the potential urban footprint is determined as the largest contiguous intersection of the "potential maximum developable range" and the circle with the predicted radius.

The following algorithm summarizes the procedure and illustrates it with an example of Deng Feng County.

Algorithm 2.1 *Consider the following steps:*

1. *Identify the potential maximum developable range of a county. Deng Feng County's developable range is painted as a turquoise area in both panels of Figure 3. It remained unchanged between 2000 and 2015 because the geographical conditions are time-invariant.*

2. *Use the nighttime light data and identify the actual urban footprint of a county in 2000. The actual urban footprint of Deng Feng is the highlighted area (in deep blue and red color) of Figure 3a (the left panel).*

3. *Identify the largest contiguous portion of the actual footprint. Then, identify its centroid and draw the smallest circle enclosing it. This is the circle in Figure 3a with radius denoted by* $r_{c,2000}$.

4. *Predict the equivalent area circle's radius* $\hat{r}_{c,2015}$ *for the year of 2015:*

   (a) *Let subscript c denote a generic county. Using population census data from 1982 and 2000, calculate the average annual population growth rate:*

   $$\widehat{rpop}_c = \frac{\log(pop_{c,2000}) / \log(pop_{c,1982})}{2000 - 1982},$$

   where $pop_{c,t}$ *is the population of county c in year t.*

   (b) *Use this rate for trend extrapolation to obtain a mechanically predicted population for each year* $t \in \{2001, 2002, \cdots, 2015\}$*:*

   $$\log(\widehat{pop}_{c,t}) = (t - 2000) \times \widehat{rpop}_c \times \log(pop_{c,2000}).$$

(c) *Predict the potential area of the county in 2015 by running the following regression:*

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

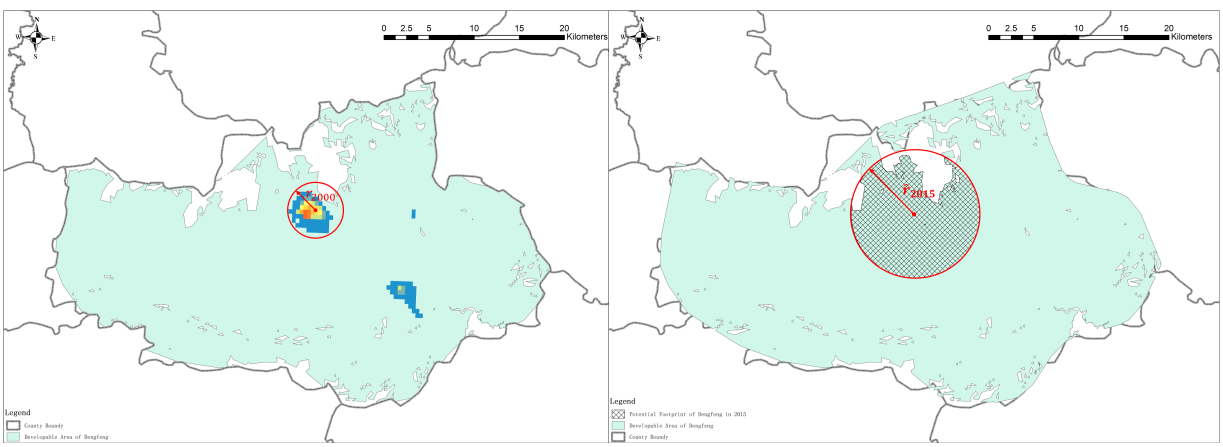
where $area_{c,2015}$ *is the area of the actual urban footprint of county* c *in* 2015, *and* f_p *is a prefecture-level fixed effect.*[4] *Let* $\widehat{area}_{c,2015}$ *be the predicted value.*

(d) *Calculate the predicted radius under the equivalent area circle* $\hat{r}_{c,2015}$ *in 2015:*

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

Draw a circle with the same centroid as in 2000 but with radius $\hat{r}_{c,2015}$. *For Deng Feng, it is the larger circle in Figure 3b (the right panel).*

5. *The potential urban footprint* $\tilde{S}_{c,2015}$ *is the intersection of the circle with radius* $\hat{r}_{c,2015}$ *and the "potential maximum developable range" from Step 1. It is the gray shadowed part of the circle in Figure 3b. The excluded part of the circle is the Song Mountain.*



(a) Actual footprint in 2000

(b) Potential footprint in 2015

Figure 3: Potential Footprint Estimation

[4] 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%.

2.2.3 Potential Urban Compactness Index

Next, we construct compactness indices based on the potential urban footprint $\tilde{S}_{c,2015}$ calculated above. The concept of "compactness" of an urban area originates from urban planning and landscape ecology (Angel et al., 2010). We focus on the Cohesion index and Range index.[5]

The Cohesion index measures the average distance between areas (or points) within a city and its centroid, thus reflecting how compact or dispersed the city's internal structure is. To calculate the Cohesion index, we first create a grid of 20,000 points 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 then calculate the average distance among all pairs for each replication, and further average them across 30 replications:

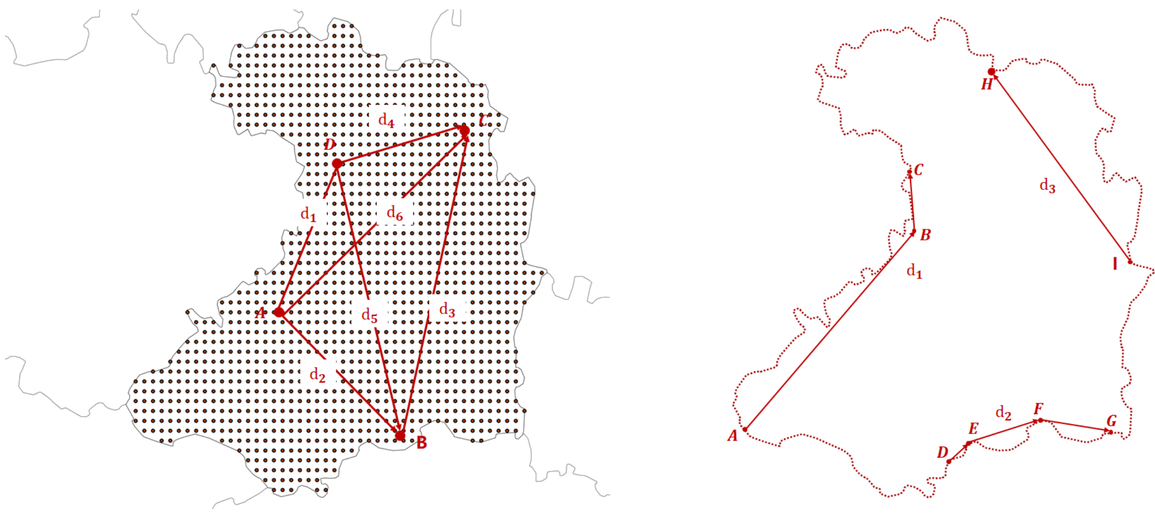
$$\text{Cohesion} = \frac{1}{30}\sum_{k=1}^{30}\text{Cohesion}_k, \quad \text{Cohesion}_k = \frac{1}{n}\sum_{i=1}^{n} d_{i,k}$$

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 4a illustrates the calculation for one replication. For illustration purposes, we only draw four randomly selected points, generating six pairs. 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:

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

The Range index measures the linear distance between the farthest points of the urban built-up area, emphasizing the overall spatial extent of the shape and the spatial span between its extreme points. A larger value indicates an elongated or irregular urban form. For each replication $k = 1, 2, \cdots, 30$, we randomly draw n pairs of points from the boundaries of the potential

[5] In addition to the Cohesion index and Range index, we also consider the Proximity index and Spin index. Table A.7 reports the results of using Proximity and Spin indices for robustness testing. All the indices are calculated via the ShapeMetrics tool in ArcGIS (the geographic information system developed by the Environmental Systems Research Institute).



(a) Example of Cohesion Index

(b) Example of Range Index

Figure 4: Examples of Compactness Indices

urban footprint and calculate their linear distance within the urban shape. For example, in Figure 4b, we randomly select three pairs: A to C, D to G, and H to I ($n = 3$). The linear path between A and C is the sum of two intervals, A to B and B to C, whereas the linear path between D and G is the sum of three intervals. We then define the range index for this replication as the maximum distance among these n pairs: $\max\{d_{1,k}, d_{2,k}, \cdots, d_{n,k}\}$. This is the range index of the k-th replication. Then, we obtain the average of the range indices across all 30 replications and normalize it using the range index of the EAC.

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

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

$$\text{and Range}_{EAC} = 2.0 \times \text{radius}_{EAC}$$

For both the Cohesion and Range indices, a smaller value means a more compact urban form. Please see Table 1 for their summary statistics.

3 Empirical Strategy

3.1 Empirical Model

In this section, we will propose an empirical model to estimate the effect of commuting time on female labor force participation. Our empirical model draws motivation from Le Barbanchon et al. (2021), who constructed a job search model whereby the flow utility of a worker is negatively impacted by commuting but differently between women and men. In equilibrium, a worker accepts a wage offer if the difference between the wage and commuting cost exceeds the discounted unemployment value. Consequently, a female job seeker would face a distinct indifference curve between wage and commuting compared to a male job seeker, highlighting how gender-based variations in commuting preferences can contribute to wage disparities. While Le Barbanchon et al. (2021) focuses on the intensive margin (wage), their framework can also explain the extensive margin of labor participation. When an unemployed worker decides to start job searching, following the spirit of Le Barbanchon et al. (2021)'s framework, he or she will compare the expected wage and expected commuting time. One proxy of the expected commuting time is the average commuting time in the city where this individual resides, and the expected wage depends on his or her characteristics and features of the local labor market. This motivates the following regression model that we consider here:

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

where Flp_{ic} is the labor participation status of woman i in county c, $commut_{ic}$ is the average urban commuting time in the county c where i resides divided by 100, X_{ic} are other control variables affecting her labor participation, p_i represent the province in which i lives, and ε_{ic} is the error term. Here, β_1 reflects the impact of average commuting duration on female labor participation. For the same reason as explained in Le Barbanchon et al. (2021), this coefficient differs from that of males, consistent with our empirical finding below. The model presented in Equation (3.1) is linear; we will estimate a binary-choice model for a robustness check in Section 4.3.

The main challenge in estimating β_1 is the endogeneity of $commut_{ic}$. In a city, the average commuting time observed at a specific point is determined by exogenous geographic factors and endogenous factors such as the city's governance policy choices. Cities with stronger governance ability are able to better deliver urban traffic planning and other economic policies that affect both commuting time and labor participation rate. OLS estimates can also be influenced by individual sorting across cities. For instance, Costa and Kahn (2000) show that high-power couples tend to sort into larger cities to solve co-located work problems. Since commuting times are often 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 Cohesion index and the Range index constructed in Section 2.2 to instrument commuting time. On one hand, urban compactness is relevant to commuting time. For more than the last three decades, China has undergone rapid urbanization characterized primarily by the rapid expansion of urban land area (Wang et al., 2020). As noticed in Angel et al. (2010), "urban sprawl" leads to changes in the spatial form of urban agglomerations, leading to increasingly "non-compact" urban forms. When other conditions are equal, a less compact city means longer distances between two points within the city and, consequently, longer commuting time. Both indices that we employed inversely measure the urban compactness. A larger value of these indices implies a less compact urban form. Table A.1 in the Appendix lists the compactness indices calculated from the potential urban footprint of various counties in Zhengzhou and the average commuting time. We find a strong positive correlation between these indices and commuting duration.

On the other hand, as argued in Harari (2020), the potential urban footprint explores the exogenous topographic obstacles along the urban area's mechanical expansion path. Therefore, the Cohesion index and the Range index constructed from the potential urban footprint are 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.

With these indices as IVs, the first stage estimation equation is given by

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

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

3.2 Further Discussion on the Validity of IVs

The validity of the instrumental variable also requires the exclusion restriction, meaning that instrumental variables can only affect labor participation through their impact on commuting time, not directly or through other channels. We will examine possible pathways below.

First, couples in which both partners work may reside in places with more compact urban formations and shorter commutes, which would potentially threaten the causal identification in this paper. Another possible threat due to sorting is that high-power couples have the capability of living in large cities with higher wages and productivity and also longer commutes due to congestion.[6] To verify the validity of the 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 five years and regress individual characteristics on the compactness indices. Table A.3 reports the results: columns 1 and 2 represent the probability of a woman and her spouse earning a college degree; column 3 shows the probability of being a high-powered couple; and column 4 is the number of children born. The results show that our instrumental variables are not correlated with any of these observable personal characteristics, which supports the validity of our identification strategy.

In addition to addressing concerns at the individual level, we also examine if the IV is correlated with a set of economic, social, and geographical characteristics, which include housing price, GDP per Capita, road density, population, and distance to coastline. These factors can generate additional channels for the IVs to affect labor participation. For example, the urban form may correlate with local geographical features, such as the distance to the coast or nearby lakes. These features can have non-monetary values for some workers, creating a sorting issue (see Diamond, 2016). Urban compactness affects housing prices, and higher (or lower) housing prices may decrease (or increase) the incentive to work due to welfare effects. Another possible channel is the local economic development level (per capita 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). On the other hand, the shape of the potential urban form, derived based on the mechanically predicted population growth, may be correlated with the local GDP, thereby threatening the

[6] As in Costa and Kahn (2000), high-powered couples are defined in this paper as couples where both spouses have earned a college degree.

validity of IVs. To safeguard against these concerns, we check if each of these factors is correlated with our IVs. The results, reported in Table A.4, show no significant correlation between either index and any of these factors.

In summary, we do not find evidence against the compactness indices being valid instrumental variables. Although we cannot completely rule out all other pathways through which potential urban footprint directly affects female labor participation, we believe their impact is unlikely to be significant—economically or statistically.

4 Empirical Results

4.1 OLS Regression

We first report the OLS estimates of the linear probability model as a baseline reference.[7] From columns 1 to 3 of Table 2, we see that commuting time and women's labor participation are negatively associated. 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 is associated with a decrease of 0.254 percentage points in women's labor participation rate (see column 3). The signs of the coefficients of other control variables appear to 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. Columns 4-6 of Table 2 report estimation results for men. Notably, men's labor participation and commuting time are also negatively associated, but with a smaller (yet significant) magnitude.

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 aforementioned. We, therefore, use the compactness indices constructed in Section 3 as IVs and perform a 2SLS estimation. Table A.5 in the appendix reports the first-stage regression results. Using either the normalized cohesion index

[7] 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 the IV-Probit model are discussed in the robustness analysis (Section 4.3).

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

	Women's labor participation			**Men's labor participation**		
	(1)	(2)	(3)	(4)	(5)	(6)
Commute	-0.346^{***}	-0.264^{***}	-0.254^{***}	-0.141^{***}	-0.092^{***}	-0.079^{***}
	(0.032)	(0.029)	(0.028)	(0.019)	(0.016)	(0.016)
Age		0.056^{***}	0.056^{***}		-0.007^{***}	-0.007^{***}
		(0.002)	(0.002)		(0.001)	(0.001)
$(\text{Age}/10)^2$		-0.069^{***}	-0.069^{***}		0.009^{***}	0.009^{***}
		(0.003)	(0.003)		(0.002)	(0.002)
Age_hus		-0.003^{**}	-0.003^{**}		0.009^{***}	0.009^{***}
		(0.001)	(0.001)		(0.001)	(0.001)
$(\text{Age\_hus}/10)^2$		0.005^{***}	0.005^{***}		-0.013^{***}	-0.013^{***}
		(0.001)	(0.001)		(0.002)	(0.002)
School		0.022^{***}	0.022^{***}		-0.003^{***}	-0.003^{***}
		(0.001)	(0.001)		(0.000)	(0.000)
School_hus		-0.005^{***}	-0.006^{***}		0.009^{***}	0.009^{***}
		(0.001)	(0.001)		(0.000)	(0.000)
Other controls	No	Yes	Yes	No	Yes	Yes
Fix Effect	Province	Province	Prefecture	Province	Province	Prefecture
Observations	135,780	135,780	135,780	104,060	104,060	104,060
R-squared	0.024	0.040	0.093	0.113	0.113	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. Standard errors are in parentheses.

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.

The main regression results of our paper are detailed in Table 3–Panel A. The p-value of the J-test is far above the 10% level, indicating that the hypothesis of the exogeneity of the two instrumental variables cannot be rejected. In 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.

Columns 1 and 2 of Table 3 (Panel A) use the Cohesion index as the instrumental variable; columns 3 and 4 use the Range index; 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 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 0.498 percentage points. This result is comparable to Black et al. (2014), who find that in major U.S. cities, each additional minute of commuting reduces the labor force participation rate of married women with children under five by 0.78 percentage points for those with a high school education and by 0.61 percentage points for those with a college education. For married women without young children, the corresponding declines are 0.62 and 0.40 percentage points, respectively, for women with high school and college education. 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). This can explain up to 41.1% of the 58.3 percentage points range of female labor participation across different counties in our data set.

Our result can also partly explain why China's female labor participation rate tends to decline. China's urban area has been expanding continuously since entering the 21st century, with a large influx of labor in big cities. This fact, coupled with the rising number of privately owned cars, has led to an increase in commuting duration in major Chinese cities. In China, the primary economic source often comes from the husband. City expansion and traffic congestion increase commuting duration, shifting more family caregiving responsibilities to wives and 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 accounts for more than 40% of the change over this period.[8]

Panel B of Table 3 reports the estimation results on how commuting time affects men's labor participation for comparison purposes. Again, we observe significant and negative impacts of commute on men's labor participation across all configurations. Focusing on column (6), where

[8] 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.

Table 3: The Impact of Commuting Duration on the Labor Participation Rate (2SLS)

	Cohesion Index		Range Index		Both Indices	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female's labor participation						
Commute	-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)
$(\text{Age}/10)^2$		-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)
$(\text{Age\_hus}/10)^2$		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
1st stage F-Stat	11.8	10.6	57.1	42.2	30.8	23.2
J-Test (P-value)					0.828	0.660
Observations	135,780	135,780	135,780	135,780	135,780	135,780
Panel B: male's labor participation						
Commute	-0.319^{***}	-0.188^{*}	-0.377^{***}	-0.273^{***}	-0.364^{***}	-0.249^{***}
	(0.097)	(0.105)	(0.094)	(0.096)	(0.085)	(0.085)
Age		-0.007^{***}		-0.007^{***}		-0.007^{***}
		(0.001)		(0.001)		(0.001)
$(\text{Age}/10)^2$		0.009^{***}		0.008^{***}		0.008^{***}
		(0.002)		(0.002)		(0.002)
Age_hus		0.009^{***}		0.009^{***}		0.009^{***}
		(0.001)		(0.001)		(0.001)
$(\text{Age\_hus}/10)^2$		-0.013^{***}		-0.013^{***}		-0.013^{***}
		(0.002)		(0.002)		(0.002)
School		-0.003^{***}		-0.003^{***}		-0.003^{***}
		(0.000)		(0.000)		(0.000)
School_hus		0.010^{***}		0.010^{***}		0.010^{***}
		(0.001)		(0.001)		(0.000)
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
1st stage F-Stat	10.9	9.6	56.1	41.2	30.1	22.5
J-test (P-value)					0.558	0.433
Observations	104,060	104,060	104,060	104,060	104,060	104,060

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.

both cohesion and range indices are used as the IV, we note that the impact size for men is about half of that for women. This finding is consistent with our earlier discussion. Men are often more responsible for generating income in a representative Chinese family. Therefore, the elasticity of labor participation concerning commuting time is lower. The gender difference has also been noted in the literature; for instance, Petrongolo and Ronchi (2020, Section 4) document that women have a stronger preference for shorter commutes.

Comparing the OLS and IV estimation results (for both female and male labor participation), we found the OLS estimates are biased towards zero across all configurations. By ignoring the endogeneity of commuting time, OLS estimation misreads the magnitude of the causal effect of commuting time on labor participation for both men and women. The sign of the bias is consistent with our earlier discussion that there is a possible positive correlation between commuting time and the unobserved factors that affect labor participation.

4.3 Robustness Analysis

4.3.1 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 go on to estimate the Probit model to obtain consistent estimates of the parameters.

Table A.6 shows the marginal effects of urban commuting duration on female labor participation (covariates evaluated at averages); 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.

4.3.2 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 other indices and used them as instrumental variables to test the robustness of our conclusions. Table A.7 lists the estimation results, which are qualitatively similar to our baseline model.

4.3.3 Using male's average commuting time

Our main regression uses the county's average commuting time of both male and female workers as the core explanatory variable. However, because there is a large variation in the female labor force participation rate across different regions, and because males are still dominant in generating family income in China, we conduct a robustness analysis using the county's average male commuting time as the key explanatory variable. The results are collected in Table A.8 and are similar to the main regression. We still observe a negative response of female and male labor force participation to males' average commuting time, and the magnitude for females is larger than that of males.

4.3.4 Industry structure

The industrial structure may simultaneously affect urban commuting and female labor participation. Therefore, we add the share of the secondary and tertiary industries in GDP at the county levels and re-estimate the impact of urban commuting on female labor participation using the 2SLS method. The results in Table A.9 show that the impact of commuting on female labor participation remains significantly negative, further confirming the robustness of our empirical findings.

4.3.5 Urban Size

The total land area of a district or county may also simultaneously affect both urban commuting and female labor participation. This is because a larger land area may lead to longer average commuting distances and increased commuting times. A larger land area may also accommodate more enterprises, resulting in more employment opportunities. Table A.10 incorporates the land area of each district and county into the primary regression model to examine whether it affects the main conclusions. The results show that after accounting for land area, the primary regression results remain unchanged.

4.3.6 Excluding Movers

colorblackTo further eliminate the effect of sorting, we exclude households that migrated in the recent five years, and we conduct 2SLS estimation based on the no migration occurrence subsamples. We discover that the conclusion remains consistent with the baseline results—again suggesting the sorting issue does not have a substantial dent on the empirical results in this paper: the negative impact changes from 0.5 percentage points to 0.55 percentage points with both IVs being used. The difference is only about a quarter of the standard error and hence not statistically significant. Please see Table A.11. Naturally, based on our sample, the very low share of the sample (7.6%) with cross-county migration in the last five years is directly tied to China's strict household registration system and large migration costs. Thus, sorting is not a serious issue in our context.

4.3.7 Repeated cross-sectional data

Lastly, we use data from the China Health and Nutrition Survey (CHNS) to replicate the conclusions of this study. Although the 1% Census data covers all the prefectures and has the advantage of a large sample size and strong representativeness, it is cross-sectional. Therefore, we conduct a robustness check using CHNS data. Here, we leverage the repeated cross-sectional nature of CHNS to address potential sorting issues related to city characteristics that remain unchanged over time.

CHNS is one of the largest and longest-running data collection projects on health and nutrition in China, jointly conducted by the Chinese Center for Disease Control and Prevention (CDC), the University of North Carolina at Chapel Hill, and other international partners. CHNS employs a multi-stage, stratified cluster random sampling method to select representative samples. The survey covers a wide range of indicators, including personal information, nutrition and health, socioeconomic status, and lifestyle. Since its inception in 1989, follow-up surveys have been conducted in 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015. Commuting time data has been available since 2004, so we use only CHNS data from 2004 onwards. On the cross-sectional dimension, the CHNS dataset covers 12 provincial-level administrative regions, including Beijing, Liaoning, Heilongjiang, Shanghai, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi Zhuang Autonomous Region, Guizhou, and Chongqing, containing surveys on both urban and rural residents in these areas. Compared with the 1% Census data, CHNS covers fewer counties (fewer provinces and fewer counties within each province) and, therefore, has a smaller sample size. For this exercise, we use the same set of control variables as those in the baseline regression model based on personal and socio-economic information (please see descriptive statistics in Table A.12).

Similar to the baseline regression, we estimate the impact of urban commuting time on female labor participation using both OLS and 2SLS, but now, we include county and year dummies. For comparison, we also estimate its impact on male labor participation. The results are presented in Table A.13. We can see that regardless of whether OLS or 2SLS estimation is used, urban commuting has a significantly negative impact on female labor participation. In contrast, its impact on male labor participation is numerically smaller, and when all control variables and fixed effects are included (column 8), the 2SLS estimate does not pass the significance test at 10%. The results based on CHNS data once again confirm the negative impact of urban commuting on female labor participation, while its impact on male labor participation is not significant. This is consistent in direction with the main regression results.

5 Heterogeneity Analysis

5.1 Education

Previous literature has theoretically and empirically demonstrated that if the wife's income constitutes a smaller proportion in 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 smaller magnitude of the causal effect for women with higher education levels. To verify this, we include a dummy variable $College \in \{0, 1\}$, indicating whether the woman has a degree above college or not, and also include an interaction term $College * Commute$. We can see from Table 4 (column 1) that for women with a college education, the impact of commuting time is 0.216 less than those without a college education (coefficient of the interaction term). However, this difference is not significant at 10% level, although its sign is consistent with our expectation.

Table 4: Heterogeneity Analysis

Heterogeneity in:	College (1)	Kids (2)	Dist. to Coast (3)	BigCity (4)	Road Density (5)	Subway (6)
Commute	-0.564^{***}	-0.209	-1.916^{**}	-1.064^{*}	-0.583^{**}	-0.808^{***}
	(0.209)	(0.259)	(0.791)	(0.565)	(0.251)	(0.258)
Commute*College	0.216					
	(0.294)					
College	0.078					
	(0.127)					
Commute*kids		-0.770^{***}				
		(0.257)				
kids		0.301^{***}				
		(0.103)				
Commute*Distance			0.277^{**}			
			(0.127)			
Distance to coast			-0.091^{*}			
			(0.047)			
Commute*Bigcity				0.866		
				(0.580)		
Big city				-0.325		
				(0.212)		
Commute*Road den.					0.185	
					(0.166)	
Road density					-0.089	
					(0.090)	
Commute*subway2010						1.179^{***}
						(0.363)
subway2010						-0.461^{***}
						(0.150)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
1st stage F-stat	11.35	11.60	4.55	3.19	2.31	8.63
J-test (P-value)	0.952	0.892	0.115	0.975	0.693	0.638
Observations	135,780	135,780	133,660	135,780	134,302	135,780

Note: Robust standard errors clustered at the county and survey year level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

5.2 Fertility

When infants or young children require care in the family, the role of women in family work significantly increases in China. The negative impact of longer commuting duration on married women's labor participation will be more pronounced. To verify the heterogeneity in this dimension, we conduct another regression by introducing a dummy variable $Kids \in \{0, 1\}$, indicating whether the woman has at least one child or not, and its interaction term with commute. As we can see from column 2 of Table 4, the coefficient in front of the interaction term is significant and negative. This result verifies that women with childcare responsibilities are more sensitive to commuting time. Our result is similar to that of 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 the Reform and Opening-up policy in 1978, China has prioritized the development of coastal cities, allowing these cities to become prosperous first and then drive the development of inland regions. As a result, the eastern coast regions and big cities have aggregated more resources, such as higher education, healthcare, and entertainment. They, in general, have a more open culture. Does the impact of urban commuting on female labor participation also vary in their relative location to the coastline? To examine this, we calculate the distance from each county to the nearest coastline. We then interact this variable with commuting time and add both to the main regression model. The estimation results are reported in Column 3 of Table 4. We find that the coefficient of the interaction term is significantly positive, indicating that the farther a city is from the coastline, the less negative the impact of commuting on female labor participation becomes. Since cities closer to the coastline are generally more economically developed, this finding suggests that urban commuting mainly exerts a negative effect on female labor participation in more developed regions. The second regional heterogeneity that we consider here is whether the woman resides in a big city or not. We use the dummy variable $BigCity \in \{0, 1\}$ to indicate whether it is one of the top 70 largest cities in China or not. The regression results are reported in column 4 of Table 4. The coefficient for the interaction term is positive but not significant.

5.4 Transportation Infrastructure

A city's transportation infrastructure can significantly affect urban commuting and employment choices. For example, the subway system can reduce surface traffic pressure and provide commuters with an additional transportation option. Because subway transportation is more predictable, the availability of a subway system can significantly alleviate the anxiety caused by commuting for city workers, thereby reducing commuting duration's impact on women's labor participation. However, the availability of the subway system in a city can be correlated with the confounders that determine female labor participation, for instance, the governing ability of the current local government. It may also be associated with the geographical factors that affect the IVs. Cities with lots of lakes may have a less regular urban shape, and the cost of building subways can be high. To mitigate the potential endogeneity, we create a lagged dummy variable, $subway2010$, to denote whether a city had a subway in 2010 (five years before the date of our data).[9] The results show that the coefficient of the interaction term is significantly positive, suggesting that the existence of Subway reduces the magnitude of the negative impact of commuting. Indeed, in the cities with subways, the impact of urban commuting on the labor participation of women is small and not statistically significant. In contrast, in cities without subways, the impact is significantly negative. Please see column 6 of Table 4. The estimation results suggest that when a city opens a subway, the adverse effects of commuting duration on women's labor participation can be greatly mitigated by enriching the mode of transportation. We also include an interaction term of road density with commuting time for another robustness check. There, we find a positive but not significant coefficient before the interaction term of commuting time and road density (column 5 of Table 4). It also suggests that a better road network can help alleviate the negative impact of commuting, albeit its effect is less than that of the subway system.

6 Conclusion

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

[9] We also use the presence of a subway in 2015 as a cross-check. The results are qualitatively the same and collected in Table A.14.

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 about 40% 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. We also find that the negative impact on labor participation also exists for males, albeit with a smaller magnitude. This finding is consistent with what has been documented in the literature.

Our heterogeneity analysis results show that the magnitude of the impact also varies with the female's education, the geographical location of their residence, family responsibility for childcare, and the quality of local transportation infrastructure (particularly the presence of the subway). The size of the impact is smaller for females with higher education levels and less family responsibility, consistent with some empirical studies based on data from developed countries (Black et al., 2014; Carta and De Philippis, 2018). We find that, in inland areas, the impact of urban commuting tends to be smaller than in areas closer to the East Coast. When the subway is available, the negative impact of commuting time becomes insignificant.

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 greater 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, our results show that improving the richness of transportation methods can reduce commuting anxiety and improve 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: Descriptive Statistics of County-Level Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Ncohesion	1,789	1.108	0.211	0.996	5.486
Nrange	1,789	1.247	0.188	1.033	2.369
Per capita GDP (10K rmb)	1,165	3.699	3.070	0.644	38.988
House price (100 rmb/m^2)	697	68.327	63.718	18.830	727.820
Road density (km/km^2)	1,768	0.773	1.434	0.001	23.682
Distance to coastline (km)	1,784	434.0	335.2	0.009	2569.7
Total population (10K)	1,539	57.802	38.275	2.760	547.490
Average Annual Wage	1,000	50,783	9,624	27,215	93,926
Average age	1,789	40.434	1.800	29.750	51.000
Husbands' average age	1,789	44.022	2.162	35.394	56.000
Average schooling years	1,789	9.484	1.459	1.000	15.500
Husbands' average schooling years	1,789	9.833	1.258	5.667	15.014
Han Chinese share	1,789	0.948	0.141	0.000	1.000
Rural hukou share	1,789	0.619	0.251	0.000	1.000
Share of rented housing	1,789	0.092	0.119	0.000	0.768
Average number of children	1,789	1.525	0.356	0.000	3.471
Husbands' labor participation rate	1,789	0.884	0.105	0.000	1.000

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

	(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: Urban Form and Other City Economic and Geographic Characteristics

Variables	House price		Per Capita GDP		Road density	
	(1)	(2)	(3)	(4)	(5)	(6)
Ncohesion	1.225		0.099		−0.109	
	(3.374)		(0.187)		(0.098)	
Nrange		12.352*		0.156		0.039
		(6.511)		(0.323)		(0.150)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	697	697	1,165	1,165	1,768	1,768
R-squared	0.836	0.837	0.717	0.717	0.624	0.624

Variables	Distance to Coastline		Log of Total Population		Log of Average Wage	
	(7)	(8)	(9)	(10)	(11)	(12)
Ncohesion	−0.035		0.042		0.033	
	(0.024)		(0.059)		(0.032)	
Nrange		−0.027		−0.161		0.037
		(0.028)		(0.102)		(0.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,780	1,780	1,539	1,539	1,000	1,000
R-squared	0.823	0.823	0.567	0.568	0.722	0.722

Notes: To maintain consistency with the main regression model, all regressions include the control variables at the county average level (age and schooling years for both wives and husbands, share of Han Chinese, rural Hukou and housing that is rented, number of children, husbands labor participation), and regional dummies.Robust standard errors clustered at county level in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: 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
Panel A: Female						
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)
Main controls	No	Yes	No	Yes	No	Yes
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135, 780	135, 780	135, 780	135, 780	135, 780	135, 780
Panel B: Male						
Ncohesion	0.056***	0.049***			0.030*	0.029*
	(0.017)	(0.016)			(0.016)	(0.016)
Nrange			0.101***	0.083***	0.087***	0.069***
			(0.013)	(0.013)	(0.015)	(0.015)
Main controls	No	Yes	No	Yes	No	Yes
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104, 060	104, 060	104, 060	104, 060	104, 060	104, 060

Note: Main controls are the same as in Table 3. 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<0.10.

Table A.6: Estimation Based on the Control Function Method

	Cohension Index	Range Index	Both Indices
Variables	(1)	(2)	(3)
Commute	-0.559**	-0.343*	-0.414**
	(0.247	(0.190)	(0.185)
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
Observation	135576	135576	135576

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

Table A.7: Using Proximity Index and Spin Index as IVs

	Proximity Index		Spin Index	
Variables	(1)	(2)	(3)	(4)
Commute	-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)
$(\text{Age}/10)^2$		-0.069^{***}		-0.069^{***}
		(0.003)		(0.003)
Age_hus		-0.003^{***}		-0.003^{***}
		(0.001)		(0.001)
$(\text{Age\_hus}/10)^2$		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
1st stage F-Stat	31.8	25.5	28.2	23.6
Observations	135,780	135,780	135,780	135,780

Note: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The Spin index is calculated in a similar way as the Cohesion index, with the distance being replaced by the square of distance. The proximity index is calculated as the average distance from all internal locations within the city to the urban centroid.

Table A.8: Replication of Table 3 with Men's Commuting Time

Variables	Cohesion Index (1)	(2)	Range Index (3)	(4)	Both Indices (5)	(6)
Panel A: Female's labor participation						
Commute	-0.814^{**}	-0.579^{*}	-0.739^{***}	-0.437^{**}	-0.758^{***}	-0.480^{**}
	(0.329)	(0.328)	(0.190)	(0.190)	(0.190)	(0.194)
Age		0.056^{***}		0.056^{***}		0.056^{***}
		(0.002)		(0.002)		(0.002)
$(\text{Age}/10)^2$		-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)
$(\text{Age\_hus}/10)^2$		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
1st stage F-Stat	8.9	7.7	49.5	36.2	30.8	19.4
J-test (P-value)					0.807	0.632
Observations	133,208	133,208	133,208	133,208	133,208	133,208
Panel B: Male's labor participation						
Commute	-0.320^{***}	-0.187^{*}	-0.369^{***}	-0.264^{***}	-0.358^{***}	-0.242^{***}
	(0.107)	(0.107)	(0.098)	(0.099)	(0.089)	(0.088)
Age		-0.007^{***}		-0.007^{***}		-0.007^{***}
		(0.001)		(0.001)		(0.001)
$(\text{Age}/10)^2$		0.009^{***}		0.009^{***}		0.009^{***}
		(0.002)		(0.002)		(0.002)
Age_hus		0.009^{***}		0.009^{***}		0.009^{***}
		(0.001)		(0.001)		(0.001)
$(\text{Age\_hus}/10)^2$		-0.013^{***}		-0.013^{***}		-0.013^{***}
		(0.002)		(0.002)		(0.002)
School		-0.003^{***}		-0.003^{***}		-0.003^{***}
		(0.000)		(0.000)		(0.000)
School_hus		0.010^{***}		0.010^{***}		0.010^{***}
		(0.001)		(0.001)		(0.000)
Other controls	No	Yes	No	Yes	No	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
1st stage F-Stat	8.2	7.0	48.5	35.3	19.9	18.8
J-test (P-value)					0.650	0.492
Observations	102,043	102,043	102,043	102,043	102,043	102,043

Note: 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<0.10, ** p<0.05, *** p<0.01.

Table A.9: Controlling Industry Structure

	Cohension Index	Range Index	Both Indices
	(1)	(2)	(3)
Dep. Var	Flp	Flp	Flp
Commute	-0.530^{*}	-0.448^{**}	-0.472^{**}
	(0.304)	(0.195)	(0.193)
Secondary industry share	-0.253^{***}	-0.258^{***}	-0.256^{***}
	(0.053)	(0.050)	(0.050)
Tertiary industry share	-0.303^{***}	-0.314^{***}	-0.311^{***}
	(0.085)	(0.078)	(0.078)
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
1st stage F-Stat	9.21	39.20	21.33
J-test (P-value)			0.771
Observations	131,725	131,725	131,725

Note: Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.10: Controlling Urban Area Size

	Cohension Index	Range Index	Both Indices
	(1)	(2)	(3)
Dep. Var	Flp	Flp	Flp
Commute	-0.573^{**}	-0.484^{**}	-0.514^{***}
	(0.292)	(0.193)	(0.191)
City area	-0.006	-0.005	-0.005
	(0.004)	(0.003)	(0.003)
Ccontrols	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
1st stage F-Stat	10.97	40.59	22.57
J-test (P-value)			0.743
Observations	135,780	135,780	135,780

Note: Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.11: 2SLS Estimation without Migrants

	(1)	(2)	(3)
Dep. Var	Flp	Flp	Flp
Commute	-0.668^{**}	-0.492^{**}	-0.547^{***}
	(0.327)	(0.202)	(0.204)
Controls	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
1st stage F-Stat	9.34	38.09	20.87
J-test (P-value)			0.551
Observations	125,395	125,395	125,395

Note: Robust standard errors clustered at the county level are displayed in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.12: Summary Statistics of CHNS Dataset

Variable	Observation	Mean	Std. Dev.	Min	Max
Flp	10,964	0.691	0.462	0.000	1.000
Commute	10,964	0.496	0.278	0.179	1.404
Age	10,964	39.222	7.397	20.000	50.000
Age_hus	10,964	41.043	7.735	20.000	60.000
School	10,948	8.849	3.556	0.000	18.000
School_hus	10,944	9.705	3.126	0.000	18.000
Han Chinese	10,964	0.885	0.319	0.000	1.000
Rural	10,964	0.671	0.470	0.000	1.000
Childnum	10,964	1.723	0.913	1.000	9.000
Rent	10,964	0.029	0.168	0.000	1.000
Flp_hus	10,964	0.854	0.353	0.000	1.000
Ncohesion	9,797	1.142	0.275	0.517	2.183
Nrange	9,797	1.346	1.173	0.377	6.213

Table A.13: Regression Results Using CHNS Data

Variables	Female Labor Participation				Male Labor Participation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Commute	0.010	0.015	-1.013^{**}	-0.865^{**}	-0.018	-0.019	-0.753^{*}	-0.462
	(0.026)	(0.023)	(0.499)	(0.417)	(0.020)	(0.016)	(0.452)	(0.323)
Age		0.061^{***}		0.076^{***}		-0.005		0.006
		(0.010)		(0.013)		(0.009)		(0.011)
$(\text{Age}/10)^2$		-0.081^{***}		-0.100^{***}		0.010		-0.004
		(0.012)		(0.016)		(0.011)		(0.014)
Age_hus		0.016^{*}		0.011		0.005		-0.000
		(0.009)		(0.011)		(0.009)		(0.010)
$(\text{Age\_hus}/10)^2$		-0.019^{*}		-0.013		-0.013		-0.007
		(0.011)		(0.013)		(0.012)		(0.013)
School		0.013^{***}		0.014^{***}		-0.003^{*}		-0.002
		(0.002)		(0.002)		(0.001)		(0.001)
School_hus		0.000		-0.000		0.008^{***}		0.007^{***}
		(0.002)		(0.002)		(0.001)		(0.002)
Other controls	No	Yes	No	Yes	No	Yes	No	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st stage F-Stat			3.13	3.25			2.12	2.24
J-test (P-value)			0.4577	0.694			0.874	0.868
Observations	10,964	10,929	9,797	9,768	9,862	9,829	8,818	8,791

Note: Robust standard errors clustered at the county and survey year level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.14: Heterogeneity in Opening Subways

Variables	(1)	(2)
Commute	-1.461^{***}	-1.010^{***}
	(0.402)	(0.391)
Commute × Subway2015	1.534^{***}	1.125^{***}
	(0.439)	(0.402)
Subway2015	-0.582^{***}	-0.432^{***}
	(0.161)	(0.139)
Controls	No	Yes
Province dummy	Yes	Yes
First stage F statistics	6.17	4.64
Hansen J statistics (P-value)	0.682	0.736
Observations	135,780	135,780

Note: Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A.15: Descriptive Statistics for Different Cutoffs

	Commute_ave ≥ 30.4 N=101949		Commute_ave < 30.4 N=33831		Difference (2)-(1)	Commute_ave ≥ 43.1 N=34201		Commute_ave < 43.1 N=101579		Difference (5)-(4)
Variables	Mean	S.D.	Mean	S.D.		Mean	S.D.	Mean	S.D.	
Flp	0.701	0.458	0.779	0.415	0.077***	0.686	0.464	0.732	0.443	0.046***
Commute	0.413	0.0944	0.274	0.0218	-0.139***	0.522	0.0805	0.330	0.0504	-0.191***
Age	40.12	7.241	40.38	7.293	0.259***	39.66	7.303	40.36	7.230	0.702***
Age_hus	43.50	8.762	43.65	8.759	0.147***	43.03	8.963	43.71	8.686	0.681***
School	9.736	3.255	8.970	2.813	-0.766***	10.35	3.556	9.273	2.977	-1.078***
School_hus	10.10	3.070	9.412	2.630	-0.692***	10.67	3.350	9.683	2.803	-0.985***
Han Chinese	0.953	0.211	0.966	0.181	0.013***	0.953	0.211	0.957	0.202	0.004***
Rural	0.581	0.493	0.747	0.435	0.166***	0.481	0.500	0.670	0.470	0.190***
Childnum	1.516	0.797	1.616	0.768	0.100***	1.427	0.800	1.579	0.784	0.152***
Rent	0.114	0.318	0.106	0.308	-0.008***	0.156	0.363	0.0975	0.297	-0.058***
Flp_hus	0.885	0.319	0.929	0.257	0.044***	0.868	0.339	0.906	0.292	0.038***
Ncohesion	1.129	0.245	1.090	0.158	-0.038***	1.167	0.285	1.103	0.201	-0.064***
Nrange	1.264	0.197	1.200	0.138	-0.064***	1.303	0.222	1.229	0.168	-0.075***
Nproximity	1.072	0.0948	1.051	0.0614	-0.021***	1.085	0.0995	1.061	0.0830	-0.024***
Nspin	1.192	0.278	1.130	0.161	-0.062***	1.230	0.297	1.158	0.237	-0.072***

Notes: Robust standard errors clustered at the county level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

References

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). An evaluation of instrumental variable strategies for estimating the effects of catholic schooling. *Journal of Human resources*, 40(4):791–821.

Angel, S., Parent, J., and Civco, D. L. (2010). Ten compactness properties of circles: measuring shape in geography. *The Canadian Geographer/Le Géographe canadien*, 54(4):441–461.

Angel, S., Sheppard, S., Civco, D. L., Buckley, R., Chabaeva, A., Gitlin, L., Kraley, A., Parent, J., Perlin, M., et al. (2005). *The dynamics of global urban expansion*. World Bank, Transport and Urban Development Department Washington, DC.

Angrist, J. and Evans, W. N. (1996). Children and their parents' labor supply: Evidence from exogenous variation in family size. *NBER Working paper*, NBER W5778.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The quarterly journal of economics*, 122(2):775–805.

Black, D. A., Kolesnikova, N., and Taylor, L. J. (2014). Why do so few women work in new york (and so many in minneapolis)? labor supply of married women across us cities. *Journal of Urban Economics*, 79:59–71.

Blau, F. D. and Kahn, L. M. (2000). Gender differences in pay. *Journal of Economic perspectives*, 14(4):75–100.

Bloom, D. E., Canning, D., Fink, G., and Finlay, J. E. (2009). Fertility, female labor force participation, and the demographic dividend. *Journal of Economic growth*, 14:79–101.

Cao, X., Hu, Y., Zhu, X., Shi, F., Zhuo, L., and Chen, J. (2019). A simple self-adjusting model for correcting the blooming effects in dmsp-ols nighttime light images. *Remote Sensing of Environment*, 224:401–411.

Carta, F. and De Philippis, M. (2018). You've come a long way, baby. husbands' commuting time and family labour supply. *Regional Science and Urban Economics*, 69:25–37.

Chen, S., Chen, Y., Lei, Z., and Tan-Soo, J.-S. (2021). Chasing clean air: Pollution-induced travels in china. *Journal of the Association of Environmental and Resource Economists*, 8(1):59–89.

Chen, X. and Ge, S. (2018). Social norms and female labor force participation in urban china. *Journal of Comparative Economics*, 46(4):966–987.

Chen, Z., Yu, B., Ta, N., Shi, K., Yang, C., Wang, C., Zhao, X., Deng, S., and Wu, J. (2019). Delineating seasonal relationships between suomi npp-viirs nighttime light and human activity across shanghai, china. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 12(11):4275–4283.

Cogan, J. (1980). Fixed costs and labor supply.

Costa, D. L. and Kahn, M. E. (2000). Power couples: changes in the locational choice of the college educated, 1940–1990. *The Quarterly Journal of Economics*, 115(4):1287–1315.

Cruces, G. and Galiani, S. (2007). Fertility and female labor supply in latin america: New causal evidence. *Labour Economics*, 14(3):565–573.

Currie, J. and Walker, R. (2011). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics*, 3(1):65–90.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980–2000. *American economic review*, 106(3):479–524.

Duranton, G., Henderson, V., and Strange, W. (2015). *Handbook of regional and urban economics*. Elsevier.

Farré, L., Jofre-Monseny, J., and Torrecillas, J. (2023). Commuting time and the gender gap in labor market participation. *Journal of Economic Geography*, 23(4):847–870.

Gimenez-Nadal, J. I., Molina, J. A., and Zhu, Y. (2018). Intergenerational mobility of housework time in the united kingdom. *Review of Economics of the Household*, 16:911–937.

Gutiérrez-i Puigarnau, E. and van Ommeren, J. N. (2015). Commuting and labour supply revisited. *Urban Studies*, 52(14):2551–2563.

Harari, M. (2020). Cities in bad shape: Urban geometry in india. *American Economic Review*, 110(8):2377–2421.

Hare, D. (2016). What accounts for the decline in labor force participation among married women in urban china, 1991–2011? *China Economic Review*, 38:251–266.

He, X. and Zhu, R. (2016). Fertility and female labour force participation: Causal evidence from urban c hina. *The Manchester School*, 84(5):664–674.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161.

Juhn, C. and Potter, S. (2006). Changes in labor force participation in the united states. *Journal of Economic Perspectives*, 20(3):27–46.

Kawabata, M. and Abe, Y. (2018). Intra-metropolitan spatial patterns of female labor force participation and commute times in tokyo. *Regional Science and Urban Economics*, 68:291–303.

Lahoti, R. and Swaminathan, H. (2016). Economic development and women's labor force participation in india. *Feminist Economics*, 22(2):168–195.

Le Barbanchon, T., Rathelot, R., and Roulet, A. (2021). Gender differences in job search: Trading off commute against wage. *The Quarterly Journal of Economics*, 136(1):381–426.

Letu, H., Hara, M., Yagi, H., Naoki, K., Tana, G., Nishio, F., and Shuhei, O. (2010). Estimating energy consumption from night-time dmps/ols imagery after correcting for saturation effects. *International journal of remote sensing*, 31(16):4443–4458.

Levin, A. T., Hanage, W. P., Owusu-Boaitey, N., Cochran, K. B., Walsh, S. P., and Meyerowitz-Katz, G. (2020). Assessing the age specificity of infection fatality rates for covid-19: systematic review, meta-analysis, and public policy implications. *European journal of epidemiology*, 35(12):1123–1138.

Liu, S., Jin, T., Li, M., and Zhou, S. (2024). Fertility policy adjustments and female labor supply: estimation of marginal treatment effect using chinese census data. *Journal of Human Resources*, 59(6):1865–1892.

Mehrotra, S. and Parida, J. K. (2017). Why is the labour force participation of women declining in india? *World Development*, 98:360–380.

Newman, P. and Kenworthy, J. (1999). *Sustainability and cities: overcoming automobile dependence*. Island press.

Petrongolo, B. and Ronchi, M. (2020). Gender gaps and the structure of local labor markets. *Labour Economics*, 64:101819.

Rivers, D. and Vuong, Q. H. (1988). Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of econometrics*, 39(3):347–366.

Simeonova, E., Currie, J., Nilsson, P., and Walker, R. (2021). Congestion pricing, air pollution, and children's health. *Journal of Human Resources*, 56(4):971–996.

Staiger, D. and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3):557–586.

Stancanelli, E. and Soest, A. V. (2012). Retirement and home production: A regression discontinuity approach. *American Economic Review*, 102(3):600–605.

Wang, Z., Zhang, Q., and Zhou, L.-A. (2020). Career incentives of city leaders and urban spatial expansion in china. *Review of Economics and Statistics*, 102(5):897–911.