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Childcare and Maternal Employment: Evidence from Vietnam

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Abstract

Little literature currently exists on the effects of childcare use on maternal labor market outcomes in a developing country context, and recent studies offer mixed results. We attempt to fill these gaps by analyzing several of the latest rounds of the Vietnam Household Living Standards Survey spanning the early to mid-2010s. Addressing endogeneity issues with a regression discontinuity estimator based on children's birth months, we find a sizable effect of childcare attendance on women's labor market outcomes, including their total annual wages, household income, and poverty status. The effects of childcare attendance differ by women's characteristics and are particularly strong for younger, more educated women. Furthermore, childcare has a medium-term effect and positively impacts men's labor market outcomes as well.

Keywords: Gender equality, child care, maternal employment, women's empowerment, Vietnam.

JEL codes: J13, J16, J22, H42.

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1. Introduction

Women earn less income and are less likely to participate in the labor market, especially in low- and middle-income countries (World Bank, 2012). There are several ways to increase women's involvement in economic activities, such as micro-credit programs, self-help groups, or programs that are specially designed to help improve their access to infrastructure and technology.[1] In this paper, we study a simple but important factor—childcare—that can release women from domestic work and encourage them to participate in the labor market. Specifically, we examine the impacts on women's labor market outcomes of pre-school (age 1-5) childcare in Vietnam.

Analyzing the most recent household surveys for Vietnam in the past decade, we find that childcare (attendance) has a strong effect on women's participation in the labor market, as well as the probability of their working in a formal wage-earning job. Childcare also helps increase women's total annual wages and household income per capita and reduces poverty. The effect of childcare is larger for younger children than older ones. For younger children, moreover, a medium-term effect exists after 2 years, increasing the probability that women will have a wage-earning job by 38 percentage points and reducing self-employed farm work. We also find heterogeneous effects of childcare on maternal employment, where its impact on the probability of having a wage job is larger for younger and highly-educated women. Interestingly, childcare positively impacts the probability of men having a wage-earning job as well.

A key challenge in measuring the effects of childcare is the endogeneity issue. Women who send children to childcare services differ from those who do not (e.g., they may be richer or simply have less time for childcare). We address this problem by using the threshold in the birth months of children—which is exogenously given—as an instrumental variable for childcare attendance. In Vietnam, children's enrollment in kindergartens or primary schools is based on the running age (or current age) instead of the full age (or completed age), and the school year for public kindergarten and primary school starts in September. We can thus compare labor outcomes for women whose children were born in adjacent months in two contiguous, but different, years. In particular, a child who was born

[1] For recent reviews, see Brody et al. (2017) and Winther et al. (2017).

in January in any given year is more likely to start kindergarten or primary school one year later than a child who was born in December of the preceding year, despite an age difference of only one month. We also conduct a series of robustness and placebo analyses to test the validity of the instrument as well as estimation results.

Our paper makes several new contributions to the literature. First, while there is a considerable literature on the impacts of childcare subsidies for richer countries (e.g., see Akgunduz and Plantega (2018) for a recent review), only a handful of studies consider the developing country context. The effects of childcare on parental employment can vary significantly between the former and the latter countries because of their systematic differences in childcare and labor market institutions. For example, the self-employment rate ranges between 30 and 80 percent of the employed labor force in developing countries (World Bank, 2013). Our study on Vietnam—the poorest of those studied in the current literature—thus adds to this growing literature.

Furthermore, the empirical findings on the effect of childcare on parental employment are not conclusive. While most recent studies find a significant, positive effect of childcare use on women' labor supply (e.g., Bauernschuster and Schlotter, 2015; Martínez and Perticará, 2017), a number of other studies do not (e.g., Cascio, 2009; Havnes and Mogstad, 2011). Reviews by Blau and Currie (2006) and Akgunduz and Plantega (2018) show a large variation in the elasticity of maternal employment to childcare costs across different studies, resulting from differences in samples of women and children, estimation methods, and country contexts. The few existing recent studies on middle-income countries offer mixed evidence as well. Focusing on women with at least one child age 4 in Argentina, Berlinksi, Galiani, and McEwan (2011) find a positive impact for childcare use on women's labor force participation (LFP) and work hours. Yet, Li (2017) recently observes no such effects on urban Chinese women.[2] We add to these studies by investigating nationally representative household surveys for Vietnam and all children age 1-5.

[2] Li (2017), however, finds some positive impact on women's LFP for informal childcare provided by grandparents. Other studies indirectly examine the impacts of childcare use through the presence in the household of young children or older people (Maurer-Fazio et al., 2011) or available childcare facilities in the community (Du and Dong, 2013). For earlier studies on childcare and women's employment for developing countries, see, e.g., Lokshin, Glinskaya, and Garcia (2004) for Kenya, Hallman et al. (2005) and Quisumbing, Hallman, and Ruel (2007) for Guatemala, and those reviewed in Akgunduz and Plantega (2018).

Second, most studies focus on certain aspects of childcare, particularly women's employment, since women are typically assumed to be the main caregivers for children. Our study looks at a wide range of outcome variables, including employment outcomes (i.e., self-employed, employed, farm and non-farm, skilled employment, and wage work), household-level outcomes (i.e., income, poverty, household size, migration, and co-residence with grandparents), both in the short term and the medium term. In particular, we show that childcare can significantly shift women's occupations from self-employment to paid employment in Vietnam. By examining a larger number of outcomes, particularly in a developing country context, we aim to provide a more comprehensive analysis of the effects of childcare on maternal employment. Furthermore, our study is one of very few revealing a positive, but weaker, effect of childcare on men's labor market outcomes.

Finally, we offer the first study that rigorously examines the impacts of childcare for Vietnam. Vietnam is an interesting case to study for several reasons. The country has averaged a solid annual growth rate of around 6% during the past two decades. Yet almost half (44%) the working population is still self-employed in the agriculture sector, and more than two-thirds (68%) of those who work are self-employed.[3] Furthermore, gender inequality still remains a challenge in Vietnam. Women are less likely to participate in the formal work sector and whereas the proportion of men working in a wage job is 42%, the corresponding figure for women is only 30%. This lower female participation rate in the labor market is likely the result of women having to stay at home to take care of their young children. Indeed, although Vietnam has accomplished almost universal primary school enrollment (Dang and Glewwe, 2018), more than half (53%) of children age 1-5 do not attend childcare. Our findings for the strong effects of childcare on women's labor market outcomes suggest that improving access to childcare, especially for small children, can lead to more effective labor policies and also to women's empowerment.

This paper consists of six sections. We describe the data sets in the next section, before presenting in Section 3 descriptive analysis of childcare and maternal employment in

[3] Unless otherwise noted, our estimates are based on the Vietnam Household Living Standards Survey (VHLSS) in 2016.

Vietnam. We discuss the estimation method and provide the empirical results, respectively, in Sections 4 and 5. We conclude in Section 6.

2. Data sets

The main data set used in this study is the most recent Vietnam Household Living Standards Surveys (VHLSS) from 2010 to 2016. The VHLSSs have been conducted every two years by the General Statistics Office of Vietnam (GSO) with technical support from the World Bank in Vietnam since 2002. The latest VHLSS was conducted in 2016. In this study, we use the 2010-2016 VHLSS instead of those carried out before 2010, since the more recent surveys contain more information on employment consisting of monthly wages and formal employment.

The 2009 Population and Housing Census is used as the sampling frame. Of 10,896 communes, 3,133 were chosen as the primary sampling units. A village was randomly selected from each commune, and around 15 households were selected randomly from the village. Each VHLSS covers around 46,000 households selected from 3,063 areas of the master sample frame, and is divided into 2 types: (1) The sample for the income survey includes 36,756 households and collects information to assess non-monetary living standards at the national, regional and provincial/city level; (2) The sample for the income-expenditure survey includes 9,189 households and collects sufficient information for further assessment and analysis of monetary living standards at the national and regional level.

In this study, we used the full sample of the VHLSS to increase the number of children born in January and February. The total number of households and household members sampled in VHLSS are as follows:

- VHLSS 2010: 46,995 households with 185,696 household members.
- VHLSS 2012: 46,996 households with 182,042 household members.
- VHLSS 2014: 46,335 households with 178,267 household members.
- VHLSS 2016: 46,380 households with 175,340 household members.

The VHLSS contain very detailed data on individuals, households and communes. Household data include durables, assets, production, income and expenditures, and participation in government programs. Individual data consist of information on demographics, education, employment, health, and migration. It should be noted that the VHLSS contain data on the year and month but not the full date of birth of individuals.[4]

3. Childcare systems and descriptive analysis

3.1. Childcare in Vietnam

In Vietnam, kindergartens are generally available for children age 3 to 5, but some kindergartens also admit children age 18 months or older. Vietnam's law on universal primary education require that children 6 years old and older attend a primary school, with the exception of children with health problems or those living in isolated areas. It should be noted that the admission age for school entrance in Vietnam reflects a child's current age rather than completed age. Following this practice, hereafter, when we discuss a child's age for admission to childcare, we refer to running age rather than completed age.

Children under the age of three can attend early childcare centers, but access to early childhood care centers remains limited in Vietnam, with only 26% of villages in rural Vietnam providing such centers.[5] Kindergartens are more widely available, with 49% of villages having at least a kindergarten. The VHLSS does not collect data on the availability of childcare centers for urban areas. However, using individual-level data, we can compute the proportion of urban and rural children attending childcare centers and kindergartens. In 2016, 44% of urban children age below 6 attended childcare centers and kindergartens, while this rate for rural children was lower at 35%.

In Vietnam, children are entitled to a place in a kindergarten from the age of 3 through just before attending primary school. School, including kindergarten, in the country starts from September each year. Thus, for example, if a child was born in 2000 (regardless of birth

[4] We acknowledge that if the VHLSSs do not capture the top-income population groups, our analysis may not be relevant to these groups.

[5] Unless noted otherwise, our estimates are based on the 2016 VHLSS. Vietnam includes 63 provinces and provincial-level cities. Each province (and provincial-level city) is split into districts, and each district is split further into communes. Communes are the smallest administrative units in Vietnam. In 2016, there were 713 districts and 11,164 communes in Vietnam. Each commune contains around 3-15 villages. In urban areas, communes are called wards.

month), she or he can attend a kindergarten from September 2003, and attend a primary school from September 2006.[6]

The education system in Vietnam is provided mainly by the state, with 90% of children age 3-5 attending public kindergartens and the rest going to private kindergartens. More children below the age of 3, however, are enrolled in private childcare centers. The proportion of children age below 3 attending private and public childcare centers was 27% and 73% in 2016, respectively.

For simplicity, we refer in this study to childcare centers for small children below 3 and kindergartens for children age 3-5 as "childcare (centers)". Figure 1 presents the percentage of children attending childcare by age. Less than 1% of children below the age of one attended childcare in 2016. The number of children age one attending childcare is also small, at around 3%. Childcare attendance increases significantly by age, especially from 3 years and up. Specifically, 48% of children age 3, 69% of children age 4, and 80% of children age 5 attended kindergartens in 2016. Figure 1 also shows an increase in the enrollment rate of children over time. For all age groups, the percentage of children attending childcare was significantly higher in 2016 than 2010.

In this paper, we focus on childcare attendance for children age 1-5. We do not consider children younger than one year old, since in our data sets almost no such children attend childcare. We also exclude children age 6, since this is the age when most children start attending the first grade of primary school.

3.2. Maternal employment

We examine the employment outcomes of women with at least one child age below 6 over the period 2000-2016 in Table 1. These outcomes are measured by different variables, including current working status, wage-earning job, farm and non-farm employment, skilled

[6] Children attend childcare centers and kindergartens from Monday to Friday. The school day at these institutions and at primary schools often starts at 7.30 a.m. and ends at 4.30 p.m. But this time schedule is not fixed. Some childcare centers (and kindergartens) admit children on Saturday and allow them to be picked up later than 4.30 p.m.

occupation, and a formal job as the main occupation during the past 12 months. These women's average age hovers around 32 and ranges from 17 to 58.

The working rate of women in 2016 was 93%. For comparison, Table A.1 in the Appendix also reports men's employment rate, which is 6 percentage points higher with almost all men (99%) working. This male-female gap in the employment rate, however, was stable during the period. The 2014 and 2016 VHLSS include questions concerning the reasons for not working. These are very different for men and women. Figure A.1 in the Appendix presents the distribution of women and men by reasons for not working. In 2016, 90% of women did not work outside the home because they were occupied with housework. These activities include caring for one's own home, caring for grandchildren so the daughter can work, caring for elderly women, or any additional range of tasks. Compared with women, the proportion of men not working outside the home for the same reason was much lower at 23% in 2016. For men, the main reasons for not working were retirement, sickness and disability. The unemployment rate (the unemployed comprise those who were unable to find a job during the past year) was very low, less than 1% in 2016.

Among working people, men work more hours (209 hours) in a month than women (190) in 2016. The gender gap in the number of people in a wage-earning job is larger, though this gap decreased over time. In 2016, around half of all men (51%) had a wage-earning job, while the corresponding figure was less than half for women (38%). This means that more than half of all women (55%) were self-employed. We classify self-employed work into farm and non-farm employment. In 2016, 18% of women had non-farm employment and 37% of women worked on farms.

We also examine the quality of employment, which we categorize into skilled employment and formal employment. While men were more likely to have a skilled job than women, women had a higher rate of formal employment than men, perhaps because women prefer a stable job with social insurance.[7] Women are also more likely to work in the textile,

[7] Formal employment is defined as a job with social insurance. The social contribution or payroll tax in Vietnam is equal to 34% of the monthly salary, of which 23.5% is paid by employers and 10.5% by workers. Workers making a social insurance contribution are eligible for health insurance, employment subsidies and pensions (on retirement).

garment and footwear industries in foreign direct investment sectors, which employ more formal workers.

The VHLSS collect data on respondents' wages over the past 30 days and their total wages over the past 12 months, as well as their working hours during the past 30 days. Several workers have more than one job and are asked about the wages and working hours of their main and secondary jobs. Thus, we compute total wages from the main and secondary jobs for our analysis.[8] The real hourly wage of women increased from 18,100 to 23,500 VND during 2010-2016. Monthly and yearly wages also increased over time. However, the gender gap in wages also increased over time. In 2010, the average annual wage for men was 9% higher than that for women but in 2016, the annual wage for men was 18% higher than that for women.[9]

3.3. Childcare and maternal employment

Figure 2 compares by children's age several employment variables for women whose children attend childcare versus those whose children do not. The difference in the working rate between the two groups is small. However, there is a clear gap in terms of wage-earning jobs. The gap is larger for those with smaller children than those with older children. Similarly, women whose children attend childcare have a higher proportion of formal jobs, more working hours, and higher wages than women with children who do not attend childcare. The difference in these employment variables also tends to be larger for younger children than older children.

Figure 2 shows a correlational—rather than a causal—relationship between women's employment and childcare because there can be unobserved factors that affect both childcare attendance and maternal employment. The next sections discuss our estimation method and empirical findings on the causal effects of childcare attendance on maternal employment.

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[8] We also conduct analysis using wages from the main jobs alone, and estimation results are very similar because wages from secondary jobs are equal to only around 4% of those from the main jobs.

[9] Further breakdown of women's employment by urban/ rural areas (Table A.2) suggests that while the percentage of women working is higher in rural areas, the percentage of urban women working in non-farm work, skilled work, or formal work is higher. Urban women also work more hours and earn more wages per hour than rural women.

4. Estimation method

To measure the impact of childcare attendance on maternal employment, we use a regression discontinuity method. Development and discussion of regression discontinuity design methods can be found in a large number of studies (e.g., Van der Klaauw, 2002; Imbens and Lemieux, 2008; and Lee and Lemieux, 2010). In regression discontinuity designs (RDD), a treatment group is selected for treatment if the value of at least one observed variable crosses a cut-off threshold. In particular, there exists a conditioning variable *Z,* such that the treatment variable, denoted by *D,* is equal to 1 if and only if *Z* is larger than a specific value $Z=c$. We can identify the treatment effect by comparing outcomes for individuals (denoted by *Y*) just above and below the threshold *c*: $\tau_{RD} = Y^{+} - Y^{-}$.

The proportion of children attending childcare increases by age, and as discussed earlier, children's current age is used to determine their enrollment eligibility. We thus use birth months as the conditioning variable that determines childcare attendance. Specifically, we compare the employment of women whose children were born in December and January in two contiguous years. Since the school year starts in September, a child born in January of a given year is more likely to start attending childcare 1 year later than a child born in December of the previous year, even though the two children differ in age by only 1 month.[10]

Figure 3 shows the proportion of children age 1-5 attending childcare by birth month in two consecutive years. Older children were born from July to December, while younger children were born from January to June of the following year. Children born in January are one month younger than those born in December. Panel A of Figure 3 presents a graph using data from the pooled sample of children. Other panels of the figure present graphs for different age groups. For example, for children age 1-2, panel B of the figure shows the percentage of childcare attendance of children age 2, born in July to December, and of children of the age of one and born from January to June. Older children have a higher rate of childcare attendance. However, there is an obvious, large gap in the incidence of childcare attendance between children born in December and those born in January.

[10] The VHLSS contain data on age (year and month), but not an individual's full date of birth. Thus, we cannot use the date of birth as the conditioning variable. But we also offer robustness checks in Section 5 where we vary the width of the months around the cut-off threshold.

Since birth month does not strictly determine childcare attendance, we apply fuzzy regression discontinuity to measure the effect of childcare on maternal employment. Fuzzy regression discontinuity identifies the local effect of enrollment at the threshold, as follows:

$$\tau_{FRD} = \frac{Y^{+} - Y^{-}}{D^{+} - D^{-}}, \qquad (1)$$

where Y^{+} and Y^{-} are the employment of women of children born in December and those born in January in two consecutive years, respectively. D^{+} and D^{-} represent the probability of being enrolled in childcare.

Figure 4 depicts several employment variables of women whose children were born between July and December of a given year and those born between January and June of the following year. It shows that women with children born in December tend to have a higher rate of wage-earning jobs and higher wages than women with children born in January of the following year.

To estimate the effect of childcare attendance on maternal employment, we use the estimator in equation (1). Practically, we estimate this effect using an instrumental regression, which can be explained into two stages as follows. In the first stage, we estimate the effect of being born in December on the probability of attending childcare

$$D_{i,j} = \alpha + \beta Dec_{i,j} + X_{i,j}'\gamma + \epsilon_{i,j}. \qquad (2)$$

where $D_{i,j}$ is a dummy variable that indicates a mother i with a child j who currently attends a childcare center. $Dec_{i,j}$ is a dummy variable which is equal to 1 if the child was born in December and 0 if she/he was born in January of the following year. $X_{i,j}$ and $\epsilon_{i,j}$ are vectors of observed and unobserved characteristics of women, respectively. We use a small set of exogenous control variables, including age, gender, ethnic minorities, women's number of years of schooling, and year dummies.[11] These control variables are also basic demographic explanatory variables of employment and wages. It should be noted that control variables should be exogenous and unaffected by the treatment variable of interest, that is childcare attendance in this case (Angrist and Pischke, 2009; Heckman et al., 1999). We aim to estimate

[11] See Dang (2012) for further discussion on differences in living standards for the different ethnic groups in Vietnam.

the total effect of childcare attendance on outcomes rather than the partial effect of the childcare attendance with other variables held constant (Duflo et al., 2008).

We limit the sample to women whose children were born in December and January of two consecutive years and therefore differ in age by only 1 month. In the terminology of regression discontinuity design, the bandwidth is 1 month. In the pooled sample of VHLSS, there are 3,869 children age 1-5 born in December and January. There are six twins, and we drop these twins from the sample. The final number of observations for analysis is 3,863.

The main reason that we focus on a 1-month bandwidth is that parents can choose seasons or even the month of birth for their children. A wider bandwidth is more likely to be associated with bias. However, we also try to extend the bandwidth to 2 and 3 months for sensitivity analysis. For example, a 2-month bandwidth means that we compare women with children born in November and December with women whose children were born in January and February of the following year. A wider bandwidth can improve efficiency since it allows for a larger number of observations. However, it can also increase estimation bias, since children born in October to December may differ significantly from those born in January to March in different aspect such as health and non-cognitive skills which can affect parental employment. Thus, we use the results from a 1-month bandwidth for interpretation.

In the second stage, we regress the employment variable of women on the childcare attendance of children as follows

$$Y_{i,j} = \delta + \theta D_{i,j} + X'_{i,j}\pi + u_{i,j}. \qquad (3)$$

where $Y_{i,j}$ is the employment variable of interest. Equation (3) is estimated using instrumental variable regression, where the instrumental variable for childcare attendance is a dummy variable indicating whether the child is born in December.

Our dependent variables include both continuous and dummy variables. For continuous variables, such as log of wages and log of the number of working hours, we use 2SLS. When the dependent variable is a binary, 2SLS regression can be applied for the linear probability model with a dummy endogenous variable (e.g., Angrist 2001). A major limitation of 2SLS is that explanatory variable estimates can be smaller than -1 or larger than 1, which is unrealistic. This problem is more likely to arise when the value of dependent variables is close to 0 or 1 (e.g., Long, 1997). To address this, we use a bivariate probit model (see, e.g., Wooldridge, 2010), which jointly estimates Equations (2) and (3) with maximum likelihood methods. We also report results from 2SLS and control function models to check for robustness. For interpretation, we use the results from the bivariate probit model.

5. Empirical results

5.1. Testing the instrumental variable

The RDD method relies on the assumption that the conditioning variable cut-off is exogenous or random. Thus, the key identification strategy in this paper is the exogeneity of being born in December versus January for children age 1-5. This instrumental variable is assumed to affect childcare attendance and not to be correlated with the error terms of the outcome equation. This means that the variable "born in December" can affect maternal employment only through the channel of childcare attendance (conditional on control variables). To test the exogeneity of being born in December, we first compare the proportion of children born in different months. Figure 5 shows that the proportion of children born in December is slightly lower than the proportion of children born in January. However, the difference is not statistically significant.[12] Thus there is no evidence that the threshold or cut-off is not random.

The month of birth is stated on birth certificates and is difficult to manipulate. Moreover, if a number of people manipulate their children's birth month on their birth certificate in order to send their children to childcare earlier, the proportion of children with a reported birth month in December will be higher than the proportion of children with a reported birth month in January. Thus, there is no evidence of manipulation of birth months in our data.

The number of children born in October is larger than the number born in other months. Without in-depth studies on this issue, it is difficult to provide an accurate explanation for the higher rate of births in October. In Vietnam, traditional New Year festivals often take place in late January and early February. People have a long holiday

[12] If the conditioning variable is continuous, we can use the manipulation test developed by McCrary (2008) to test the exogeneity of the conditioning variable. In our study, the conditioning variable is binary (children born in December versus January). Thus, we simply compare the proportion of children born in these two months.

during the festival and may possibly be more likely to have sexual relations during this time. As a result, the fertility rate increases after 9 months. The higher proportion of children born in October warns against using the 3-month bandwidth as the instrument for childcare attendance.

To further test the exogeneity of the instrumental variable, we run OLS regression of this variable on the exogenous demographic characteristics of women (age, gender, ethnicity and the number of years of schooling). Table A.3 reports the regression results. It should be noted that the dependent variables are dummy variables indicating "women whose children were born in December in the sample of December/January births," "women whose children were born in November and December in the sample of children born from November to February," and "women whose children were born from October to December in the sample of children born from October to March." The explanatory variables are variables of women rather than variables of children.

Table A.3 shows that in the sample with a 1-month bandwidth, i.e., children born in December and January of consecutive years, being born in December is not correlated with maternal characteristics. All the explanatory variables are of very small magnitude and not statistically significant at the conventional levels. However, in the sample with 2-month or 3-month bandwidths, the ethnicity and years of schooling of the women are significant, though the variables have very small magnitudes. For example, a 1-year increase in the number of years of schooling is associated with an increase in the probability of having children born in November and December (compared with children born in January and February) equal to 0.005. For the 3-month bandwidth sample, this correlation coefficient is estimated at 0.003. Again, this finding provides a warning against using 2-month as well 3-month bandwidths as the instrument for childcare attendance.

The second condition of the instrumental variable is a strong correlation between the instrumental variable and childcare attendance. We run a probit regression of childcare attendance on the instrumental variable (being born in December) and other maternal control variables. Table A.4 presents the results of the original probit. In Table 2, we report the marginal effect of the explanatory variables for interpretation. Compared with a January birth, being born in December of the previous year increases the probability of attending childcare by 0.092. The estimate is statistically significant at the 1% level.

Since younger children need more care and attention than older children, we estimate the effect of childcare attendance for children of different ages, in this study for children age from 1 (and born in December) to 3 (born in January), and children age from 3 (born in December) to 5 (born in January). In these two separate samples of children, the instrument is significant at the 1% level. We also run OLS regressions of childcare attendance on the instrumental variable (the first-stage regression) and performed Cragg-Donald and Kleibergen-Paap weak identification tests on the instruments. The test statistics are high, indicating that the instruments are very strong (Table A.4).[13]

5.2. The effect of childcare attendance on maternal employment

Panel A of Table 3 reports the coefficients of childcare attendance in instrumental variable regressions of maternal employment outcomes (model in equation 3). There are 10 outcome variables, and we estimate the effect of childcare attendance on these outcomes using samples of children of different ages. The number of regressions is 30. Tables from A.5 to A.8 in the Appendix present the full regression results. In Table 3, we report only the coefficient of childcare attendance.[14]

We find that childcare attendance has an insignificant effect on women's LFP. A possible reason is that the number of working people in Vietnam is very high, and a large proportion of them are self-employed. If children cannot attend childcare, women can care for them and at the same time be self-employed. Consequently, the effect of childcare attendance on women's working status is not significant. This result is consistent with the finding from the regression of the number of monthly working hours on childcare attendance. There are no significant effects from childcare attendance on the number of women's monthly working hours.

The effect of childcare attendance on engaging in skilled work is also small and insignificant at the conventional level. Obtaining work skills takes a long time, and children's attendance at childcare cannot improve women's work skills. Moreover, skilled workers may

[13] As a rule of thumb, if an F-statistic is under 10, the instruments may be weak (Staiger and Stock, 1997).
[14] Table A.6 in the Appendix reports the probit and OLS regressions (without instrumental variable).

be self-employed and provide childcare for their children at the same time. In our sample, 50% of skilled workers were self-employed.

Most importantly, we find a strong effect of childcare attendance on women's wage-earning jobs. Childcare attendance increases the probability of having a wage-earning job by 0.41. Sending a child to childcare can free up time for women and allow them to participate in the labor market. Childcare attendance has no effect on overall employment but a positive effect on wage-paying employment. This means that women switch from self-employed work to wage-earning work. Table 3 shows the negative effect of childcare on self-employed farm work.

There is also a significant positive effect of childcare attendance on women's formal jobs. Having a child in childcare increases the probability of women having a formal job by 0.257. Formal jobs are medium-term employment with a social insurance contribution. Thus, sending children to childcare helps women not only to participate in the labor market but also to find a medium-term, stable job.

We measure the effect of having children in childcare on the wages of wage earners. The effect of childcare attendance on monthly wages is positive but not statistically significant. However, there is a significant effect on annual wages. The increase in total wages may be due to an increase in the number of women in formal jobs as well as an increase in productivity.

In Panel A of Table 3, childcare attendance and maternal employment are measured in the current year. An important question is whether putting children in childcare has an ongoing or medium-term effect on maternal employment. To examine the medium-term effect, we regress the employment variables of women measured in one VHLSS on childcare attendance recorded in the previous VHLSS, using panel data from two consecutive surveys.[15] This approach aims to measure the 2-year lagged effect of childcare attendance on parental education. We use the same model specification as the model of current effects.

[15] Fifty percent of households sampled in one VHLSS are re-interviewed in the next one. For example, 50% of households in the 2010 VHLSS are resampled in the 2012 VHLSS. Then 50% of the households covered in the 2010-2012 VHLSS panel are resampled in the 2014 VHLSS. In addition, 25% of households in the 2012 VHLSS are also resampled in the 2014 VHLSS. Thus, in two consecutive surveys, around 50% of households feature in panel data, and around 25% of households are included in panel data in three consecutive VHLSS. In practice, the dropout or attrition rate in two consecutive surveys is around 8%.

Panel B of Table 3 reports only the coefficients of childcare attendance in these regressions. We do not find a significant effect from childcare attendance on the working status or wages of women after 2 years. However, children's attendance in childcare has a strong lagged effect on the probability of women taking a wage-earning job. Having a child attending childcare increases the probability of having a wage-earning job by 0.377 after 2 years. The effect on self-employed farm work is negative, indicating a movement from farm work to wage-earning employment.

5.3. Robustness analysis

In this section, we report several robustness checks conducted in this study. In Table 3, we estimate a bivariate probit model for binary dependent outcomes. Although bivariate probit is suitable and efficient for models with a binary dependent variable and a binary endogenous variable, it relies on assumptions of the parametric specification and distribution of errors in the latent variables (used to define the dependent variable and endogenous variable). Thus, we also estimate the effect of childcare attendance using 2SLS and control function models (Tables A.8 and A.9 in Appendix). In 2SLS, both dependent and endogenous variables are estimated using linear probability models.

We implement two types of control function model. In the first type, following Rivers and Vuong (1988), we first regress childcare attendance on the instrument and other explanatory variables using OLS, and estimate residuals from this regression. Next, we estimate a probit model of maternal employment using the childcare variable, the predicted residuals, and other explanatory variables. In the second type, we model childcare attendance on the instrument and other explanatory variables using probit, and estimate the generalized residuals (Wooldridge, 2015). We then estimate a probit model of maternal employment using the childcare variable, the generalized residuals, and other explanatory variables. Standard errors are estimated using a bootstrap with 200 replications.

Table A.9 in the Appendix reports the estimates of the effect of childcare attendance on maternal employment using 2SLS and control function estimators. The results are very similar to those obtained from bivariate models. Childcare attendance has a positive effect on the probability of having a wage-earning job and a formal job. The sign and magnitude of the effect are similar in different models.

Next, we examine the sensitivity of the estimates to the bandwidth selection. We use a 2-month bandwidth (i.e., comparing children born in November and December with those born in January and February in the following year) and a 3-month bandwidth (i.e., comparing children born in October to December with those born in January to March in the following year). Table A.10 in Appendix shows that the estimates of the effect of childcare attendance on women's employment are very similar in models using different bandwidths. The effects on wages are more significant in models using 2- and 3-month bandwidths than in models using a 1-month bandwidth. This may be because there are more observations in models using 2- and 3-month bandwidths.

5.4. Placebo and falsification analysis

Table 4 reports the reduced-form regressions of maternal employment on the instrument (i.e., children born in December), using the sample of children born in December and those born in January of the following years. It shows that women who have children in December are more likely to have a wage-paying job and are less likely to engage in self-employed farm work than women with children born in January. Table 4 reports the coefficient of the instrument from 30 regressions (3 samples multiplied by 10 outcomes). Childcare attendance is significant at the 1% level in 6 regressions, accounting for 20% of the total number of regressions.

An issue with our instrument is that on average, children born in December are still 1 month older than those born in January. One may argue that a 1-month difference in age is small but may still affect maternal employment. To test this argument, we run regressions of women's employment on a dummy variable indicating women who have children 1 month older than others. In these regressions, children are of the same age. For example, we use a sample of women with children born in January and those with children born in February. We repeat the analysis for each month up to the sample of women with children born in November and those with children born in December. The instrument in this case is "children born one month earlier." We conduct regressions for all 10 outcomes and estimate the percentage of regressions in which childcare attendance is significant at the 1% significance level. We repeat the analysis for different gaps in children's birth month: from 1-3 months, only 1 month, only 2 months, and only 3 months.

Figure 6 shows the distribution of the p-value of the variable "born earlier" in these regressions. For the birth month gap from 1-3 months, only 3.3% of regressions show a significant effect of "being born earlier" on parental outcomes. For a gap of 1 month, 1.8% of regressions show a significant effect of "being born 1 month earlier" on parental outcomes. No regressions show that the effect of being born earlier is significant at the 1% level. Thus, there is no evidence of the effect of being born earlier (for children of the same age) on parental outcomes.

5.5. Spill-over effects

Table 5 presents 2SLS regressions of several household outcomes on childcare attendance. Taking advantage of childcare has a positive effect on per capita income. Childcare attendance increases the labor market participation and wages of women and as a result, increases household income. This income effect carries over to a poverty-reducing effect. A household is defined as poor if its per capita income is below the poverty line. The probability of being poor is reduced by 0.22 when children are placed in childcare. This finding suggests the important role of childcare in Vietnam where there is a low rate of childcare and a low rate of participation by women in the labor market.[16]

It is common in Vietnam for grandparents who live with their children to take care of the grandchildren. In the 2016 VHLSS, in approximately 21% of households, grandparents live with their children. We test whether formal childcare in a center can substitute for informal childcare from grandparents by running a regression of a dummy variable "living with grandparents" on childcare attendance. The effect of childcare attendance is minimal and is not statistically significant. There are no significant effects on parental migration and household size, or the interaction terms between childcare and households having an urban

[16] We further explore whether the poverty-reducing impacts of childcare are stronger for certain disadvantaged groups such as ethnic minorities or unemployed individuals by interacting these variables with childcare attendance. Estimation results (available upon request), however, are not statistically significant.

residence permit either (results available upon request). Thus, childcare attendance affects maternal employment but not demographic composition and the migration of households.

5.6. Heterogeneous effects

To investigate the heterogeneous effects of childcare attendance on parental migration, we include interactions between childcare attendance and explanatory variables in the regression of maternal employment. We do not include all the interactions in one regression since it is very difficult to interpret the heterogeneous effect. In one regression, we include childcare attendance, an interacted variable, and interaction between childcare attendance and the interacted variable, and other control variables. If the interacted variable is discrete, we convert this variable into a set of dummies and include interactions between childcare attendance and the set of dummies in one regression. Interaction variables are also endogenous, and we use interactions between the instrument for childcare attendance (children born in December) and the interacted variables as instruments for the interaction variables. For simplicity, we estimate models with interactions using the control function method. In this method, the endogenous part of childcare attendance is controlled by the residuals from the first-stage regression. As a result, neither childcare attendance nor the interaction variables are correlated with the error term in the second-stage regression.

Tables 6 and 7 present the coefficients of childcare attendance and the interaction variables in the control function regression, in which the second stage is estimated using probit. For simplicity, we investigate the heterogeneous effect of childcare attendance only on the labor market participation of women (i.e., the dependent variable is women with a wage-paying job). Other models in Tables 6 and 7 differ in the interaction term between the childcare attendance and explanatory variables.

We first include interactions between childcare and women's demographic variables. The effect of childcare attendance does not differ for age (Model 1). However, highly-educated people are more likely to have a wage-earning job than poorly-educated people (Model 2). Schlosser (2005) and Nollenberger and Rodríguez-Planas (2011) also report findings that the effect of recourse to childcare on highly-educated women is greater than for poorly-educated women. The effect of making use of childcare centers is lower for ethnic minority women than for Kinh women (Model 3), perhaps because ethnic minorities are less likely to find job opportunities than Kinh people.

In addition to the effect of childcare attendance on women's employment, we also examine the effect on men's employment and test if there is a difference in the effect of childcare use between women and men (Model 4). Thus, we use a sample of both women and men and run a regression of parental employment on childcare attendance, a dummy indicating women and interaction between childcare and the mother. The number of observations in this model is larger than that in other models. Interestingly, the coefficient of childcare attendance is positive and statistically significant, meaning that there is a positive effect of childcare attendance on the probability of men having a wage-earning job. The marginal effect of the interaction is estimated at 0.078 and is statistically significant at the 1% level. This means that the effect of childcare use on the rate of women's employment in a wage-earning job is around 7.8 percentage points higher than the effect of childcare use on the rate of men's employment in a wage-earning job.

We also examine whether the effect differs for the gender of children. Model 5 in Table 6 shows that the effect on maternal employment of boys attending childcare is slightly lower than that of girls. In our data set, the rate of childcare attendance is 48% for boys and 49% for girls. The difference is small but still statistically significant. Vietnam is a country with a preference for boys, especially in rural areas (e.g., Guilmoto, 2012; Nguyen and Tran, 2017). The number of annual visits of boys to health care services is around 6% higher than of girls. Possibly, women must still spend more time taking care of boys than of girls, even if both children attend a health care center. As a result, the effect on maternal employment of boys attending childcare is smaller than that of girls attending childcare.

Children's order of birth is negatively correlated with maternal employment, since higher birth order implies a larger number of children and having more children is associated with a lower probability of labor market participation. The interaction between childcare and the birth order of the child is negative but not statistically significant (Model 6).

There can be differences in quality between public childcare and private childcare. We thus interact childcare attendance and different forms of childcare including public center (the reference group), semi-public center, private center, and other forms. All these interaction terms are not statistically significant (and are not shown in Table 7 for lack of space), except for that between childcare attendance with private center (Model 1 in Table 7). This interaction term is strongly statistically significant, and suggests that private childcare attendance has a stronger impact on maternal employment than public childcare. We find a lower effect from childcare attendance in communes which are far from town (Model 2), meaning that the effect is larger for communes closer to town. Possibly, employment opportunities as well as wages are higher in areas near towns, increasing the effect of childcare attendance on women's employment.

We also test the interaction of the childcare attendance and commune-level variables (availability of kindergartens in communes and access by car to villages).[17] VHLSS contain commune-level data for rural areas but not for urban areas. Thus, we use the rural data sample to estimate the models, including interactions with commune-level variables. Both the interactions are negative, but not statistically significant. We also interact childcare and urban residence, but this interaction term is not statistically significant (results not shown).

The effect of childcare attendance on maternal employment may depend on the opportunity costs of staying at home (i.e., not participating in the labor market) to take care of children. In Model 5, we test the interaction of childcare attendance with the mean wage of districts.[18] The interaction is positive and highly significant, meaning that the effect of childcare use is greater in areas with higher wages. In Model 6, we include interaction between childcare use and per capita income for the district, but this interaction is not statistically significant at conventional levels. Income includes not only wages but also self-employed income. Thus, the interaction between recourse to childcare and per capita income is positive but not statistically significant.

Small children may receive care from older siblings and grandparents. Several studies show that informal childcare provided by grandparents can increase women's labor supply (e.g., Dimova and Wolff, 2011; Li, 2017). Thus, we include interactions between childcare use and these variables (including the age and gender of the firstborn sibling, living with grandparents, household size, the proportion of elderly and children), but these interactions

[17] Good roads are defined as roads passable by cars during all the previous 12 months.
[18] Mean wages and per capita income at the provincial and district levels are obtained from Lanjouw et al. (2017).

are not statistically significant at the conventional level. The results are reported in Table A.11 in the Appendix.

6. Conclusion

In this paper, we offer the first study that rigorously investigates the prevalence of childcare, and the effect of pre-school childcare attendance on parental, especially maternal, employment in Vietnam. We find that the percentage of children attending childcare is less than 1% and 3% respectively, for children younger than age 1 and at age 1, although this figure improves for older children. We find childcare to have a very small, insignificant effect on parental work, which may be due to the high rate of self-employment in the country. However, we find that childcare has a strong effect on women's labor market participation and probability of having a formal job. Specifically, the use of childcare increases the probability of women having a wage-earning job by 41 percent and increases the probability of their having a formal job by 26 percent. Interestingly, childcare increases not only the labor market participation of women but also of men, though the effect on the latter is smaller. We also find that childcare has heterogenous effects and differs for women of different characteristics. In particular, these effects are greater for ethnic majority and highly-educated women, and for areas with higher wages or with greater opportunity costs for not participating in the labor market. There is also some evidence that private childcare has a larger impact than public childcare on women's probability of having a wage job.

These findings point to the importance of accessible childcare services in both enhancing women's labor market outcomes and reducing the gender gaps. This has important policy implications, especially given that women are given at most 6 months' maternity leave and the existing supply of public childcare may be inadequate. In particular, providing childcare in areas with higher wages can be particularly beneficial for women's access to a wage job. The opportunity costs for not participating in the labor market will be larger for women as the economy develops, which is likely to amplify the beneficial impacts of childcare.

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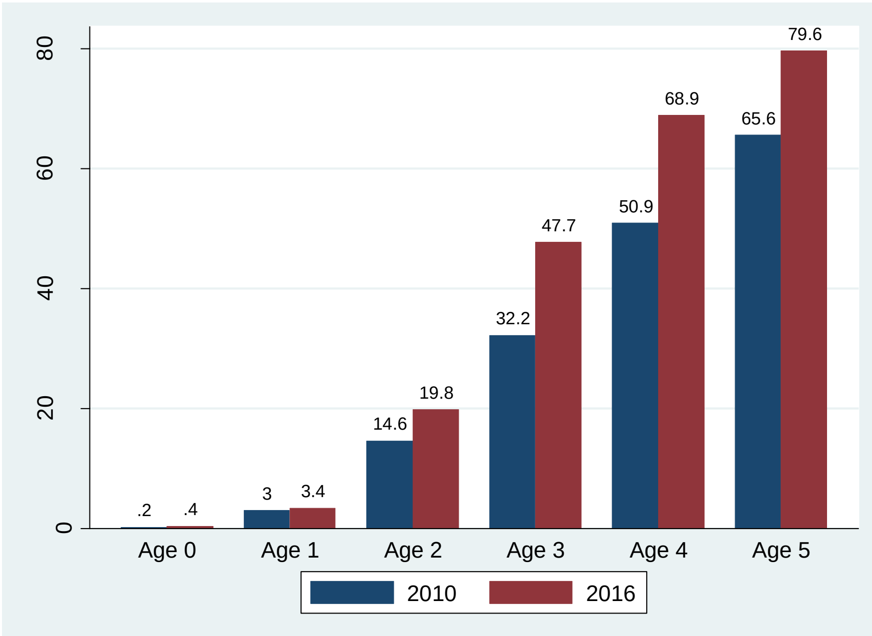
Figure 1. Percentage of children attending child care

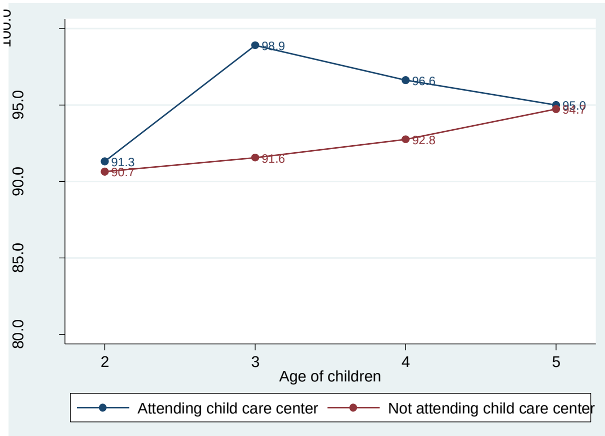


Note: This figure presents the level of child care attendance by children age 1-5.

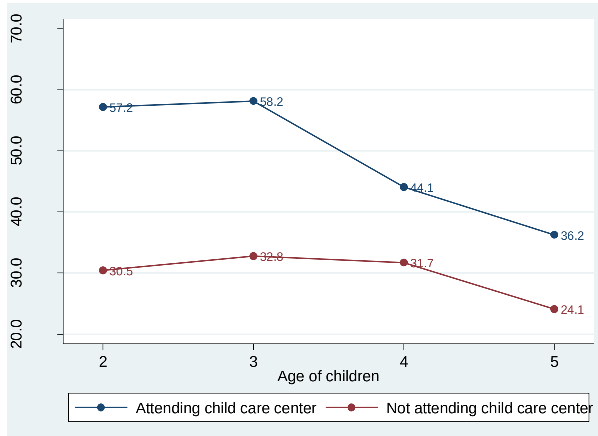
Source: Estimation from VHLSS 2010 and 2016.

Figure 2. Maternal employment and children's attendance at child care centers

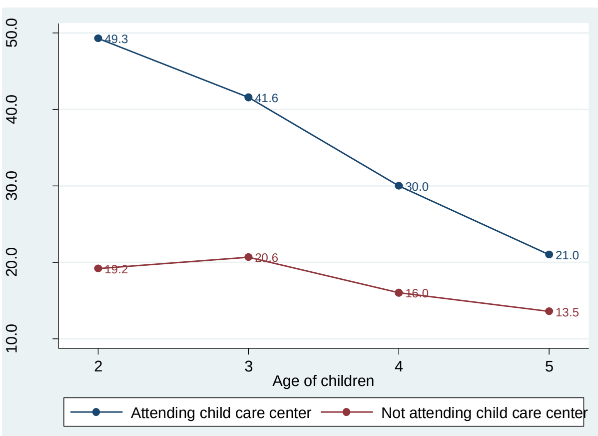
Panel A. Percentage of women working and child care attendance



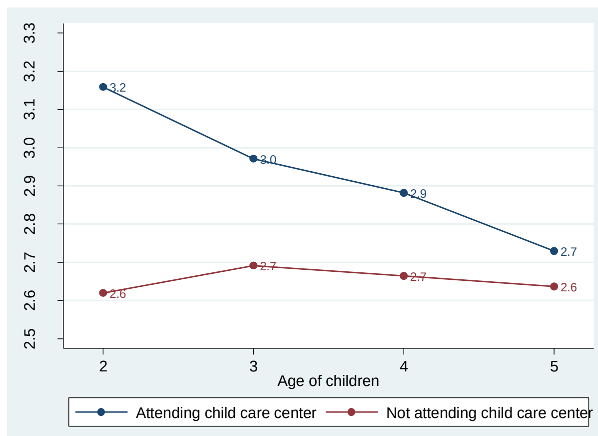
Panel b. Percentage of women have a wage job and child care attendance



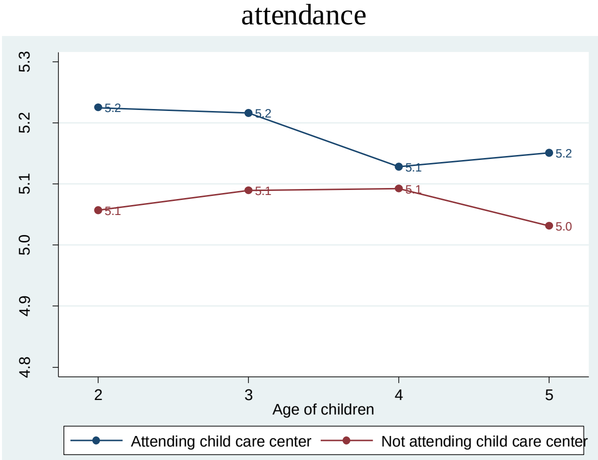
Panel C. Percentage of women with a formal job and child care attendance



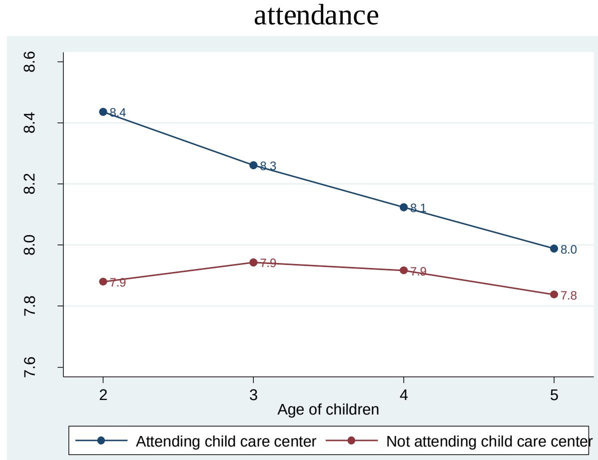
Panel D. Working hours of women and child care attendance



Panel E. Hourly wage of women and child care attendance



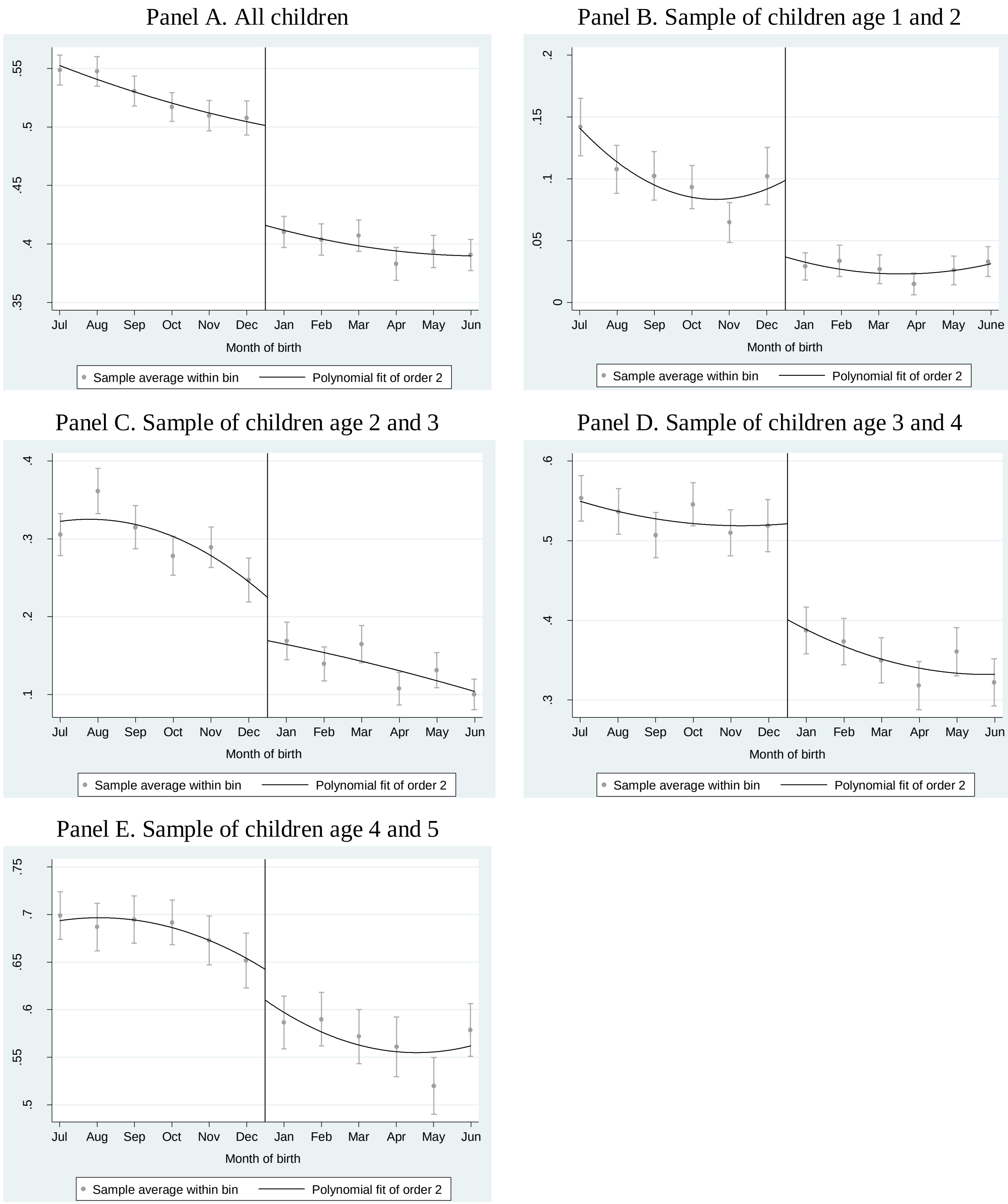
Panel F. Monthly wage of women and child care attendance



Note: The vertical axis indicates the employment variables of the parent, and the horizontal axis gives the children's age.

Sources: Authors' estimation from VHLSS 2010, 2012, 2014 and 2016.

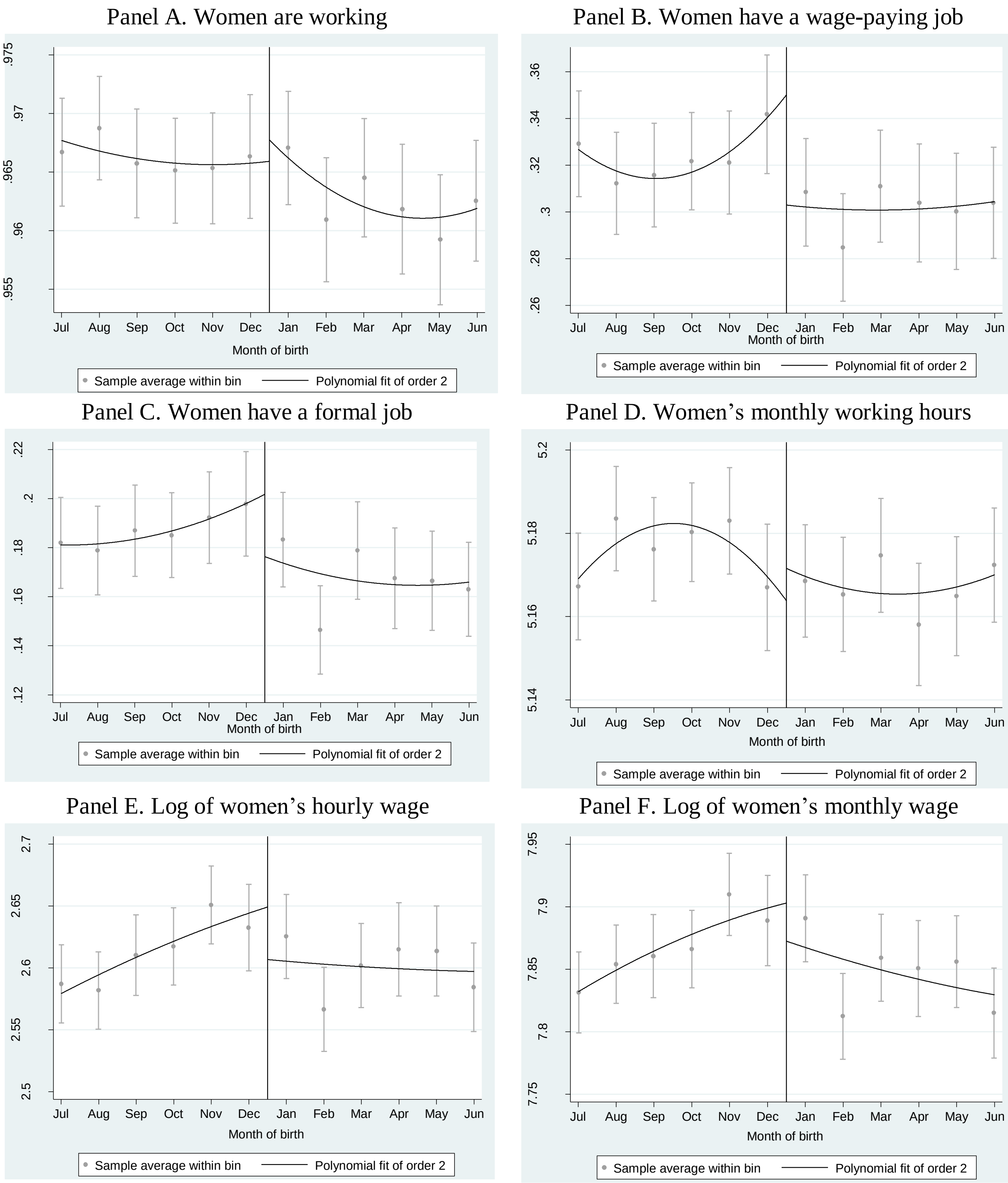
Figure 3. The proportion of enrolled school-age children and month of birth



Note: The vertical axis gives the proportion of children attending child care, and the horizontal axis presents the birth months of children with contiguous birth months. Children born in December are 1 month older than those born in January.

Sources: Authors' estimation from VHLSSs 2010, 2012, 2014 and 2016.

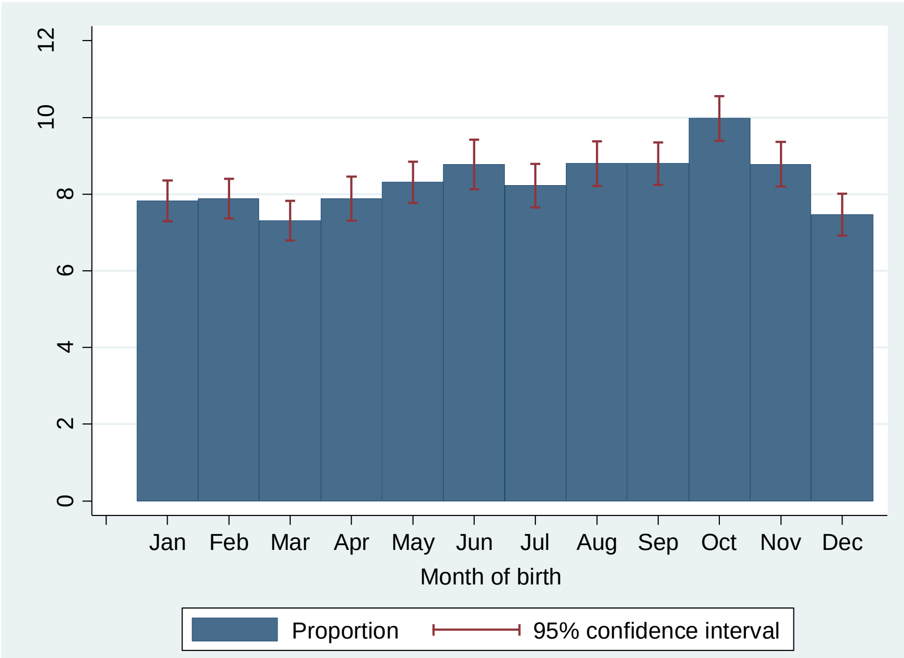
Figure 4. Women's employment and children's month of birth



Note: The vertical axis indicates women's wages and type of employment, and the horizontal axis gives the birth month of children with contiguous birth months. Children born in December are 1 month older than those born in January.

Sources: Authors' estimation from VHLSS 2010, 2012, 2014 and 2016.

Figure 5. Distribution of children by month of birth

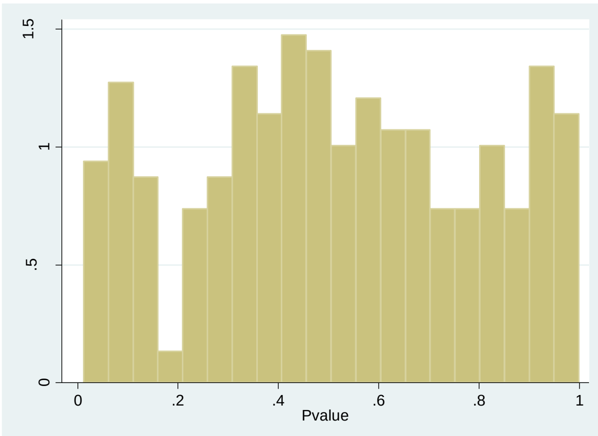


Note: The figure presents the proportion and the 95% confidence interval of the proportion of children age 1-6 by month of birth.

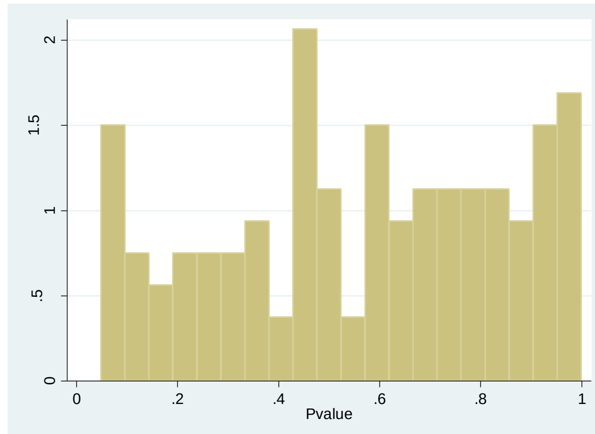
Sources: Authors' estimation from VHLSS 2010, 2012, 2014 and 2016.

Figure 6. P-value in the placebo analysis

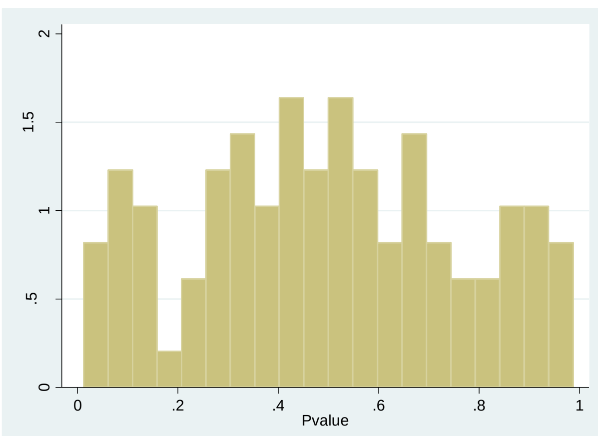
Panel A. 1-3 months difference: 3.3% with P-value<=0.05



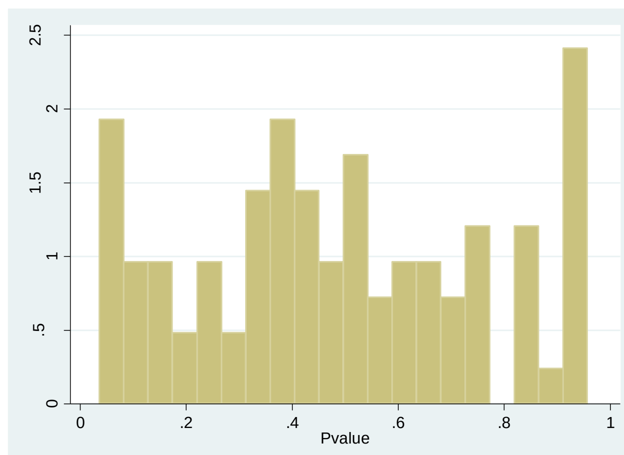
Panel B. 1-month difference: 1.8% with P-value<=0.05



Panel C. 2-month difference: 3.0% with P-value<=0.05



Panel D. 3-month difference: 5.5% with P-value<=0.05



Note: This figure shows the distribution of the p-value of the variable “born earlier” in the reduce-form regressions of maternal employment on “born earlier” (1, 2, or 3 months earlier).
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table 1. Employment of women

Variables	VHLSS 2010	VHLSS 2012	VHLSS 2014	VHLSS 2016
% working	91.8	93.2	92.5	93.5
	(0.4)	(0.5)	(0.5)	(0.5)
% in a wage-earning job	30.9	33.4	35.5	37.6
	(0.7)	(1.0)	(1.0)	(1.1)
% self-employed in a nonfarm job	16.5	14.6	13.7	18.0
	(0.6)	(0.7)	(0.7)	(0.8)
% self-employed in a farm job	44.4	45.1	43.4	37.9
	(0.8)	(1.0)	(1.0)	(1.1)
% in a skilled job	45.0	47.2	49.3	53.5
	(0.8)	(1.0)	(1.0)	(1.1)
% in a formal job	15.1	18.6	21.5	23.7
	(0.7)	(0.8)	(1.0)	(0.9)
Number of working hours per month	180.0	187.2	188.7	188.0
	(1.3)	(1.5)	(1.6)	(1.6)
Hourly wage (thousand VND)	18.1	19.5	20.4	24.2
	(0.8)	(0.7)	(0.5)	(0.0)
Monthly wage (thousand VND)	3252.4	3554.0	3845.2	4404.3
	(89.1)	(99.1)	(79.9)	(0.0)
Yearly wage (thousand VND)	39013.0	41878.6	46334.3	52749.0
	(1434.5)	(1331.3)	(1131.8)	(0.0)

Note: This table reports the employment variables of women with children age 1 to 5. Variables of wage-paying jobs, skilled jobs, and formal jobs are defined using the main occupation over the past 12 months. Employment consists of wage-paying employment, self-employed non-farm work, and self-employed farm work.
Wages are defined as the total wages, including main and secondary jobs.
Standard errors of the mean are in parentheses.
Wages are measured in 2016 prices.
Source: Estimation from VHLSS 2012, 2014, and 2016.

Table 2. First-stage probit regression of child care attendance on the instrumental variable (marginal effects)

Explanatory variables	Dependent variable is child care attendance		
	Pooled sample	Children age 1-3	Children age 3-5
Instrument (child born in December)	0.092***	0.080***	0.097***
	(0.017)	(0.018)	(0.024)
Age	0.046***	0.033**	0.048***
	(0.013)	(0.014)	(0.017)
Age squared	-0.639***	-0.548**	-0.697***
	(0.189)	(0.213)	(0.249)
Ethnic minority	0.021	-0.029	0.049
	(0.022)	(0.021)	(0.032)
Number of years of schooling	0.016***	0.012***	0.022***
	(0.002)	(0.002)	(0.003)
Dummy year 2010	*Reference*		
Dummy year 2012	0.025	-0.033	0.013
	(0.021)	(0.021)	(0.032)
Dummy year 2014	0.039*	0.015	0.089***
	(0.022)	(0.024)	(0.033)
Dummy year 2016	0.078***	0.025	0.088***
	(0.023)	(0.024)	(0.032)
Observations	3,863	1,718	2,145
Pseudo R2	0.029	0.072	0.038

This table reports the marginal effects from the logit regression of child care attendance on the instrumental variable and control variables of women. The observations in these regressions are women of children age 1-6. Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level.

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

Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table 3. The effect of child care attendance on women's employment

Dependent variables	Panel A. Short-term effects			Panel B. Medium-term effects		
	All children	Children age 1-3	Children age 3-5	All children	Children age 1-3	Children age 3-5
Bivariate probit model (marginal effects)						
Working	-0.110	-0.170	-0.128	-0.016	0.037	0.146
	(0.126)	(0.144)	(0.090)	(0.110)	(0.060)	(0.124)
In wage-paying job	0.411***	0.490***	0.408***	0.377***	0.477***	0.333***
	(0.010)	(0.033)	(0.021)	(0.024)	(0.038)	(0.087)
In self-employed	-0.103	-0.240**	0.070	0.043	-0.004	0.089
nonfarm work	(0.105)	(0.092)	(0.149)	(0.108)	(0.150)	(0.145)
In self-employed farm	-0.454***	-0.563***	-0.440***	-0.419***	-0.384***	-0.297***
work	(0.011)	(0.053)	(0.008)	(0.032)	(0.078)	(0.103)
In skilled work	0.108	-0.146	0.043	-0.055	0.187	-0.239
	(0.835)	(1.260)	(0.238)	(0.384)	(0.143)	(0.157)
In a formal job	0.257***	0.172	0.264***	0.149	0.382	0.017
	(0.035)	(0.229)	(0.077)	(0.206)	(0.349)	(0.296)
2SLS						
Log of monthly working	0.155	0.378	-0.009	0.293	0.489	0.206
hours	(0.209)	(0.358)	(0.255)	(0.312)	(0.470)	(0.463)
Log of hourly wage	0.572	0.948	0.141	-0.275	-0.104	-0.421
	(0.460)	(0.649)	(0.568)	(0.478)	(0.511)	(0.842)
Log of wage for the last	0.525	0.951	0.113	-0.078	0.071	-0.286
month	(0.410)	(0.586)	(0.521)	(0.523)	(0.580)	(0.895)
Log of total wage for the	0.903*	1.165	0.645	-0.068	0.397	-0.527
past 12 months	(0.524)	(0.743)	(0.666)	(0.678)	(0.733)	(1.183)

This table reports the marginal effects from the bivariate probit regression and 2SLS of dummy employment variables on child care attendance and the control variables of women. For the dependent variables of wages and working hours, the regressions are 2SLS.
The observations in these regressions are women of children age 1-5.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table 4. Reduced-form regression of maternal employment on the instrument

Dependent variables	1-month bandwidth	2-month bandwidth	3-month bandwidth
Probit model (marginal effects)			
Working	-0.016	0.037	0.146
	(0.110)	(0.060)	(0.124)
In a wage-earning job	0.377***	0.477***	0.333***
	(0.024)	(0.038)	(0.087)
In self-employed nonfarm work	0.043	-0.004	0.089
	(0.108)	(0.150)	(0.145)
In self-employed farm work	-0.419***	-0.384***	-0.297***
	(0.032)	(0.078)	(0.103)
In skilled work	-0.055	0.187	-0.239
	(0.384)	(0.143)	(0.157)
In a formal job	0.149	0.382	0.017
	(0.206)	(0.349)	(0.296)
2SLS			
Log of monthly working hours	0.293	0.489	0.206
	(0.312)	(0.470)	(0.463)
Log of hourly wage	-0.275	-0.104	-0.421
	(0.478)	(0.511)	(0.842)
Log of wage for the last month	-0.078	0.071	-0.286
	(0.523)	(0.580)	(0.895)
Log of total wage for the past 12 months	-0.068	0.397	-0.527
	(0.678)	(0.733)	(1.183)

Note: This table reports the coefficient of the instrument variable in regressions of maternal employment on the instrument variable. The 1-month bandwidth sample includes women with children born in December and in January of the following year, and the instrument is a dummy indicating a child born in December.

The 2-month bandwidth sample includes women with children born in November-December and in January-February of the following year, and the instrument is a dummy indicating a child born in November-December.

The 3-month bandwidth sample includes women with children born in October-December and in January-March of the following year, and the instrument is a dummy indicating a child born in October -December.

Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level.

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

Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table 5. 2SLS regression of household-level outcomes on child care attendance

Explanatory variables	Log of income per capita	Household is poor	Living with grandparents	Women are migrating	Household size
Child care attendance	0.428*	-0.222*	0.009	0.029	0.047
	(0.237)	(0.124)	(0.053)	(0.050)	(0.363)
Ethnic minority	-0.970***	0.547***	0.021***	-0.017***	0.527***
	(0.030)	(0.018)	(0.008)	(0.005)	(0.058)
Dummy year 2010	*Reference*				
Dummy year 2012	0.328***	-0.011	0.039***	-0.008	0.112**
	(0.034)	(0.019)	(0.006)	(0.006)	(0.050)
Dummy year 2014	0.530***	-0.070***	0.034***	-0.007	0.094*
	(0.039)	(0.021)	(0.007)	(0.007)	(0.057)
Dummy year 2016	0.678***	-0.106***	0.041***	0.005	0.127**
	(0.041)	(0.021)	(0.009)	(0.009)	(0.061)
Constant	9.316***	0.323***	-0.008	0.014	4.193***
	(0.101)	(0.053)	(0.022)	(0.021)	(0.153)
Observations	3,863	3,863	3,863	3,863	3,863

Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table 6. Regression of the probability of having a wage job with interactions between child schooling and demographic variables of children and women (probit models)

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Child care attendance	0.786***	0.564***	0.693***	0.595***	0.713***	0.786***
	(0.112)	(0.168)	(0.127)	(0.112)	(0.122)	(0.112)
Child care attendance * age	-0.004					
	(0.003)					
Child care attendance * schooling years		0.012**				
		(0.005)				
Child care attendance * ethnic minority			-0.076*			
			(0.045)			
Child care attendance * mother				0.078***		
				(0.027)		
Child care attendance * boy					-0.061*	
					(0.033)	
Child care attendance * birth order						-0.006
						(0.021)
Age	-0.010	-0.008	-0.009	-0.007	-0.010	0.001
	(0.015)	(0.015)	(0.015)	(0.010)	(0.015)	(0.015)
Age squared	0.130	0.074	0.086	0.010	0.102	-0.014
	(0.224)	(0.227)	(0.228)	(0.134)	(0.227)	(0.226)
Ethnic minority	-0.133***	-0.133***	-0.110***	-0.186***	-0.134***	-0.126***
	(0.022)	(0.022)	(0.027)	(0.016)	(0.022)	(0.022)
Number of years of schooling	0.021***	0.018***	0.021***	0.017***	0.021***	0.019***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Dummy year 2010	*Reference*					
Dummy year 2012	0.042*	0.047*	0.043*	0.115***	0.044*	0.048**
	(0.024)	(0.024)	(0.024)	(0.018)	(0.024)	(0.024)
Dummy year 2014	0.034	0.038	0.035	0.124***	0.036	0.040
	(0.026)	(0.026)	(0.026)	(0.020)	(0.026)	(0.026)
Dummy year 2016	0.036	0.043	0.038	0.125***	0.039	0.043
	(0.029)	(0.029)	(0.029)	(0.022)	(0.029)	(0.029)
Generalized residuals	-0.422***	-0.381***	-0.411***	-0.648***	-0.415***	-0.403***
	(0.111)	(0.113)	(0.112)	(0.148)	(0.111)	(0.111)
Women (mother=1, father=0)				-0.190***		
				(0.016)		
Boy					0.024	
					(0.022)	
Birth order of children						-0.042***
						(0.014)
Observations	3,863	3,863	3,863	7,603	3,863	3,863
R-squared	0.103	0.104	0.103	0.104	0.103	0.106

Note: This table reports the coefficients of child care attendance and interactions between child care attendance and other explanatory variables in probit regressions of the probability of women working in wage-paying jobs. We first model the child care attendance on the instrument and other explanatory variables using probit, and estimate the generalized residuals (Wooldridge, 2015). Then we estimate a probit model of maternal employment using the child care variable, the generalized residuals, interactions, and other explanatory variables. Standard errors are estimated using bootstrap with 200 replications. Standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

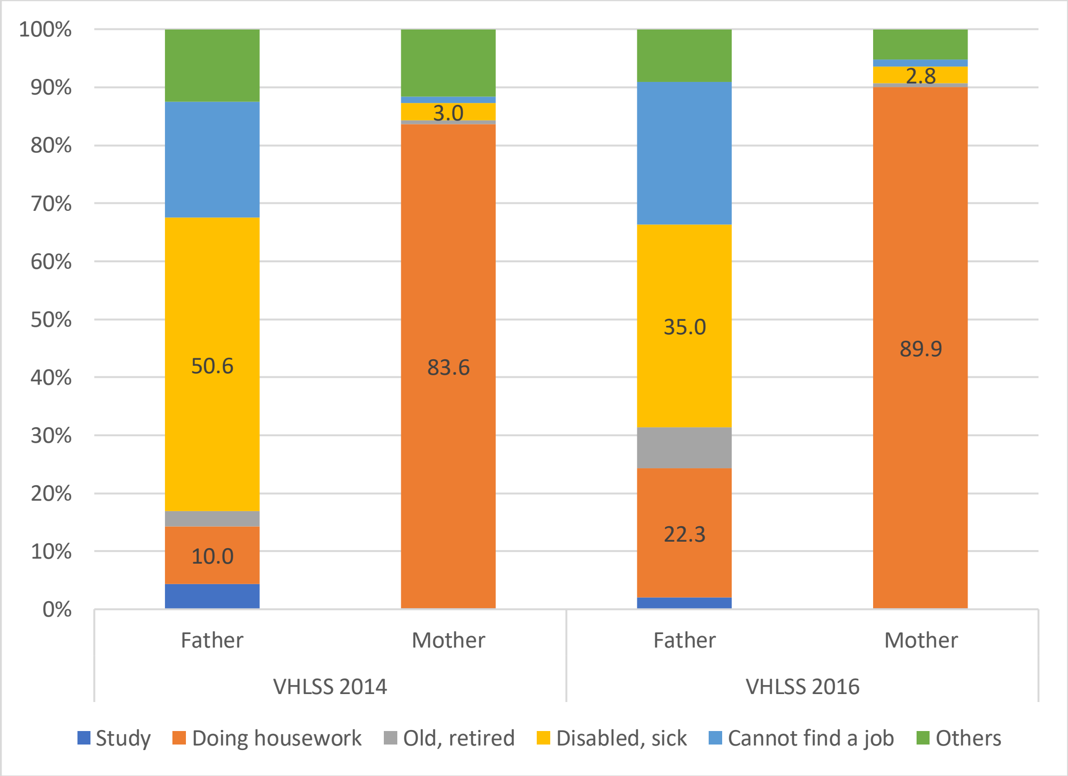
Table 7. Regression of the probability of having a wage job with interactions between child care attendance and commune variables

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Child care attendance	2.047***	0.451**	0.423**	0.459**	-0.150	0.178
	(0.693)	(0.204)	(0.206)	(0.202)	(0.397)	(0.432)
Child care attendance * private center	0.491***					
	(0.129)					
Child care attendance * distance to nearest town		-0.005***				
		(0.002)				
Child care attendance * village accessible by car			-0.061			
			(0.043)			
Child care attendance * kindergarten in village				-0.052		
				(0.035)		
Child care attendance * log of district mean wage					0.106**	
					(0.048)	
Child care attendance * log of district per capita income						0.043
						(0.036)
Age	-0.034	-0.004	-0.005	-0.007	-0.010	-0.013
	(0.054)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Age squared	0.356	0.024	0.038	0.071	0.104	0.141
	(0.802)	(0.227)	(0.226)	(0.226)	(0.230)	(0.230)
Ethnic minority	-0.393***	-0.084***	-0.108***	-0.113***	-0.124***	-0.031
	(0.090)	(0.024)	(0.022)	(0.022)	(0.022)	(0.028)
Number of years of schooling	0.059***	0.014***	0.014***	0.015***	0.021***	0.018***
	(0.013)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dummy year 2010	*Reference*					
Dummy year 2012	0.128	0.029	0.030	0.031	0.027	-0.012
	(0.083)	(0.025)	(0.026)	(0.026)	(0.027)	(0.025)
Dummy year 2014	0.105	0.038	0.107**	0.044	0.006	-0.056**
	(0.092)	(0.028)	(0.051)	(0.028)	(0.031)	(0.027)
Dummy year 2016	0.112	0.044	0.100*	0.041	0.002	-0.078***
	(0.089)	(0.031)	(0.052)	(0.031)	(0.036)	(0.030)
Generalized residuals	0.059***	-0.183	-0.186	-0.206*	-0.399***	-0.342***
	(0.428)	(0.118)	(0.118)	(0.118)	(0.113)	(0.112)
Distance to the nearest town (km)		-0.001				
		(0.001)				
Village accessible by car			0.087**			
			(0.043)			
Kindergarten in village				0.073***		
				(0.022)		
Log of district mean wage					0.019	
					(0.035)	
Log of district per capita income						0.177***
						(0.027)
Observations	3,863	2,853	2,853	2,853	3,821	3,863
R-squared	0.105	0.071	0.065	0.067	0.101	0.123

Note: This table reports the coefficients of child care attendance and interactions between child care attendance and other explanatory variables in probit regressions of the probability of women working in a wage-earning job. We first model child care attendance on the instrument and other explanatory variables using probit, and estimate the generalized residuals (Wooldridge, 2015). Then we estimate a probit model of maternal employment using the child care variable, the generalized residuals, interactions, and other explanatory variables. Standard errors are estimated using bootstrap with 200 replications. Standard errors are corrected for sampling weights and cluster correlation at the commune level.
Village variables (kindergarten, distance to the nearest town, accessible by car) are available only for the rural sample. Thus, the number of observations in regressions using the interaction between child care attendance and these village variables is lower than other regressions.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Appendix

Figure A.1. The main reasons for not working



Source: Estimation from VHLSSs 2014 and 2016

Table A.1. Employment of men

Variables	VHLSS 2010	VHLSS 2012	VHLSS 2014	VHLSS 2016
% working	98.9	99.1	99.2	98.9
	(0.2)	(0.2)	(0.2)	(0.3)
% in a wage-earning job	43.3	48.8	50.8	52.2
	(0.8)	(1.0)	(1.1)	(1.1)
% self-employed in a nonfarm job	13.7	14.3	13.1	16.0
	(0.5)	(0.7)	(0.7)	(0.8)
% self-employed in a farm job	41.9	36.0	35.3	30.6
	(0.8)	(1.0)	(1.0)	(1.0)
% in a skilled job	58.8	59.8	61.2	61.9
	(0.8)	(1.0)	(1.0)	(1.1)
% in a formal job	15.8	18.0	18.3	20.5
	(0.6)	(0.8)	(1.1)	(0.9)
Number of working hours per month	199.8	209.0	207.2	206.9
	(1.2)	(1.5)	(1.5)	(1.6)
Hourly wage (thousand VND)	17.5	21.8	23.6	27.0
	(0.6)	(0.7)	(0.6)	(1.3)
Monthly wage (thousand VND)	3500.4	4374.1	4684.8	5360.3
	(97.7)	(102.9)	(97.5)	(128.9)
Yearly wage (thousand VND)	42233.3	50885.2	53548.0	62592.6
	(1468.9)	(1506.1)	(1321.4)	(1690.6)

Note: This table reports the employment variables of men with children age 1 to 5. Variables of wage-paying jobs, skilled jobs, and formal jobs are defined using the main occupation over the past 12 months. Employment consists of wage-paying employment, self-employed non-farm work, and self-employed farm work.
Wages are defined as the total wages including main- and secondary jobs.
Standard errors of the mean are in parentheses.
Wages are measured in 2016 prices.
Source: Estimation from VHLSSs 2012, 2014, and 2016

Table A.2. Employment of women by residence area

Variables	Rural			Urban		
	VHLSS 2012	VHLSS 2014	VHLSS 2016	VHLSS 2012	VHLSS 2014	VHLSS 2016
% working	95.9	94.6	95.2	87.8	90.0	86.9
	(0.4)	(0.5)	(0.6)	(0.0)	(0.0)	(0.0)
% in a wage-earning job	27.1	30.9	31.3	50.0	50.0	54.0
	(1.0)	(1.1)	(1.2)	(0.0)	(0.0)	(0.0)
% self-employed in a nonfarm job	12.2	10.9	16.1	23.7	23.5	22.2
	(0.7)	(0.7)	(1.0)	(0.0)	(0.0)	(0.0)
% self-employed in a farm job	56.5	52.8	47.8	14.1	16.6	10.7
	(1.1)	(1.2)	(1.3)	(0.0)	(0.0)	(0.0)
% in a skilled job	40.7	42.0	45.2	72.1	71.6	70.9
	(1.1)	(1.2)	(1.3)	(0.0)	(0.0)	(0.0)
% in a formal job	12.4	14.9	17.4	36.4	37.0	40.8
	(0.7)	(0.9)	(1.0)	(0.0)	(0.0)	(0.0)
Number of working hours per month	181.1	185.4	184.4	202.3	204.5	203.5
	(1.8)	(1.8)	(1.9)	(0.0)	(0.0)	(0.0)
Hourly wage (thousand VND)	15.1	16.9	18.8	26.6	27.1	31.1
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Monthly wage (thousand VND)	2850.0	3216.9	3607.1	5004.2	5044.3	5561.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Yearly wage (thousand VND)	30899.6	36132.2	40304.2	66569.1	67196.2	73370.4
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)

Note: This table reports the employment variables of women with children age 1 to 5. Variables of wage-paying jobs, skilled jobs, and formal jobs are defined using the main occupation over the past 12 months. Employment consists of wage-paying employment, self-employed non-farm work, and self-employed farm work.
Wages are defined as the total wages, including main and secondary jobs.
Standard errors of the mean are in parentheses.
Wages are measured in 2016 prices.
Source: Estimation from VHLSS 2012, 2014, and 2016.

Table A.3. OLS regression of the instrument on demographic variables of women

Explanatory variables	Dependent variables		
	Children born in December (one-month bandwidth)	Children born in November and December (two-months bandwidth)	Children born in October to December (two-months bandwidth)
Age	0.000	-0.010	-0.009
	(0.012)	(0.008)	(0.006)
Age squared	-0.012	0.122	0.121
	(0.178)	(0.122)	(0.091)
Ethnic minority	-0.037	-0.033**	-0.023*
	(0.024)	(0.016)	(0.012)
Number of years of schooling	0.003	0.005***	0.003**
	(0.002)	(0.002)	(0.001)
Dummy year 2010	*Reference*		
Dummy year 2012	-0.036	-0.015	-0.000
	(0.024)	(0.016)	(0.013)
Dummy year 2014	-0.065***	-0.018	0.000
	(0.025)	(0.017)	(0.013)
Dummy year 2016	-0.020	0.015	0.016
	(0.025)	(0.017)	(0.013)
Constant	0.488**	0.650***	0.663***
	(0.197)	(0.134)	(0.102)
Observations	3,863	8,159	12,730
R-squared	0.004	0.004	0.002

Heteroskedasticity-robust standard errors in parentheses. The standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.

Table A.4. First-stage of school attendance on the instrument

Explanatory variables	Probit model			OLS		
	Pooled sample	Children age 1- 3	Children age 3-5	Pooled sample	Children age 1- 3	Children age 3- 5
Instrument (child born in December)	0.090***	0.081***	0.094***	0.248***	0.390***	0.246***
	(0.017)	(0.018)	(0.023)	(0.046)	(0.085)	(0.061)
Age	0.041***	0.026***	0.044***	0.122***	0.164**	0.120***
	(0.011)	(0.010)	(0.015)	(0.034)	(0.069)	(0.043)
Age squared	-0.569***	-0.435***	-0.637***	-1.715***	-2.725**	-1.757***
	(0.158)	(0.146)	(0.218)	(0.507)	(1.072)	(0.628)
Ethnic minority	0.021	-0.015	0.046	0.056	-0.150	0.125
	(0.021)	(0.020)	(0.031)	(0.060)	(0.118)	(0.081)
Number of years of schooling	0.015***	0.013***	0.021***	0.042***	0.061***	0.054***
	(0.002)	(0.002)	(0.003)	(0.006)	(0.011)	(0.008)
Dummy year 2010	*Reference*					
Dummy year 2012	0.023	-0.029	0.013	0.067	-0.173	0.033
	(0.020)	(0.022)	(0.031)	(0.056)	(0.116)	(0.080)
Dummy year 2014	0.037*	0.014	0.086***	0.104*	0.074	0.226***
	(0.021)	(0.025)	(0.032)	(0.059)	(0.113)	(0.084)
Dummy year 2016	0.074***	0.028	0.086***	0.206***	0.121	0.225***
	(0.022)	(0.025)	(0.032)	(0.059)	(0.112)	(0.084)
Constant	-0.548***	-0.395**	-0.451*	-3.034***	-4.228***	-2.578***
	(0.173)	(0.168)	(0.251)	(0.554)	(1.119)	(0.711)
Weak identification test						
Cragg-Donald Wald F statistic				34.9	35.6	24.5
Kleibergen-Paap rk Wald F statistic				28.3	29.4	20.0
Observations	3,863	1,718	2,145	3,863	1,718	2,145
Pseudo R-squared	0.036	0.055	0.051	0.029	0.072	0.038

Dependent variable is the school enrolment.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald F statistic are test statistics of weak instruments. As a rule of thumb, if a F- statistic is under 10, the instruments might be weak (Staiger and Stock 1997).
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.

Table A.5. Probit and OLS regressions of maternal employment on child care attendance (all sample)

Explanatory variables	Probit (marginal effects)						OLS			
	Working	Have a wage job	Have a self-employed nonfarm work	Have a self-employed farm work	Have a skilled work	Have a formal job	Log of total monthly working hours	Log of hourly wage	Log of wage during the last month	Log of total wage in the past 12 months
Child care attendance	0.028***	0.056***	0.025*	-0.064***	0.088***	0.031**	0.054***	0.060	0.061	0.144***
	(0.010)	(0.019)	(0.013)	(0.019)	(0.021)	(0.012)	(0.021)	(0.041)	(0.038)	(0.046)
Age	0.001	0.025*	0.024**	-0.038***	0.077***	0.040***	0.073***	0.048	0.079**	0.118***
	(0.008)	(0.013)	(0.009)	(0.014)	(0.016)	(0.011)	(0.016)	(0.037)	(0.033)	(0.039)
Age squared	-0.001	-0.390*	-0.285**	0.515**	-1.081***	-0.640***	-1.051***	-0.544	-1.071**	-1.566***
	(0.112)	(0.201)	(0.138)	(0.208)	(0.242)	(0.166)	(0.236)	(0.558)	(0.499)	(0.587)
Ethnic minority	0.074***	-0.016	-0.145***	0.334***	-0.311***	-0.061***	-0.017	-0.270***	-0.436***	-0.578***
	(0.009)	(0.025)	(0.011)	(0.023)	(0.023)	(0.015)	(0.028)	(0.066)	(0.065)	(0.078)
Number of years of schooling	0.002	0.028***	-0.001	-0.033***	0.051***	0.037***	0.009***	0.068***	0.072***	0.102***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)
Dummy year 2010	*Reference*									
Dummy year 2012	0.067***	0.065***	-0.004	0.046*	0.054**	0.051**	0.037	0.182***	0.332***	0.333***
	(0.009)	(0.025)	(0.016)	(0.027)	(0.027)	(0.020)	(0.029)	(0.069)	(0.060)	(0.077)
Dummy year 2014	0.045***	0.059**	-0.034**	0.055**	0.020	0.048**	0.031	0.340***	0.500***	0.530***
	(0.010)	(0.026)	(0.016)	(0.027)	(0.028)	(0.020)	(0.029)	(0.068)	(0.060)	(0.074)
Dummy year 2016	0.041***	0.088***	-0.005	-0.020	0.042	0.073***	0.022	0.457***	0.592***	0.641***
	(0.011)	(0.026)	(0.017)	(0.027)	(0.028)	(0.021)	(0.027)	(0.069)	(0.060)	(0.074)
Constant							3.739***	0.761	5.406***	6.720***
							(0.272)	(0.612)	(0.530)	(0.631)
Observations	3,863	3,863	3,863	3,863	3,863	3,863	3,638	1,345	1,379	1,381
R-squared	0.0546	0.0592	0.0556	0.151	0.207	0.260	0.022	0.275	0.373	0.406

Heteroskedasticity-robust standard errors in parentheses. The standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.

Table A.6. Bivariate probit and 2SLS regression of maternal employment on childcare attendance (all sample)

Explanatory variables	Bivariate probit						2SLS			
	Working	Have a wage job	Have a self-employed nonfarm work	Have a self-employed farm work	Have a skilled work	Have a formal job	Log of total monthly working hours	Log of hourly wage	Log of wage during the last month	Log of total wage in the past 12 months
Child care attendance	-0.637	1.472***	-0.439	-1.540***	0.350	1.212***	0.155	0.572	0.525	0.903*
	(0.610)	(0.054)	(0.426)	(0.052)	(2.743)	(0.156)	(0.209)	(0.460)	(0.410)	(0.524)
Age	0.035	-0.010	0.130***	-0.011	0.189	0.134***	0.069***	0.013	0.047	0.064
	(0.052)	(0.033)	(0.044)	(0.031)	(0.137)	(0.051)	(0.018)	(0.051)	(0.047)	(0.057)
Age squared	-0.393	0.050	-1.593**	0.131	-2.638	-2.216***	-0.995***	-0.011	-0.574	-0.753
	(0.770)	(0.506)	(0.645)	(0.461)	(1.929)	(0.771)	(0.262)	(0.780)	(0.709)	(0.866)
Ethnic minority	0.689***	-0.323***	-0.848***	0.645***	-0.849***	-0.333***	-0.018	-0.250***	-0.422***	-0.556***
	(0.115)	(0.065)	(0.112)	(0.063)	(0.075)	(0.094)	(0.028)	(0.072)	(0.068)	(0.085)
Number of years of schooling	0.024**	0.049***	0.006	-0.034***	0.127**	0.151***	0.008*	0.061***	0.065***	0.090***
	(0.011)	(0.007)	(0.010)	(0.007)	(0.054)	(0.014)	(0.004)	(0.008)	(0.008)	(0.010)
Dummy year 2010	*Reference*									
Dummy year 2012	0.561***	0.102*	-0.005	0.114**	0.134	0.198**	0.036	0.194***	0.332***	0.334***
	(0.094)	(0.061)	(0.074)	(0.055)	(0.096)	(0.084)	(0.029)	(0.073)	(0.063)	(0.082)
Dummy year 2014	0.373***	0.085	-0.136*	0.145**	0.045	0.177**	0.028	0.308***	0.461***	0.465***
	(0.093)	(0.062)	(0.080)	(0.058)	(0.119)	(0.085)	(0.030)	(0.075)	(0.071)	(0.090)
Dummy year 2016	0.367***	0.096	0.022	0.077	0.095	0.224**	0.015	0.404***	0.534***	0.546***
	(0.092)	(0.062)	(0.080)	(0.057)	(0.221)	(0.087)	(0.031)	(0.084)	(0.079)	(0.102)
Constant	0.206	-1.075**	-3.213***	0.703	-4.426**	-4.785***	3.784***	1.175	5.822***	7.403***
	(0.850)	(0.548)	(0.697)	(0.512)	(1.907)	(0.864)	(0.288)	(0.765)	(0.696)	(0.855)
Observations	3,863	3,863	3,863	3,863	3,863	3,863	3,638	1,345	1,379	1,381

The sample used for this regression consists of women with children being born in December and January of two consecutive years. Children born in December is one month older than those born in January of the following year. The instrument for the childcare attendance is children being born in December.
Heteroskedasticity-robust standard errors in parentheses. The standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.

Table A.7. Bivariate probit and 2SLS regression of maternal employment on childcare attendance (sample of children age 1 to 3)

Explanatory variables	Bivariate probit							2SLS		
	Working	Have a wage job	Have a self-employed nonfarm work	Have a self-employed farm work	Have a skilled work	Have a formal job	Log of total monthly working hours	Log of hourly wage	Log of wage during the last month	Log of total wage in the past 12 months
Child care attendance	-0.910	1.706***	-0.990***	-1.723***	-0.459	0.831	0.378	0.948	0.951	1.165
	(0.711)	(0.134)	(0.321)	(0.162)	(3.953)	(1.140)	(0.358)	(0.649)	(0.586)	(0.743)
Age	-0.118	-0.021	0.045	-0.016	0.154**	0.168*	0.068***	0.002	0.070	0.077
	(0.075)	(0.053)	(0.061)	(0.051)	(0.066)	(0.088)	(0.026)	(0.070)	(0.062)	(0.072)
Age squared	1.942*	0.301	-0.454	0.101	-2.180*	-2.567*	-0.975**	0.273	-0.828	-0.900
	(1.172)	(0.806)	(0.939)	(0.774)	(1.160)	(1.349)	(0.405)	(1.111)	(0.973)	(1.141)
Ethnic minority	0.567***	-0.290***	-0.868***	0.724***	-0.764***	-0.362**	0.004	-0.164	-0.397***	-0.519***
	(0.153)	(0.104)	(0.156)	(0.094)	(0.238)	(0.165)	(0.045)	(0.125)	(0.111)	(0.139)
Number of years of schooling	0.026*	0.065***	0.007	-0.046***	0.135***	0.180***	0.006	0.052***	0.053***	0.083***
	(0.013)	(0.011)	(0.014)	(0.010)	(0.012)	(0.036)	(0.006)	(0.012)	(0.011)	(0.014)
Dummy year 2010	*Reference*									
Dummy year 2012	0.462***	0.165*	-0.107	0.094	0.150	0.252*	0.062	0.165	0.313***	0.293**
	(0.131)	(0.096)	(0.109)	(0.092)	(0.220)	(0.132)	(0.043)	(0.133)	(0.106)	(0.132)
Dummy year 2014	0.294**	0.172*	-0.062	0.040	0.001	0.280**	0.012	0.261**	0.448***	0.505***
	(0.132)	(0.098)	(0.101)	(0.094)	(0.115)	(0.125)	(0.044)	(0.109)	(0.088)	(0.107)
Dummy year 2016	0.264**	0.219**	-0.079	-0.002	0.088	0.382***	0.016	0.357***	0.528***	0.544***
	(0.123)	(0.101)	(0.108)	(0.098)	(0.135)	(0.145)	(0.046)	(0.107)	(0.091)	(0.116)
Constant	2.553**	-0.958	-1.666*	0.675	-3.773***	-5.612***	3.827***	1.430	5.524***	7.361***
	(1.193)	(0.863)	(0.980)	(0.827)	(0.942)	(1.521)	(0.419)	(1.084)	(0.953)	(1.109)
Observations	1,718	1,718	1,718	1,718	1,718	1,718	1,589	593	610	611

The sample used for this regression consists of women with children being born in December and January of two consecutive years. Children born in December is one month older than those born in January of the following year. The instrument for the childcare attendance is children being born in December.
Heteroskedasticity-robust standard errors in parentheses. The standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.

Table A.8. Bivariate probit and 2SLS regression of maternal employment on childcare attendance (sample of children age 3 to 5)

Explanatory variables	Bivariate probit						2SLS			
	Working	Have a wage job	Have a self-employed nonfarm work	Have a self-employed farm work	Have a skilled work	Have a formal job	Log of total monthly working hours	Log of hourly wage	Log of wage during the last month	Log of total wage in the past 12 months
Child care attendance	-0.784**	1.382***	0.299	-1.567***	0.139	1.191***	-0.009	0.141	0.113	0.645
	(0.398)	(0.093)	(0.631)	(0.049)	(0.776)	(0.284)	(0.255)	(0.568)	(0.521)	(0.666)
Age	0.132**	0.011	0.172**	-0.020	0.248***	0.127*	0.080***	0.050	0.050	0.089
	(0.066)	(0.044)	(0.071)	(0.042)	(0.069)	(0.075)	(0.025)	(0.060)	(0.058)	(0.073)
Age squared	-1.847*	-0.194	-2.188**	0.193	-3.499***	-2.134*	-1.125***	-0.565	-0.644	-1.057
	(0.947)	(0.663)	(1.029)	(0.620)	(1.022)	(1.126)	(0.351)	(0.918)	(0.889)	(1.114)
Ethnic minority	0.839***	-0.358***	-0.875***	0.650***	-0.898***	-0.321***	-0.023	-0.309***	-0.421***	-0.593***
	(0.157)	(0.082)	(0.129)	(0.078)	(0.105)	(0.116)	(0.037)	(0.084)	(0.089)	(0.105)
Number of years of schooling	0.031**	0.036***	0.002	-0.024***	0.131***	0.140***	0.010	0.068***	0.074***	0.093***
	(0.013)	(0.010)	(0.016)	(0.008)	(0.020)	(0.027)	(0.006)	(0.012)	(0.012)	(0.014)
Dummy year 2010	*Reference*									
Dummy year 2012	0.590***	0.125	0.011	0.071	0.101	0.219*	0.029	0.266***	0.407***	0.421***
	(0.124)	(0.081)	(0.103)	(0.075)	(0.087)	(0.113)	(0.038)	(0.088)	(0.080)	(0.103)
Dummy year 2014	0.522***	-0.020	-0.247**	0.299***	0.115	0.058	0.048	0.417***	0.545***	0.442**
	(0.129)	(0.083)	(0.122)	(0.076)	(0.116)	(0.125)	(0.043)	(0.140)	(0.137)	(0.180)
Dummy year 2016	0.453***	0.054	0.037	0.096	0.135	0.163	0.023	0.532***	0.634***	0.621***
	(0.142)	(0.082)	(0.118)	(0.077)	(0.113)	(0.127)	(0.039)	(0.123)	(0.122)	(0.160)
Constant	-1.219	-1.557**	-4.218***	1.148	-5.360***	-4.717***	3.639***	0.606	5.776***	6.868***
	(1.139)	(0.748)	(1.121)	(0.711)	(1.021)	(1.307)	(0.390)	(0.881)	(0.837)	(1.067)
Observations	2,145	2,145	2,145	2,145	2,145	2,145	2,049	752	769	770

The sample used for this regression consists of women with children being born in December and January of two consecutive years. Children born in December is one month older than those born in January of the following year. The instrument for the childcare attendance is children being born in December.
Heteroskedasticity-robust standard errors in parentheses. The standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.

Table A.9. The effect of child care attendance on maternal employment using different models

Dependent variables	2SLS	Control function with the first step a linear probability model (marginal effects)	Control function with both probit (marginal effects)
Working	-0.160	-0.149	-0.213
	(0.123)	(0.166)	(0.169)
In a wage-earning job	0.526***	0.511***	0.393***
	(0.199)	(0.087)	(0.129)
In self-employed nonfarm work	-0.104	-0.124	-0.099
	(0.141)	(0.109)	(0.123)
In self-employed farm work	-0.582***	-0.495***	-0.446***
	(0.202)	(0.060)	(0.084)
In skilled work	0.029	0.079	0.002
	(0.177)	(0.154)	(0.158)
In a formal job	0.244*	0.262*	0.227
	(0.146)	(0.140)	(0.146)

Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level. For the control function estimators, standard errors are estimated by bootstrap with 200 replications.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table A.10. The effect of child care attendance on maternal employment using different models and bandwidths

Dependent variables	2-month bandwidth	3-month bandwidth
Bivariate probit model (marginal effects)		
Working	-0.031	-0.031
	(0.073)	(0.059)
In a wage-earning job	0.405***	0.398***
	(0.008)	(0.007)
In self-employed nonfarm work	-0.073	-0.061
	(0.064)	(0.050)
In self-employed farm work	-0.409***	-0.374***
	(0.019)	(0.024)
In skilled work	0.233**	0.155
	(0.130)	(0.138)
In a formal job	0.255***	0.265***
	(0.026)	(0.018)
2SLS		
Log of monthly working hours	0.242	0.207*
	(0.147)	(0.107)
Log of hourly wage	0.489*	0.490**
	(0.294)	(0.223)
Log of wage for the last month	0.603**	0.519**
	(0.298)	(0.221)
Log of total wage for the past 12 months	0.705*	0.773***
	(0.378)	(0.287)

Note: This table reports the marginal effects from the bivariate probit regression of dummy employment variables on child care attendance over the previous 2 years. For the dependent variables of wages and working hours, the regressions are 2SLS. This table reports only coefficients of child care attendance.
The observations in these regressions are women of children age 1-5.
Heteroskedasticity-robust standard errors in parentheses. Standard errors are corrected for sampling weights and cluster correlation at the commune level.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSS 2010, 2012, 2014 and 2016.

Table A.11. Regression of the probabity of having a wage job with interactions between child schooling and demographic variables

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Child care attendance	0.731***	0.707***	0.636**	0.563*	0.692***	0.717***
	(0.133)	(0.123)	(0.272)	(0.291)	(0.231)	(0.220)
Child care attendance * Age of first-born child	-0.006					
	(0.004)					
Child care attendance * Gender of first-born child		-0.033				
		(0.034)				
Child care attendance * Lagged household size			0.014			
			(0.030)			
Child care attendance * Lagged proportion of children				0.354		
				(0.232)		
Child care attendance * Lagged proportion of elderly					-0.050	
					(0.409)	
Child care attendance * Lagged grandparents in household						-0.112
						(0.083)
Age	0.025	-0.011	-0.000	0.003	-0.006	-0.007
	(0.018)	(0.015)	(0.030)	(0.032)	(0.031)	(0.031)
Age squared	-0.315	0.111	-0.013	-0.088	0.050	0.058
	(0.268)	(0.227)	(0.445)	(0.469)	(0.454)	(0.457)
Ethnic minority	-0.122***	-0.134***	-0.104**	-0.114***	-0.114***	-0.117***
	(0.025)	(0.022)	(0.043)	(0.042)	(0.042)	(0.041)
Number of schooling years	0.017***	0.021***	0.026***	0.026***	0.027***	0.026***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Dummy year 2010						
Dummy year 2012	0.018	0.043*				
	(0.026)	(0.024)				
Dummy year 2014	0.011	0.036	-0.037	-0.038	-0.039	-0.039
	(0.028)	(0.026)	(0.037)	(0.037)	(0.037)	(0.037)
Dummy year 2016	0.018	0.037	-0.045	-0.049	-0.049	-0.049
	(0.031)	(0.029)	(0.041)	(0.040)	(0.041)	(0.041)
Generalized residuals	-0.405***	-0.420***	-0.397*	-0.402**	-0.411**	-0.428**
	(0.124)	(0.111)	(0.205)	(0.204)	(0.205)	(0.206)
Age of first-born child	-0.005					
	(0.003)					
Gender of first-born child		0.019				
		(0.022)				
Lagged household size			-0.036*			
			(0.019)			
Lagged proportion of children				-0.281**		
				(0.136)		
Lagged proportion of elderly					0.128	
					(0.232)	
Lagged grandparent living in household						0.095
						(0.063)
Observations	3,109	3,863	1,107	1,107	1,107	1,107
R-squared	0.100	0.103	0.122	0.123	0.119	0.121

Note: This table reports the coefficients of childcare attendance and interactions between childcare attendance and other explanatory variables in probit regressions of the probability of having a wage job of women. We first model the child care attendance on the instrument and other explanatory variables using probit, and estimate the generalized residuals (Wooldridge, 2015). Then we estimate a probit model of maternal employment using the child care variable, the generalized residuals, interactions, and other explanatory variables.
The standard errors are estimated using bootstrap with 200 replications. The standard errors are corrected for sampling weights and cluster correlation at the commune level. *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation from VHLSSs 2010, 2012, 2014 and 2016.