BOFIT Discussion Papers
7 • 2021

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# Who cares: Deciphering China's female employment paradox

THE BANK OF FINLAND INSTITUTE FOR EMERGING ECONOMIES

BOFIT Discussion Papers
Editor-in-Chief Zuzana Fungáčová

BOFIT Discussion Papers 7/2021
18.5.2021

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ISBN 978-952-323-376-8, online
ISSN 1456-5889, online

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Bank of Finland
Helsinki 2021

# Contents

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## Abstract

Female post-childbirth labor market participation and labor intensity are extraordinarily high in China, given that public childcare subsidies are limited and supportive policies for childbearing female employees are largely absent. Establishing a panel dataset that tracks female employment and childbirth, we find that such a paradox is well-explained by the intra-family childcare support provided by grandparents. Correcting the selection bias that stems from women's fertility choices using the propensity score matching difference-in-difference model, we find that women without grandparental support suffer a substantial drop in post-childbirth employment, while women with grandparental support even experience a rise in employment after childbirth. It takes women without grandparental support twice as long to recover their employment after childbirth. Finally, we find that childbirth does not decrease women's labor intensity due to a lack of labor market flexibility, and that women face a stay-or-quit dilemma when grandparental childcare support is absent.

Keywords: grandparental childcare, PSM-DID, fertility choice, female employment, labor intensity
JEL Classification: C24, J13, J22

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**Acknowledgements**
The authors thank participants in various seminars at Norges Bank, Bank of Finland, and ASSA Annual Meeting, San Diego, for helpful comments. This paper should not be reported as representing the views of Norges Bank, and the views expressed are those of the author and do not necessarily reflect those of Norges Bank.

# 1 Introduction

Childcare is one of the main reasons for interruptions in women's career paths and human capital accumulation. In most of the advanced economies in the world, heavy public investment in childcare and supportive policies for female employees have been the keys to maintaining relatively high labor market participation rates for women and low human capital losses associated with childbearing. Compared with these countries, female employment in China presents something of a paradox. On the one hand, in China, public investment in childcare is very low and protections for working mothers are rather limited; on the other hand, China's female labor market participation rate is not only far higher than in other emerging market economies, but also exceeds those of the Scandinavian countries, long known for gender equality and high female employment. The question of how women in China reconcile the conflict between childcare and employment, and achieve an unusually high employment rate and labor intensity, remains largely unanswered.

In recent decades, China's female labor market participation rate has consistently been among the world's highest. According to the International Labor Organization (ILOSTAT, 2018), the employment rate for women above the age of 15 is as high as 61.3% in China – not only far higher than in the US (56%) and the EU countries (50%), but also higher than in the Scandinavian countries (58% for Denmark, 61% for Sweden, 60.2% for Norway). Higher female employment usually reflects better social protections and supportive policies for female employees (Mandel and Semyonov 2006). For instance, longer paid maternity leave and more extensive childcare provision significantly improve the labor market participation rate for women aged 25–55 (Besamusca et al. 2015), and providing more flexible jobs also improves female employment (Gomes 2012, Blau and Kahn 2013). However, both supportive policies for childbearing women and public provision of childcare in China are, if not non-existent, then by no means satisfactory. For instance, China's public expenditure on kindergartens only accounts for 0.16% of GDP, far below that of most OECD countries (such as 0.9% for New Zealand, 0.7% for Norway, 0.65% for the UK, and 0.45% for Germany). Due to low public investment, the supply of affordable public kindergartens is limited in China, the minimum admission age for kindergartens (3 years old) is too high, and pre-school / day-care services are virtually non-existent. For working mothers, the statutory maternity leave in China is only 98 days, which is one of the lowest among 43 OECD / emerging market economies. In addition, there is no compulsory paternity leave in China, either; as a result, the burden of childcare in China falls almost entirely on the shoulders of young women.

In addition to the unusually high labor market participation rate, women's labor intensity in China is also among the world's highest, and their jobs are highly inflexible, too. As of 2017, average weekly working hours for employed women in China is 45.5, far higher than in advanced economies such as the US (34), the Netherlands (27), Norway (31) and Denmark (32). According to the China Family Panel Survey (CFPS, 2012–2016), pre-childbirth women work an average of 47 hours per week, while the figure for post-childbirth women is 46.1, ie there is only a slight difference. This might reflect the fact that it is hardly possible for working mothers to switch to jobs with more flexible working hours: the choice for working mothers is not how many hours to work, but rather, whether they work or not.

Given low public investment in childcare and poor social protections for working mothers in China, the burden of childcare is largely shouldered by grandparents. In a 2007 survey conducted by Shanghai Population and Family Planning Commission, 88.7% of grandparents were involved in taking care of their own grandchildren, and 53.3% of grandparents took on major childcare responsibilities on a daily basis. The China Health and Retirement Longitudinal Study (CHARLS) shows that 50% of grandparents regularly take on major responsibilities for taking care of their grandchildren — much higher than in many other countries. In contrast, in the US and Europe, grandparent-provided childcare is in general not very common (except in Mediterranean countries such as Italy), largely due to weaker family bonds and widely available daycare services provided by the market as well as by public institutions. In the US, only 16% of grandparents are regularly involved in childcare (Health and Retirement Study, HRS, 2008, see Lumsdaine and Verneer 2015), 15% in Germany / Austria, 30% in Italy / Spain and 2% in Denmark / Sweden (Survey of Health, Ageing and Retirement in Europe, SHARE, 2004).[1] In China, even though childcare services are available in the market, few households actually rely on them. For example, among 2,281 children below the age of three in the whole sample of China Family Panel Studies (CFPS) 2014, only three are fully taken care of by babysitters hired from the market during the daytime. Instead, assistance provided by grandparents is almost always indispensable for a large share of families.

It seems that grandparental childcare is the key to explaining the co-existence of an unusually high employment rate and high labor intensity for working mothers in China. Indeed, using data from European countries (SHARE), Dimova and Wolff (2011) find that grandparental childcare significantly improves young mothers' labor force participation rate as well as their labor supply intensity. In a cross-country study, Aassve et al. (2012) find that such an impact is significant and positive in some of the European countries (France, Germany, Bulgaria and Hungary),

[1] It is worth noting that grandparental childcare in the surveys from China is by definition more intensive: In China regular grandparental childcare is defined as grandparents being the *main* responsible persons on a *daily* basis (such as in the CHARLS and the China Family Panel Survey, CPFS), while in the HRS for the US the threshold for a household using grandparental childcare on a regular basis is that grandchildren are looked after by grandparents for more than 672 hours over 12 months (Lumsdaine and Verneer 2015), and in SHARE for Europe the threshold is just "at least twice a week" (Arpino et al. 2014). Taking into account the difference in definitions, the contrast between China and US / Europe is even more striking.

while not significant in other countries (such as Georgia, the Netherlands and Russia). Using survey data from the US (NLSY79), Posadas and Vidal-Fernández (2013) find that grandparental childcare increases young mothers' labor force participation rate by 9%, and the effect is particularly stronger for ethical minorities and single mothers. Arpino et al. (2014) document a similar positive effect using Italian data with instrumental variables, and such an effect is stronger for mothers with less education and younger children. García-Morán and Kuehn (2017) and Compton and Pollak (2014) find that the labor force participation rate is higher for young mothers living closer to their parents as these grandparents are more likely to provide childcare. Based on a natural experiment conducted in the context of Italian pension reform, Bratti et al. (2016) find that grandmothers' retirement increases young mothers' employment rate by 13% while such an effect does not exist for grandfathers, suggesting that childcare is more likely to be provided by grandmothers.

As most of the studies are based on observations of post-childbirth women, they are more capable of quantifying the impact of grandparental care on child-caring women. However, women's fertility choices are endogenous such that their fertility decisions are affected by their employment choices, and the availability of grandparental care affects women's choices with regard to both childbirth and employment. Therefore, the impact of childbirth on female employment under various modes of childcare is better identified only if this endogeneity issue is properly addressed.

Several recent studies attempt to address the endogeneity issue in different ways. Using legislation on abortion as an instrumental variable, based on a cross-country panel dataset covering 97 countries, Bloom et al (2009) identify a strong significant negative correlation between the birth rate and the female employment rate. Using children's sex as the instrumental variable for the number of children, Angrist and Evans (1998) and Cruses and Galiani (2007) find that having more than 2 children significantly reduces women's labor supply. Using a sample of women treated in fertility clinics, who are likely to have a similar willingness to have a child, the first child causes a 26.3 percentage point fall in female employment according to Cristia (2008).

Although the endogeneity issue has been addressed in various ways, there is so far little research on how childbirth affects female employment when grandparental childcare is available. In this paper, we use a micro-level dataset that contains information on female employment, childbirth, and grandparental childcare, construct records that track women's childbearing and employment, identify the impact of childcare on female employment with / without grandparental childcare, and address the endogeneity of women's fertility choices through fixed-effect panel regression and a propensity score matching difference-in-difference (PSM-DID) model.

Our paper contributes to the existing literature in five ways: First, we identify the impact of childbirth on female employment with or without grandparental support, and directly quantify the contribution of grandparental support to reducing career interruptions for women as a result of childbirth; second, by constructing panel data that keep track of women's childbirth and employment, and using fixed-effect panel regression as well as the PSM-DID method, we provide novel estimates that address the endogeneity problem stemming from women's self-selection on fertility; third, we explore the duration of women's absence from the labor market owing to childbirth, as well as labor market intensity for childbearing women with / without grandparental support, and further reveal the mechanism of grandparental childcare in improving young mothers' labor supply; fourth, we provide an explanation of China's female employment paradox, i.e. how women in China maintain both a high employment rate and high labor intensity despite poor public childcare support. We show that it is the retired grandparents that take the burden of childcare and compensate to a great extent for poor public childcare provision. Finally, our study reveals a hidden cost of forthcoming retirement policies that aim to raise the retirement age. Retaining old workers in the labor force may shift the burden of childcare to young mothers, thus crowding out their employment.

Section 2 describes the data and key variables, and Section 3 constructs the econometric models for our analysis. First, we use panel regression with fixed effect and random effect to control for the unobserved variables, then we construct a PSM-DID model to address the endogeneity in fertility decisions and quantify the impact of childbirth on the employment of women with / without grandparental support. Section 4 provides further discussions such as the persistence of the impact. Finally, Section 5 provides policy implications and concludes.

# 2 Data

## 2.1 Data description

Our dataset is constructed from China Family Panel Studies (CFPS). This is a nationally representative, biannual longitudinal survey of Chinese communities, families, and individuals launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University, China. The project aims to promote a better understanding of the economic, as well as the non-economic, well-being of the contemporary Chinese population, and it collects individual-, family-, and community-level longitudinal data across the country. The survey contains rich information covering topics such as economic activities, education outcomes, family dynamics and relationships, migration, and health. Using CFPS survey data from 2010, 2012, 2014 and 2016, we established the panel data to keep track of the same women over time, in order to better understand the differences in their employment before and after childbirth, as well as to address to self-selection problem in fertility and employment decisions.

In our sample, we require that the individuals that first appeared in the observations must be women of age 20–49 who have never had a child before, based on the following reasons: First, the minimum marriage age for women, set by the Marriage Law of China, is 20; given that children born outside marriage relationships are rare in China and women are receiving longer schooling nowadays, the likelihood of women below 20 giving birth is rather low. Second, the statutory minimum retirement age for women in China is 50 (for blue-collar workers, 55 for public employees); women older than 50 would face different employment choices and thus must be excluded from our sample. Finally, we focus on those who had never had a child when they first appeared in the observations; as some of them had a child during our sample period 2010–2016, this allows us to divide our sample into treatment and control groups, in order to investigate the changes in employment after childbirth.

Since 2010 was the start year of the survey, all observations in our constructed 2010 subsample are eligible women or women who had never had a child before the survey. Both 2012 and 2014 subsamples include those who had already entered the sample in the previous surveys, plus those who entered the sample for the first time for various reasons.[2] Since 2016 was the last year of the survey, all observed women in the 2016 subsample appeared at least once in the previous surveys.[3] Combining the subsamples from the four surveys and deleting the women who appeared only once during 2010–2016, we obtain a sample with 7,551 observations. Those observations correspond to 2,776 women, of which 1,322 are observed twice, 909 are observed three times, and 545 are observed four times. On average, each eligible woman is observed 2.72 times in the sample. See more details in Table 1.

Table 1 Tracking of the observed women

| Year | Obs. | First-time entries | Tracked in 2012 | Tracked in 2014 | Tracked in 2016 |
|---|---|---|---|---|---|
| 2010 | 1,136 | 1,136 | 912 | 833 | 793 |
| 2012 | 1,940 | 1,028 | -- | 1,537 | 1,409 |
| 2014 | 2,302 | 612 | -- | -- | 1,835 |
| 2016 | 2,173 | 0 | -- | -- | -- |

As shown above, 80% of eligible women in 2010 are still observed in 2012, 73% of them remain in the 2014 survey, and 70% in 2016. Among all observed women in 2012, 79% of them are still observable two years later, and 73% of them are available four years later. Of observed women in

[2] Including those who passed the age of 20 in the years covered by the surveys, those who joined the family through marriage, etc.

[3] Some early observed women may also disappear in the late surveys because of divorce, lost contact, etc.

2014, 80% remain in the 2016 survey. This implies that the surveys keep good track of the families, with relatively few observed samples lost, and most of those because of lost contacts.

## 2.2 Key variables

We take key variables from the CFPS that describe the characteristics of individual women, their households, and their communities.

*Motherhood*: Dummy variable, equals to 1 if the observed woman is a mother and 0 otherwise;

*Grandparental childcare ($GPC$)*: Dummy variable. For a working mother $i$, if at least one of her children below the age of 11 is mainly taken care of by grandparent(s) during the day time[4] on a daily basis, she is defined as receiving grandparental childcare and her $GPC_i = 1$; otherwise $GPC_i = 0$;

*Employment status ($WORK$)*: Dummy variable. If a young womae $i$ is in the labor force (including those on maternity leave) at the time of survey, $WORK_i = 1$; otherwise $WORK_i = 0$;

*Weekly working hours*: A woman's average weekly working hours in the year of survey, including overtime;

*College degree ($EDU_i$)*: Dummy variable, equal to 1 if woman $i$'s highest degree is a college degree or above, 0 otherwise;

*Woman being urban resident ($URBAN_i$)*: Dummy variable, equal to 1 if the location of woman $i$'s residence is classified as "urban" by the National Bureau of Statistics of China;

*Studentship*: Dummy variable, equal to 1 if the woman is attending school (full-time or part-time), 0 otherwise;

*Marriage*: Dummy variable, equal to 1 if the woman is married or cohabiting, 0 otherwise;

*Log household's per capita net income, excluding the woman's*: The logarithm of woman $i$'s household's annual per capita net income in CNY (including her partner's income and transfers, but excluding the woman's income);

*Household's total assets*: In CNY;

*Home ownership*: Dummy variable, equal to 1 if the household at least partially owns the property, 0 otherwise;

*Home size*: In square meters;

*Hardship in housing*: Dummy variable, equal to 1 if the household has insufficient home space (below 10 square meters per capita), 0 otherwise;

[4] The CFPS asks about childcare providers for both daytime and nighttime. As most people work during the daytime when there is the most conflict between childcare and jobs, we therefore define $GPC$ as grandparents' providing childcare during the daytime.

*Average property price for the community*: In CNY per square meter. For urban communities, the price is defined as the average transaction price in the community for the previous month of the survey; for rural communities where most properties are not listed in the housing market, the price is defined as the average building cost;
*Number of kindergartens in the community*: The number of kindergartens within the community;
*Number of primary schools in the community*: The number of primary schools within the community;
*Community's birth rate*: The number of newborns per 1,000 inhabitants in the year prior to the survey.

Table 2 presents the summary statistics of the variables.

Table 2 Summary statistics

| Variables | Obs. | Mean | Std dev | Min | Max |
|---|---|---|---|---|---|
| Motherhood | 7,551 | 0.238 | 0.426 | 0 | 1 |
| Grandparental childcare | 7,551 | 0.082 | 0.274 | 0 | 1 |
| Employment | 7,551 | 0.614 | 0.487 | 0 | 1 |
| Weekly working hours | 7,351 | 27.1 | 27.0 | 0 | 112 |
| Age | 7,551 | 25.9 | 5.18 | 20 | 56 |
| College degree | 7,544 | 0.305 | 0.461 | 0 | 1 |
| Urban residency | 7,153 | 0.334 | 0.472 | 0 | 1 |
| Studentship | 7,551 | 0.130 | 0.336 | 0 | 1 |
| Marriage | 7,549 | 0.485 | 0.500 | 0 | 1 |
| Household's net per capita income, excluding the woman's (CNY) | 7,068 | 11,986 | 22,205 | –100,350 | 814,600 |
| Household's net asset (CNY) | 7,129 | 459,357 | 926,195.3 | –607,000 | 1.61e07 |
| Home ownership | 7,551 | 0.832 | 0.374 | 0 | 1 |
| Home size (sqm) | 7,087 | 137.1 | 106.3 | 5 | 2,000 |
| Hardship in housing[5] | 5,378 | 0.156 | 0.363 | 0 | 1 |
| Average property price for the community | 7,513 | 3,619 | 6,363.7 | 500 | 55,000 |
| Number of kindergartens in the community | 7,141 | 1.002 | 1.506 | 0 | 30 |
| Number of primary schools in the community | 7,141 | 0.726 | 0.713 | 0 | 5 |
| Community's birth rate | 7,074 | 9.847 | 10.99 | 0 | 200 |

[5] Due to changes in the questionnaire design, this variable is missing for the 2016 survey. However, our econometric models do not need this variable for 2016.

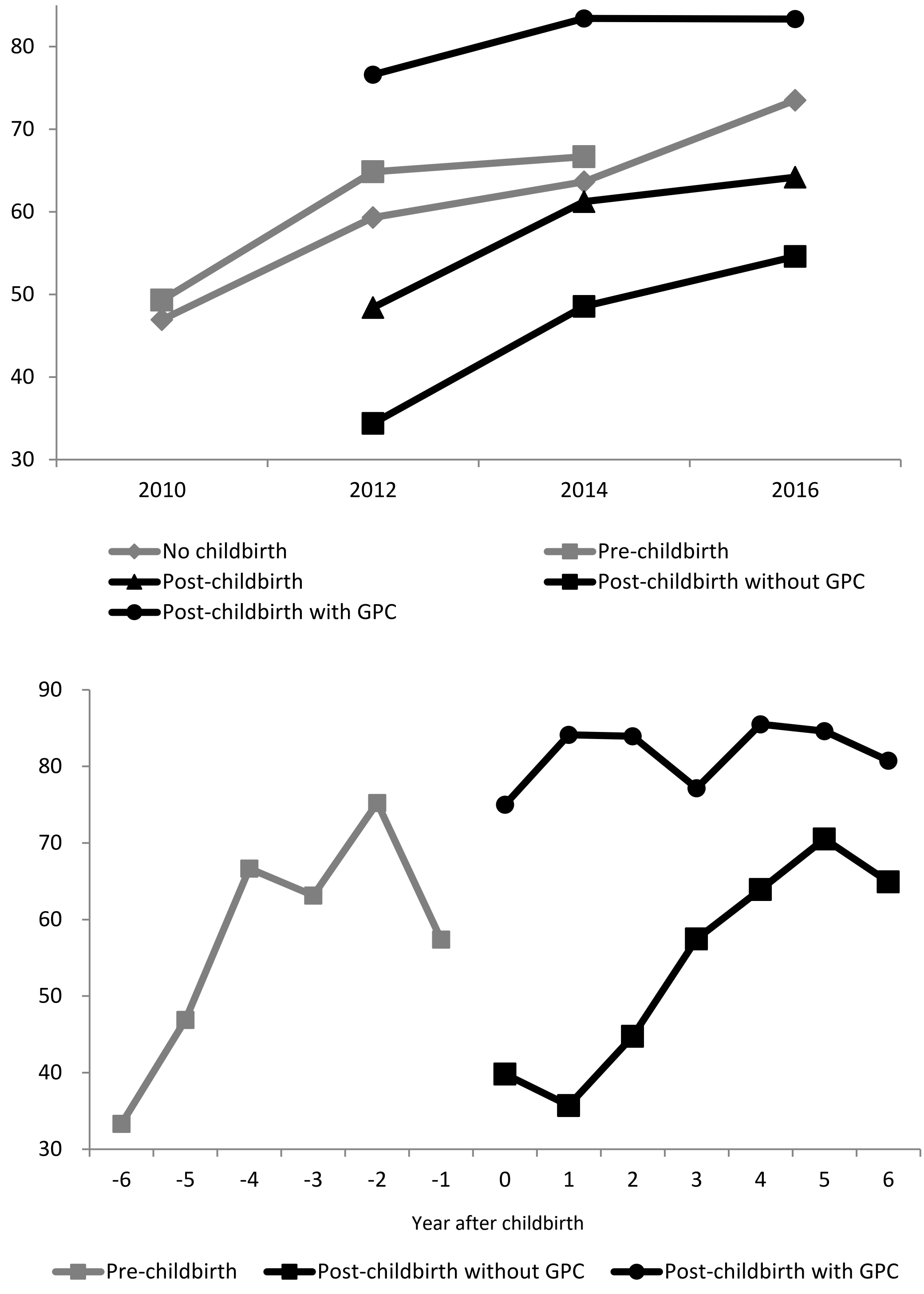
## 2.3 Stylized facts

Among 2,776 women in our sample, 1,066 or 38.4% of them gave birth during the sample period. Of these, 480 or 45.03% received childcare assistance from grandparents after childbirth. We divide all women in our sample into two subsamples: 1,710 women who never had a child and 1,066 who had a child; the latter can be further divided into two subgroups: Those before giving birth and those after giving birth. In Panel A of Figure 1, we present the employment rates for those who never had a child ("No childbirth"), those before giving birth ("Pre-childbirth"), and those after giving birth ("Post-childbirth"). It can be seen that the employment rates for "No childbirth" and "Pre-childbirth" groups are very close, implying that the employment choice for women before childbirth is not much different from those who never had a child. Furthermore, the employment rate for the "Post-childbirth" group is slightly lower, implying that there is indeed a motherhood penalty in female employment.

However, if we further divide the "Post-childbirth" group into those who receive grandparental childcare (480 women, "Post-childbirth with GPC") and those who receive no grandparental childcare (586 women, "Post-childbirth without GPC"), we find that the drop in the employment of the post-childbirth women is largely caused by those who do not receive grandparental childcare; for example, compared with women without children, the employment rate for post-childbirth women without grandparental childcare falls by almost 50% in 2012. In contrast, women with grandparental childcare are even more likely to work after childbirth, probably because these women need to work to compensate for grandparents' lost income due to providing childcare.

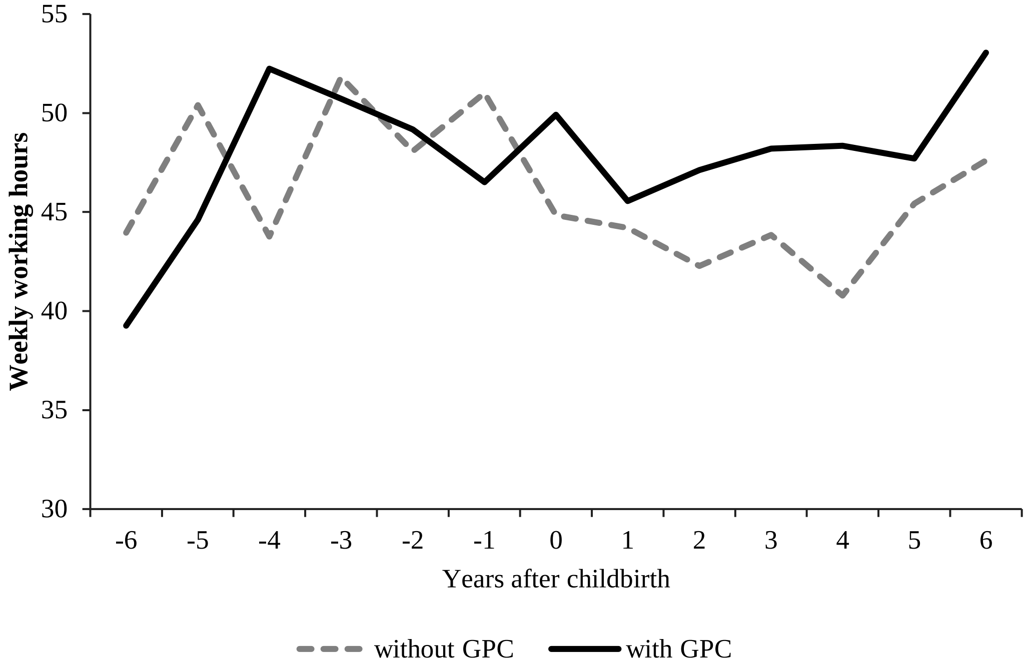
To better reflect working mothers' employment decision in the long run, Panel B focuses on those who had a child during the sample period. Define the year of a woman's first childbirth as "year 0". Before childbirth, the employment rate grows with age, while after childbirth, the patterns of employment are largely driven by the providers of childcare. For those receiving grandparental childcare ("Post-childbirth with GPC"), their employment follows the pre-childbirth trend and remains high, while for those receiving no grandparental childcare ("Post-childbirth without GPC"), their employment rate falls by almost 50% in the first two years after year 0 – although their employment starts to recover from the third year, the employment gap between these two groups persists.

Figure 1 Employment before and after childbirth




On the other hand, grandparental childcare does not seem to appreciably affect women's labor intensity. As shown in Figure 2, pre-childbirth labor intensities are very similar for women who receive post-childbirth grandparental care and those who do not, and the weekly working hours for both groups are around 45–50 hours. After childbirth, the weekly hours for those without grandparental care is comparatively slightly lower but is still as high as 40–45 hours. This might reflect the fact that the supply of part-time jobs or jobs with flexible working hours is very limited in China. The dilemma for women without grandparental support is that they either have to stay in intensive jobs or exit the labor market entirely, which explains the sharp drop in their employment during the first two years after childbirth.

Figure 2 Labor intensity before and after childbirth




# 3 Empirical analysis and results

## 3.1 Panel regression with fixed effects

First, as a baseline, we use two-way fixed-effect panel regression to analyze the impact of fertility on female employment. The model is defined as

$$Work_{pit} = \alpha + \beta_1 Birth_{pit} + X_{pit}\gamma + \delta_t + \lambda_i + \eta_p + u_{pit} \quad (1)$$

in which the subscript $p$ denotes province, $i$ denotes woman $i$, and $t$ denotes year of the survey. $Work_{pit}$ denotes whether the woman is employed, $Birth_{pit}$ denotes whether woman $i$ is a mother by the year of survey $t$, the vector $X_{pit}$ contains a group of control variables (including the woman's age, college degree, urban residency, studentship, marriage, and the household's per capita net income – excluding the woman's), $\delta_t$ captures year fixed effect, $\lambda_i$ captures individual fixed effect, and $\eta_p$ captures province fixed effect.

In order to see the heterogeneities in the impacts of childcare modes on female employment, we then add interaction term $Birth_{pit} \cdot GPC_{pit}$ to the baseline model, such that

$$Work_{pit} = \alpha + \beta_1 Birth_{pit} + \beta_2 Birth_{pit} \cdot GPC_{pit} + X_{pit}\gamma + \delta_t + \lambda_i + \eta_p + u_{pit}. \tag{2}$$

Together with the variable $Birth_{pit}$, the interaction term divides the women into three subgroups: Women that never gave birth ($Birth_{pit} = 0$, $Birth_{pit} \cdot GPC_{pit} = 0$), mothers with post-childbirth grandparental care ($Birth_{pit} = 1$, $Birth_{pit} \cdot GPC_{pit} = 1$), and mothers without post-childbirth grandparental care ($Birth_{pit} = 1$, $Birth_{pit} \cdot GPC_{pit} = 0$).

As an alternative, we may also explain the dummy variable $Work_{pit}$ as a probabilistic outcome, such that

$$Pr\left(Work_{pit} | Birth_{pit}, X_{pit}\right) = f\left(\alpha + \beta_1 Birth_{pit} + X_{pit}\gamma + \delta_t + \lambda_i + \eta_p\right) \tag{3}$$

in which $f(\cdot)$ can be accumulative distribution function $\Phi(\cdot)$ with standard normal distribution (Probit model), or $\Lambda(\cdot)$ with Logistic distribution (Logistic model). Then, we may also add interaction terms to (3), such that

$$\begin{aligned} &Pr\left(Work_{pit} | Birth_{pit}, GPC_{pit}, X_{pit}\right) \\ &\qquad = f\left(\alpha + \beta_1 Birth_{pit} + \beta_2 Birth_{pit} \cdot GPC_{pit} + X_{pit}\gamma + \delta_t + \lambda_i + \eta_p\right). \end{aligned} \tag{4}$$

Table 3 presents the results from the baseline model (1) and alternative baseline model (3), with various specifications. Columns (1) and (2) are estimates from OLS regressions, columns (3) to (7) are estimates from Probit and Logit models. The standard errors of estimated coefficients in columns (1) to (4) are heteroskedasticity robust standard errors, and the standard errors reported in column (7) are bootstrap standard errors.

It can be seen from the results that childbirth significantly lowers the female employment rate, implying that a motherhood penalty in employment does exist in China. Based on the Logit model with fixed effect from column (6), the odds ratio of female employment is 0.54, i.e., *ceteris paribus*, the ratio of the likelihood of being employed for post-childbirth women to that for pre-childbirth women is 0.54. Results from the OLS models suggest that childbirth reduces female employment by 9%, much lower than the impacts in most advanced economies.

Table 3 Results for the baseline panel regressions

| | Women's employment | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) FE OLS | (2) FE OLS | (3) RE Probit | (4) RE Logit | (5) FE Logit | (6) FE Logit | (7) FE Logit |
| Motherhood ($\beta_1$) | -0.090*** (0.022) | –0.088*** (0.022) | –0.236*** (0.064) | –0.407*** (0.110) | –0.633*** (0.136) | –0.611*** 0.137) | –0.633*** (0.126) |
| Age | 0.020 (0.027) | 0.029 (0.027) | 0.015** (0.006) | 0.025** (0.011) | 0.053 (0.187) | 0.700 (0.193) | 0.053 (0.168) |
| College degree | 0.082*** (0.028) | 0.082*** (0.028) | 0.576*** (0.061) | 1.003*** (0.107) | 0.956*** (0.365) | 1.092*** (0.391) | 0.956** (0.435) |
| Urban residency | –0.000 (0.034) | –0.004 (0.034) | 0.107* (0.061) | 0.182* (0.107) | 0.073 (0.250) | 0.056 (0.257) | 0.073 (0.277) |
| Studentship | –0.517*** (0.028) | –0.509*** (0.029) | –2.189*** (0.096) | –3.806*** (0.175) | –2.753*** (0.311) | –2.689*** (0.315) | –2.753*** (0.302) |
| Marriage | –0.199*** (0.023) | –0.199*** (0.023) | –0.537*** (0.062) | –0.941*** (0.108) | –1.334*** (0.145) | –1.339*** (0.148) | –1.334*** (0.152) |
| Log household's per capita net income | –0.009*** (0.003) | –0.008*** (0.003) | –0.029*** (0.009) | –0.049*** (0.016) | –0.060*** (0.021) | –0.061*** (0.022) | –0.060** (0.024) |
| Province FE | No | Yes | No | No | No | Yes | No |
| Individual FE | Yes | Yes | No | No | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.200 (0.595) | 0.367 (0.616) | 0.074 (0.173) | 0.133 0.301 | | | |
| Significance test | 156.38 (P=0.000) | | 877.51 (P=0.000) | 757.84 (P=0.000) | 745.27 (P=0.000) | 780.32 (P=0.000) | 321.24 (P=0.000) |
| Log likelihood | | | –3624.49 | –3623.11 | –850.69 | –833.16 | –850.69 |
| Within $R^2$ | 0.221 | 0.229 | | | | | |
| Hausman test | | | | 376.08 (P=0.000) | | | |
| Obs. | 6,796 | 6,796 | 6,796 | 6,796 | 3,344 | 3,344 | 3,344 |

Notes: (1) *** / ** / * denotes the result is significant at the 1% / 5% / 10% levels; (2) values in the parentheses are standard errors, except those specified as $P$ values; (3) heteroskedasticity robust standard errors are reported for FE OLS, RE Probit and RE Logit models, and bootstrap standard errors are reported for the FE Logit model in column (7); (4) In the models' significance tests, FE OLS is based on $F$-statistic, while RE Probit, RE Logit and FE Logit in column (7) are based on Wald $\chi^2$-statistic; (5) Hausman test is based on $\chi^2$-statistic.

Table 4 reports the results from augmented models (2) and (4) containing interaction terms with various specifications. Columns (1) and (2) are estimates from OLS regressions, columns (3) to (7) are estimates from Probit and Logit models. The results consistently show that the estimated coefficient of the variable "motherhood", $\beta_1$, is significantly negative, while the estimated coefficient of the interaction term "motherhood*GPC", $\beta_2$, is significantly positive, and $\beta_2 > -\beta_1$. Wald test further rejects the hypothesis that $\beta_1 + \beta_2 = 0$. This implies that for women without grandparental care, their post-childbirth employment rate is significantly reduced, while for women with grandparental care, their post-childbirth employment rate is improved rather than reduced. That is, grandparental childcare reduces young mothers' burden, eases the conflicts between childcare and employment, thus reducing opportunity costs to young mothers of working and largely avoiding the interruptions in young mothers' career paths. On the other hand, because of the low retirement age for female workers in China, a substantial share of women would choose to stay in the labor force after 50.[6] For these older women, forcing them to leave the labor force and take care of their grandchildren reduces their households' total income. As a result, young mothers receiving grandparental childcare may have higher incentives to work to compensate for grandparents' income losses. This explains why women with grandparental support are even more likely to work after childbirth. In addition, the absolute values of estimated $\beta_1$ in Table 3 are significantly lower than those in Table 4, suggesting that the rise in the post-childbirth employment rate of women with grandparental support largely compensates for the fall in the employment of women without grandparental support, which explains why the overall interruption to women's careers in China owing to childbirth is relatively low.

Table 4 Results from regressions with interaction terms

| | Women's employment | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1)<br>FE OLS | (2)<br>FE OLS | (3)<br>RE Probit | (4)<br>RE Logit | (5)<br>FE Logit | (6)<br>FE Logit | (7)<br>FE Logit |
| Motherhood ($\beta_1$) | –0.171***<br>(0.025) | –0.170***<br>(0.025) | –0.565***<br>(0.071) | –0.965***<br>(0.122) | –1.066***<br>(0.151) | –1.055***<br>(0.152) | –1.066***<br>(0.176) |
| Motherhood *GPC ($\beta_2$) | 0.228***<br>(0.027) | 0.231***<br>(0.027) | 1.084***<br>(0.099) | 1.875***<br>(0.175) | 1.431***<br>(0.190) | 1.471***<br>(0.194) | 1.431***<br>(0.197) |
| Age | 0.016<br>(0.026) | 0.017<br>(0.026) | 0.016**<br>(0.006) | 0.026**<br>(0.011) | 0.030<br>(0.190) | 0.057<br>(0.197) | 0.030<br>(0.164) |
| College degree | 0.084***<br>(0.028) | 0.083***<br>(0.028) | 0.562***<br>(0.061) | 0.982***<br>(0.107) | 0.962***<br>(0.371) | 1.102***<br>(0.399) | 0.962**<br>(0.425) |
| Urban residency | –0.004<br>(0.034) | –0.008<br>(0.033) | 0.096<br>(0.061) | 0.160<br>(0.106) | 0.060<br>(0.256) | 0.060<br>(0.263) | 0.060<br>(0.267) |
| Studentship | –0.515***<br>(0.029) | –0.507***<br>(0.029) | –2.183***<br>(0.096) | –3.796***<br>(0.174) | –2.793***<br>(0.313) | –2.732***<br>(0.318) | –2.793***<br>(0.389) |
| Marriage | –0.198***<br>(0.023) | –0.198***<br>(0.023) | –0.537***<br>(0.062) | –0.941***<br>(0.108) | –1.308***<br>(0.147) | –1.308***<br>(0.149) | –1.308***<br>(0.152) |
| Log household's per capita net income | –0.008***<br>(0.003) | –0.008***<br>(0.003) | –0.028***<br>(0.009) | –0.048***<br>(0.016) | –0.060***<br>(0.022) | –0.060***<br>(0.023) | –0.060***<br>(0.018) |
| Province FE | No | Yes | No | No | No | Yes | No |
| Individual FE | Yes | Yes | No | No | Yes | Yes | Yes |
| Year dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

[6] According to the China Population and Employment Statistics Yearbook, 2017, 24.7% of female employees are over the age of 50, as of 2016. The China Health and Retirement Longitudinal Study (CHARLS, 2015) shows that the employment rate of urban women aged 50-60 is 45.8%, 74% for rural females.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Constant | 0.277<br>(0.585) | 0.436<br>(0.606) | 0.059<br>(0.173) | 0.093<br>(0.301) | | | |
| Significance test | 147.2<br>(P=0.000) | | 956.56<br>(P=0.000) | 824.26<br>(P=0.000) | 808.89<br>(P=0.000) | 845.22<br>(P=0.000) | 375.22<br>(P=0.000) |
| Log likelihood | | | –3551.57 | –3549.91 | –818.875 | –800.71 | –818.875 |
| Within $R^2$ | 0.236 | 0.245 | | | | | |
| Hausman test | | | | 114.57<br>(P=0.000) | | | |
| Wald test ($\beta_1 + \beta_2 = 0$) | 4.35<br>(P=0.037) | 4.89<br>(P=0.027) | 29.25<br>(P=0.000) | 28.24<br>(P=0.000) | 3.49<br>(P=0.062) | 4.42<br>(P=0.036) | 2.19<br>(P=0.139) |
| Obs. | 6,796 | 6,796 | 6,796 | 6,796 | 3,344 | 3,344 | 3,344 |

Notes: (1) *** / ** / * denotes the result is significant at the 1% / 5% / 10% levels; (2) values in the parentheses are standard errors, except those specified as $P$ values; (3) heteroskedasticity robust standard errors are reported for FE OLS, RE Probit and RE Logit models, and bootstrap standard errors are reported for the FE Logit model in column (7); (4) In the models' significance tests, FE OLS is based on $F$-statistic, while RE Probit, RE Logit and FE Logit in column (7) are based on Wald $\chi^2$-statistic; (5) Hausman test is based on $\chi^2$-statistic; (6) For the statistic of the Wald test, OLS is based on $F$-statistic, while Probit and Logit models are based on $\chi^2$-statistic.

## 3.2 Propensity score matching difference-in-difference model

Although fixed-effect panel regression corrects the time-invariant heterogeneities in individuals and individual-invariant time heterogeneities, it does not address women's self-selection problems in fertility and employment choices: women's fertility decisions may affect their choices of employment, and their employment status may affect their fertility decisions, too. For example, women with high willingness to work may be afraid of losing competence in the jobs due to childbearing so that they may postpone childbearing or even choose to have no children. Therefore, the observed lower post-childbirth employment rate in our sample may be merely driven by post-childbirth women's lower willingness to work, rather than the lack of grandparental childcare.

In order to address the selection bias problem stemming from women's fertility choices, we further use a propensity score matching difference-in-difference (PSM-DID) model to better identify the impact of childbearing on female employment. Given that fertility is women's choice, and women that choose to have / have no children differ in their individual characteristics, the PSM-DID model attempts to match women by their propensity to have children and reduce the differences in observable characteristics between treatment and control groups, in order to fulfill the conditional-independence assumption of difference-in-difference approach and better identify the impact of fertility on female employment.

First, based on four surveys (2010, 2012, 2014, and 2016), we construct three subsamples, 2010–2012, 2012–2014, and 2014–2016. In each subsample, all women never had children before the first survey, while some of them had children before the second survey. Our treatment groups here consist of those women who gave birth between the two surveys, and our control groups consist of those women who did not give birth within the periods of the subsamples. For example, for the 2010–2012 subsample, the treatment group consists of the women who gave birth between the 2010 and 2012 surveys, while the control group consists of the women who did not give birth during 2010–2012. Then, we estimate propensity scores through Logit regression for the 2010–2012, 2012–2014, 2014–2016 subsamples, i.e., the probability of a woman giving birth between two surveys, with her characteristics being given in the first survey:

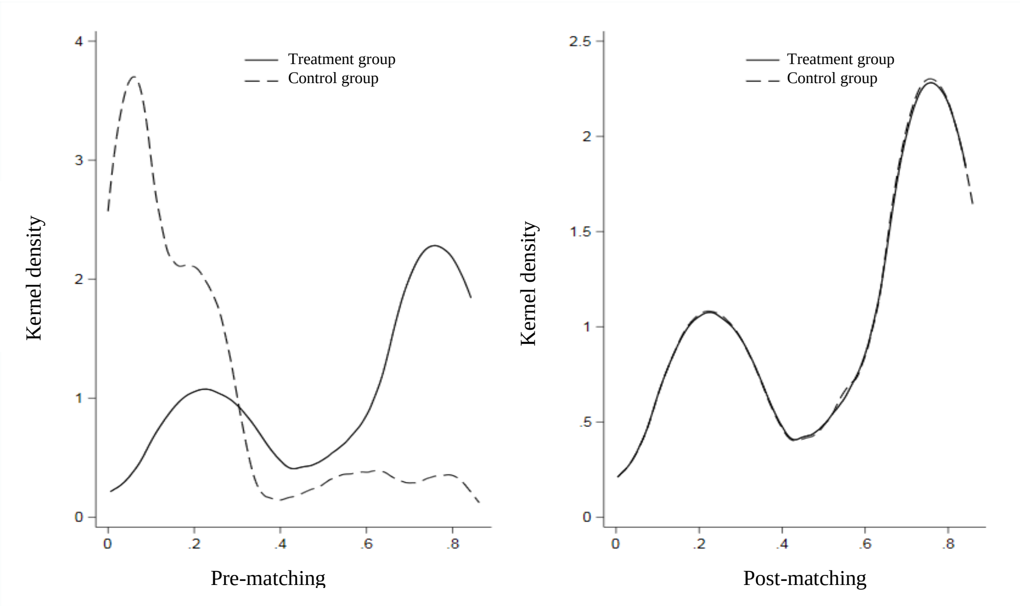
$$p_{it} = Pr\left(Birth_{it} = 1 |\, Work_{i,t-1}, X_{i,t-1}\right) = \frac{exp\left(\alpha + \beta_1 Work_{i,t-1} + X_{i,t-1}\gamma\right)}{1 + exp\left(\alpha + \beta_1 Work_{i,t-1} + X_{i,t-1}\gamma\right)}. \quad (5)$$

A woman is in the treatment group if $Birth_{it} = 1$, $Work_{i,t-1}$ denotes a woman's employment status in the first survey – to address her fertility choice based on her employment, and $X_{i,t-1}$ is a vector containing her characteristics in the first survey, including the variables describing her individual, household, and community. The variables and the results are reported in Appendix A. The results suggest that women's fertility choices are largely affected by their age, urban residency, studentship, marriage status and housing conditions; the signs of estimated coefficients are as expected.

Next, we match the women to treatment group and control group based on propensity scores. To ensure the robustness of results, we use the four most common matching methods in the literature: k-nearest neighbor, caliper, k-nearest neighbor with caliper, and kernel matching. We follow Abadie et al (2004) and set $k = 4$, so that the estimates' mean square errors are minimized. We choose matching radius to be 0.05 for both caliper matching and k-nearest neighbor matching with caliper. For kernel matching, the kernel function is the most common quadratic kernel function, and the bandwidth is set at 0.06.

Appendix B reports the test of balance for the covariates across treatment and control groups. Under all four methods, the post-matching standardized differences of covariates all fall below 5%; the pseudo $R^2$ of the Logit model falls from 20–30% to 1% after matching; the LR test shows that covariates are jointly significant before matching, but no longer so afterwards. Figure 3 compares the kernel densities between treatment and control groups. It can be seen that two groups' kernel density curves are significantly different before matching, while they almost coincide after matching.

Figure 3 Kernel densities of treatment and control groups, before and after matching




After dividing each subsample into treatment group and control group based on the propensity score matching (PSM), we estimate the average treatment effect on treated (ATT), i.e., the impact of fertility on female employment, through difference-in-difference (DID)

$$ATT = E\left[\left(Work_{i,t} - Work_{i,t-1}\right)|p_{it}, Birth_{it} = 1\right] - E\left[\left(Work_{i,t} - Work_{i,t-1}\right)|p_{it}, Birth_{it} = 0\right]. \tag{6}$$

Table 5 reports the overall impact of fertility on female employment. It can be seen that childbirth significantly reduces women's likelihood to work, both before and after matching, and the results are robust for all three subsamples under four matching methods. Take k-nearest neighbor matching as an example: The average fall in employment caused by childbirth is about 17.9%. For every subsample, ATT falls after matching, implying that there is indeed self-selection in fertility decisions, or women who prefer to work do reduce or postpone childbirth. The impact of childbirth on female employment would thus be overestimated if the selection bias were not taken into account.

## Table 5 Results from PSM-DID: Overall

| Sample | Matching methods | Matching | Mean variation in employment: w/ childbirth | w/o childbirth | ATT | Std error | $t$-statistic |
|---|---|---|---|---|---|---|---|
| 2010–2012 sub-sample | K-nearest neighbor | Before | 0.028 | 0.203 | –0.176*** | 0.044 | –4.01 |
| | | After | 0.028 | 0.202 | –0.174** | 0.074 | –2.34 |
| | Caliper | Before | 0.028 | 0.203 | –0.176*** | 0.044 | –4.01 |
| | | After | 0.028 | 0.165 | –0.137** | 0.068 | –2.00 |
| | K-nearest neighbor with caliper | Before | 0.028 | 0.203 | –0.176*** | 0.044 | –4.01 |
| | | After | 0.028 | 0.202 | –0.174** | 0.074 | –2.34 |
| | Kernel | Before | 0.028 | 0.203 | –0.176*** | 0.044 | –4.01 |
| | | After | 0.028 | 0.165 | –0.138** | 0.068 | –2.02 |
| 2012–2014 sub-sample | K-nearest neighbor | Before | –0.053 | 0.128 | –0.181*** | 0.040 | –4.57 |
| | | After | –0.054 | 0.082 | –0.136** | 0.060 | –2.28 |
| | Caliper | Before | –0.053 | 0.128 | –0.181*** | 0.040 | –4.57 |
| | | After | –0.054 | 0.082 | –0.136** | 0.054 | –2.50 |
| | K-nearest neighbor with caliper | Before | –0.053 | 0.128 | –0.181*** | 0.040 | –4.57 |
| | | After | –0.054 | 0.083 | –0.136** | 0.060 | –2.29 |
| | Kernel | Before | –0.053 | 0.128 | –0.181*** | 0.040 | –4.57 |
| | | After | –0.054 | 0.085 | –0.139** | 0.055 | –2.54 |
| 2014–2016 sub-sample | K-nearest neighbor | Before | –0.196 | 0.139 | –0.335*** | 0.045 | –7.46 |
| | | After | –0.195 | –0.002 | –0.194*** | 0.058 | –3.33 |
| | Caliper | Before | –0.196 | 0.139 | –0.335*** | 0.045 | –7.46 |
| | | After | –0.195 | 0.042 | –0.237*** | 0.057 | –4.16 |
| | K-nearest neighbor with caliper | Before | –0.196 | 0.139 | –0.335*** | 0.045 | –7.46 |
| | | After | –0.195 | –0.002 | –0.194*** | 0.058 | –3.33 |
| | Kernel | Before | –0.196 | 0.139 | –0.335*** | 0.045 | –7.46 |
| | | After | –0.195 | 0.041 | –0.237*** | 0.057 | –4.14 |

## Table 6 Results from PSM-DID: Women without GPC

| Sample | Matching methods | Matching | Mean variation in employment: w/ childbirth | w/o childbirth | ATT | Std error | $t$-statistic |
|---|---|---|---|---|---|---|---|
| 2010–2012 sub-sample | K-nearest neighbor | Before | –0.035 | 0.203 | –0.238*** | 0.050 | –4.75 |
| | | After | –0.043 | 0.255 | –0.298*** | 0.085 | –3.49 |
| | Caliper | Before | –0.035 | 0.203 | –0.238*** | 0.050 | –4.75 |
| | | After | –0.043 | 0.256 | –0.299*** | 0.079 | –3.81 |
| | K-nearest neighbor with caliper | Before | –0.035 | 0.203 | –0.238*** | 0.050 | –4.75 |
| | | After | –0.043 | 0.254 | –0.298*** | 0.085 | –3.49 |
| | Kernel | Before | –0.035 | 0.203 | –0.238*** | 0.050 | –4.75 |
| | | After | –0.043 | 0.259 | –0.302*** | 0.079 | –3.84 |
| 2012–2014 sub-sample | K-nearest neighbor | Before | –0.229 | 0.128 | –0.357*** | 0.046 | –7.69 |
| | | After | –0.233 | 0.074 | –0.307*** | 0.063 | –4.86 |
| | Caliper | Before | –0.229 | 0.128 | –0.357*** | 0.046 | –7.69 |
| | | After | –0.233 | 0.075 | –0.308*** | 0.058 | –5.26 |
| | K-nearest neighbor with caliper | Before | –0.229 | 0.128 | –0.357*** | 0.046 | –7.69 |
| | | After | –0.233 | 0.074 | –0.307*** | 0.063 | –4.86 |
| | Kernel | Before | –0.229 | 0.128 | –0.357*** | 0.046 | –7.69 |
| | | After | –0.233 | 0.074 | –0.307*** | 0.059 | –5.24 |
| 2014–2016 sub-sample | K-nearest neighbor | Before | –0.342 | 0.139 | –0.481*** | 0.052 | –9.21 |
| | | After | –0.345 | 0.057 | –0.402*** | 0.067 | –5.97 |
| | Caliper | Before | –0.342 | 0.139 | –0.481*** | 0.052 | –9.21 |
| | | After | –0.345 | 0.052 | –0.398*** | 0.063 | –6.31 |
| | K-nearest neighbor with caliper | Before | –0.342 | 0.139 | –0.481*** | 0.052 | –9.21 |
| | | After | –0.345 | 0.057 | –0.402*** | 0.067 | –5.97 |
| | Kernel | Before | –0.342 | 0.139 | –0.481*** | 0.052 | –9.21 |
| | | After | –0.345 | 0.048 | –0.393*** | 0.063 | –6.23 |

In Table 6, we focus on the women who receive no grandparental support after childbirth. It can be seen that childbirth significantly reduces women's likelihood to work, both before and after matching. Take k-nearest neighbor matching as an example: The average fall in employment caused by childbirth is about 33.3%, much higher than that in most advanced economies. However, for women with grandparental support after childbirth, as Table 7 shows, childbirth significantly reduces their employment only in the 2012–2014 subsample before matching; such an adverse effect does not exist for other pre-matching subsamples or all post-matching subsamples.

Table 7 Results from PSM-DID: Women with GPC

| Sample | Matching methods | Matching | Mean variation in employment | | | Std error | $t$-statistic |
|---|---|---|---|---|---|---|---|
| | | | w/ childbirth | w/o childbirth | ATT | | |
| 2010–2012 sub-sample | K-nearest neighbor | Before | 0.155 | 0.203 | –0.048 | 0.067 | –0.73 |
| | | After | 0.141 | 0.064 | 0.077 | 0.091 | 0.84 |
| | Caliper | Before | 0.155 | 0.203 | –0.048 | 0.067 | –0.73 |
| | | After | 0.141 | 0.124 | 0.017 | 0.086 | 0.20 |
| | K-nearest neighbor with caliper | Before | 0.155 | 0.203 | –0.048 | 0.067 | –0.73 |
| | | After | 0.141 | 0.064 | 0.077 | 0.091 | 0.84 |
| | Kernel | Before | 0.155 | 0.203 | –0.048 | 0.067 | –0.73 |
| | | After | 0.141 | 0.122 | 0.019 | 0.086 | 0.22 |
| 2012–2014 sub-sample | K-nearest neighbor | Before | 0.252 | 0.128 | 0.124** | 0.059 | 2.11 |
| | | After | 0.252 | 0.153 | 0.100 | 0.083 | 1.20 |
| | Caliper | Before | 0.252 | 0.128 | 0.124** | 0.059 | 2.11 |
| | | After | 0.252 | 0.125 | 0.127 | 0.076 | 1.68 |
| | K-nearest neighbor with caliper | Before | 0.252 | 0.128 | 0.124** | 0.059 | 2.11 |
| | | After | 0.252 | 0.143 | 0.109 | 0.083 | 1.32 |
| | Kernel | Before | 0.252 | 0.128 | 0.124** | 0.059 | 2.11 |
| | | After | 0.252 | 0.119 | 0.133* | 0.076 | 1.76 |
| 2014–2016 sub-sample | K-nearest neighbor | Before | 0.111 | 0.139 | –0.028 | 0.072 | –0.38 |
| | | After | 0.111 | 0.028 | 0.083 | 0.084 | 0.99 |
| | Caliper | Before | 0.111 | 0.139 | –0.028 | 0.072 | –0.38 |
| | | After | 0.113 | 0.049 | 0.065 | 0.082 | 0.79 |
| | K-nearest neighbor with caliper | Before | 0.111 | 0.139 | –0.028 | 0.072 | –0.38 |
| | | After | 0.113 | 0.028 | 0.085 | 0.085 | 1.00 |
| | Kernel | Before | 0.111 | 0.139 | –0.028 | 0.072 | –0.38 |
| | | After | 0.111 | 0.044 | 0.067 | 0.082 | 0.82 |

# 4 Discussion

So far we have shown that the employment rate for women without grandparental support plummets after childbirth; however, it would be also interesting to know whether such an adverse impact is temporary or permanent for affected women, and to what extent their employment recovers after childbirth. Answering these questions would help us better understand the impact of childbirth on female employment both in the short run and in the long run. In addition, as both overall and post-childbirth female labor intensities are rather high in China, it is also interesting to see how much grandparental childcare contributes to women's high post-childbirth labor intensity.

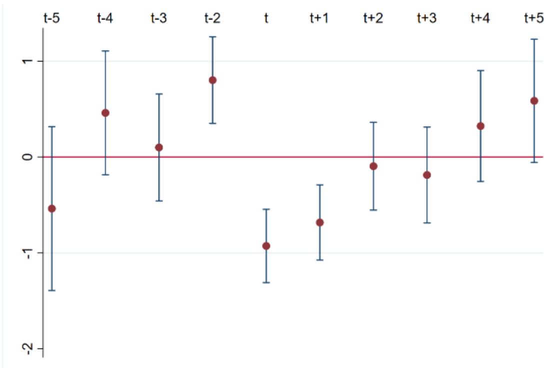
### Exiting labor market: Temporarily or permanently?

Childbirth forces some of the women to drop out of the labor market. Drop-outs may be either temporary, i.e. that women only exit the labor market when children are young and return after the children grow up, or permanent, i.e. that women stay out of the labor market for a considerable length of time, or even never return. In our paper, although we are not able to tell whether some of the mothers drop out of the labor force permanently, we can at least see how persistent the adverse impact of childbirth on employment is. First, we separate those women who had children during our sample period, denote the year of childbirth for each one of them as year $t$, then we define year dummies $Year_k$ in which $k$ ranges from 4 years before childbirth $(t-4)$ to 5 years after childbirth $(t+5)$. Using a Logit model, we explain women's employment as

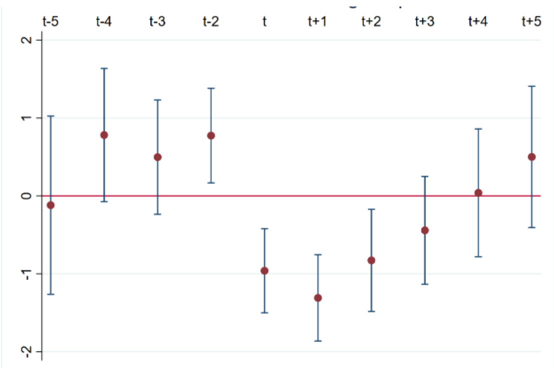
$$Pr(Work_{it} = 1 | Year_k, X_{it}) = f\left(\alpha + \sum_{k \in \binom{t-4,t-3,t-2,t-1,}{t,t+1,t+2,t+3,t+4,t+5}} \beta_k Year_k + X_{it}\gamma + \delta_t\right). \qquad (7)$$

We apply the same model for all mothers, mothers with no post-childbirth grandparental support, and mothers with post-childbirth grandparental support, respectively. The results are reported in Figure 4.

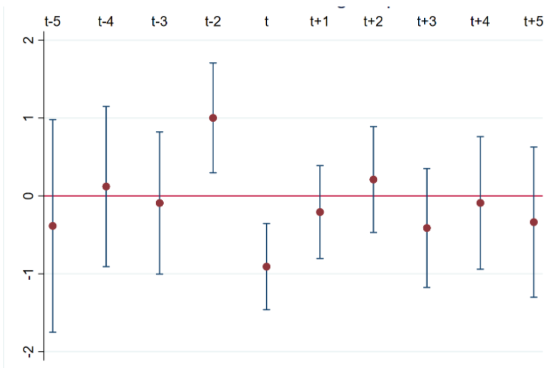
Figure 4 Persistence of the impact of childbirth on female employment




Mothers: Overall




Of which: Without grandparental childcare




With grandparental childcare

Overall, as we can see, the adverse impact of childbirth on employment persists for about three years, while in the long run, mothers tend to return to the labor market. However, the persistence differs significantly for mothers with / without grandparental support. For mothers without grandparental support, their employment starts to recover only four years after childbirth, while for those with grandparental support, their employment starts to rise only one year after childbirth. Grandparental childcare thus significantly shortens the interruption to women's careers owing to childbirth.

### Labor intensity before and after childbirth

Childbirth and childcare may not only force mothers to drop out of the labor force, but also may force them to reduce their labor intensity by shifting towards part-time jobs or jobs with flexible hours. To see the impacts on mothers' labor intensity, we focus on those mothers with positive weekly working hours and explain their labor intensity in panel regressions. The results are reported in Table 8.

Table 8 Regression results for labor density

| | Weekly working hours | | | |
|---|---|---|---|---|
| | (1)<br>RE OLS | (2)<br>FE OLS | (3)<br>RE OLS | (4)<br>FE OLS |
| Motherhood | –0.148<br>(0.939) | –0.515<br>(1.371) | –1.297<br>(1.136) | –1.836<br>(1.603) |
| Motherhood*GPC | | | 2.479**<br>(1.202) | 2.650*<br>(1.490) |
| Controls | Yes | Yes | Yes | Yes |
| Individual FE | No | Yes | No | Yes |
| Year dummy | Yes | Yes | Yes | Yes |
| Obs. | 3,706 | 3,706 | 3,706 | 3,706 |

Note: Standard errors in the parentheses are heteroskedasticity robust standard errors.

It can be seen that, in contrast to women in advanced economies, childbirth does not significantly reduce Chinese mothers' labor intensity, and the mothers receiving post-childbirth grandparental support work even more than those who did not have children. These findings are consistent with the previous results: Because the supply of part-time jobs or flexible jobs is rather limited, post-childbirth mothers who return to the labor market mostly have to maintain the same labor intensity compared with women who did not have children. This reduces women's willingness to work after childbirth, especially for those who have no grandparental support, implying that policies that incentivize the creation of part-time jobs are thus helpful in keeping working mothers in the labor force.

### Types of jobs taken by working mothers

We further investigate the types of jobs that are taken by working mothers, comparing those without grandparental support with those with this support. The results are presented in Table 9. It can be seen that almost half of women without grandparental support are either self-employed and / or work in the agricultural sector, more than double as the number of women with grandparental support. Women with grandparental support are twice as likely to be in formal employment contracts with pension and medical insurance provided by their employers, and 60% more likely to receive a housing allowance. It may be that women without grandparental support are forced into less formal and secure jobs in order to reconcile work with childcare, or women in these types of jobs are more likely to be able to reconcile work with childcare without grandparental support. We leave the explanation for our future research.

Table 9 Types of jobs: Women without grandparental support versus women with grandparental support

| | Agricultural or self-employed | Employed | Managerial | Pension provided by employer | Medical insurance provided by employer | Housing fund provided by employer |
|---|---|---|---|---|---|---|
| w/o GPC | 45.26% | 54.64% | 10.18% | 15.12% | 14.95% | 11.34% |
| w/ GPC | 21.26% | 78.74% | 12.92% | 29.53% | 29.72% | 18.70% |

# 5 Concluding remarks

The unusually high female labor market participation rate in China is in stark contrast to the low level of public expenditure on childcare and the lack of policy support for female employees. Our paper finds that intrafamily downward labor transfer is the key to understanding such a paradox. Intrafamily grandparental childcare largely fills the gap left by the lack of public childcare provision, reduces the opportunity costs to working mothers of working, improves their labor market participation, and reduces the interruption to women's careers owing to childbirth. Grandparental childcare largely explains why the post-childbirth female employment rate and labor intensity are so high, given that public childcare subsidies are rather limited. By addressing the endogeneity problem of women's fertility decisions using the PSM-DID model, we find that the employment rate for women without grandparental support falls substantially after childbirth, and the fall is even significantly larger than that in advanced economies, suggesting that women in China are not special. However, the employment rate for women with grandparental support does not fall after childbirth, instead, it even rises slightly, leading to a much smaller fall in the overall motherhood penalty in female employment. We further show that the recovery in employment for women without grandparental support takes twice as long as for women with grandparental support.

Our results have strong implications for the recent debate on postponing retirement in China. There is general agreement that the current statutory retirement age is too low and that it must be raised to relieve the mounting burden of the pension system. However, our research shows that retired workers make a considerable contribution towards the care of their grandchildren, thus allowing young mothers to maintain a high level of employment and labor intensity. Without providing more public support for childcare, postponing the retirement of older workers may shift the burden of childcare towards young mothers, thus crowding them out of the labor force. Our research therefore calls for more public investment in childcare and social protection policies for working mothers in connection with the forthcoming phasing-in of the new retirement policy.

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# Appendix

## A Estimated propensity score using Logit model

| | 2010–2012 subsample | 2012–2014 subsample | 2014–2016 subsample |
|---|---|---|---|
| Employment | –0.081<br>(0.203) | –0.266<br>(0.186) | –0.209<br>(0.230) |
| Age | 0.492**<br>(0.249) | 0.377**<br>(0.184) | 0.572**<br>(0.227) |
| Age squared, divided by 100 | –1.134**<br>(0.451) | –0.847***<br>(0.322) | –1.105***<br>(0.397) |
| College degree | –0.089<br>(0.281) | –0.325<br>(0.221) | 0.030<br>(0.235) |
| Urban residency | –0.739***<br>(0.274) | –0.137<br>(0.219) | –0.440*<br>(0.245) |
| Studentship | –1.736***<br>(0.433) | –1.929***<br>(0.405) | –2.200***<br>(0.554) |
| Marriage | 2.537***<br>(0.219) | 2.432***<br>(0.186) | 1.889***<br>(0.221) |
| Log household's per capita net income, excluding the woman's | –0.024<br>(0.044) | –0.004<br>(0.039) | 0.060<br>(0.040) |
| Home ownership | –0.280<br>(0.359) | –0.058<br>(0.307) | –0.167<br>(0.279) |
| Home size | –0.001<br>(0.001) | –0.001<br>(0.001) | 4.61e-4<br>(7.05e-4) |
| Hardship in housing | –0.624**<br>(0.277) | –0.500*<br>(0.277) | –0.618**<br>(0.287) |
| Household's total assets | –4.36e-8<br>(1.77e-7) | 1.61e-7<br>(1.57e-7) | –4.56e-8<br>(1.53e-7) |
| House price for the community | –1.75e-5<br>(2.53e-5) | 4.46e-5<br>(2.72e-5) | –4.42e-6<br>(1.67e-5) |
| Number of kindergartens in the community | –0.022<br>(0.095) | –0.015<br>(0.073) | –0.071<br>(0.080) |
| Number of primary schools in the community | –0.022<br>(0.133) | –0.109<br>(0.127) | 0.175<br>(0.171) |
| Community's birth rate | –0.009<br>(0.014) | –0.016<br>(0.014) | –0.004<br>(0.010) |
| Constant | –5.627*<br>(3.315) | –5.089**<br>(2.564) | –9.189***<br>(3.144) |
| Log likelihood | –345.35 | –467.80 | –332.01 |
| Pseudo $R^2$ | 0.3195 | 0.2839 | 0.2376 |
| Significance test for the model | 324.28<br>(P=0.000) | 370.84<br>(P=0.000) | 206.93<br>(P=0.000) |
| Observations | 820 | 1,196 | 911 |

Notes: (1) *** / ** / * denotes the result is significant on 1% / 5% / 10% level; (2) values in the parentheses are standard errors, except those specified as $P$ values; (3) Significant test for the model is based on LR $\chi^2$-statistic.

# B Covariates' balance test before and after matching

| | Matching | Pseudo $R^2$ | LR statistic | P-value | Standardized error |
|---|---|---|---|---|---|
| 2010–2012 subsample | Before | 0.317 | 322.09 | 0.000 | 26.5 |
| | K-nearest neighbor | 0.011 | 7.87 | 0.953 | 4.3 |
| | Caliper | 0.011 | 7.74 | 0.956 | 4.2 |
| | K-nearest neighbor with caliper | 0.011 | 7.87 | 0.953 | 4.3 |
| | Kernel | 0.010 | 7.33 | 0.966 | 4.2 |
| 2012–2014 subsample | Before | 0.286 | 373.16 | 0.000 | 19.5 |
| | K-nearest neighbor | 0.015 | 11.21 | 0.796 | 4.3 |
| | Caliper | 0.008 | 6.36 | 0.984 | 3.5 |
| | K-nearest neighbor with caliper | 0.015 | 11.21 | 0.796 | 4.3 |
| | Kernel | 0.008 | 6.49 | 0.982 | 3.5 |
| 2014–2016 subsample | Before | 0.239 | 207.94 | 0.000 | 20.0 |
| | K-nearest neighbor | 0.011 | 4.75 | 0.997 | 4.3 |
| | Caliper | 0.005 | 2.28 | 1.000 | 3.2 |
| | K-nearest neighbor with caliper | 0.011 | 4.75 | 0.997 | 4.3 |
| | Kernel | 0.005 | 2.38 | 1.000 | 3.2 |

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