Does paid maternity leave lead to higher birth rates?

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Introduction

Maternity leave is in this paper referred to as the period during which a woman leaves her job directly after childbirth in order to take care of the baby. In 2016 most countries offer maternity leave, yet they differ widely regarding the number of weeks granted (COMM/ENTR/R4, 2011; Statista, 2008). Comparing OECD countries, the USA is the only one, which is not offering maternity leave in all states (OECD, 2015), which makes it the only industrialized country without governmental maternity leave worldwide.

Maternity leave and its effects are a highly relevant topic for economists due to several reasons. First and foremost, our society and thus our economy depend on healthy offspring, especially when regarding the demographic development in industrialized areas like the European Union or the USA. Already today we face the so-called population pyramid in these regions, which implies a high number of old people and a relatively small number of youngsters. One way to oppose this trend is to induce births. A possible incentive is maternity leave. Moreover, maternity leave enables mothers to take care of their own health and the health of the baby. Studies found (Ruhm, 2000; Tanaka, 2005) that the introduction of maternity leave can add to the health of both mother and child. This leads to a healthier society and thus reduces the costs for the individual or the health system. If maternity leave is on top of that paid, it secures a certain level of income for the mothers, which might give them the possibility to get pregnant in the first place. If there is no monetary security, women most probably will not consider a pregnancy, because even though the baby's father might earn money it could still not be enough without the mother's monetary compensation.

As maternity leave is a highly relevant topic it does not lack of a large number of scientific publications. The effects of maternity leave attracted many researchers from various academic fields. They explored for instance its effects on health (Rossin, 2011; Tanaka, 2005), on child development (Brooks-Gunn et al., 2002; Gregg and Waldfogel, 2005; Ruhm, 2004) or the return to work after taking the leave (Lalive and Zweimüller, 2009). Family policy in combination with fertility however seems to be scarce and inconsistent (Kalwij, 2010). This may be due to the fact that most researchers focus on minor sub questions within their research. Lalive and Zweimüller (2009) for example focus on the relevance of the duration of job-protected paid parental leave for fertility. Thus they leave the original question. Averett and Whittington (2001) do the same thing. Even though their paper is called 'Does Maternity Leave Induce Birth' they do not address the general question in their paper, but two sub questions.

Furthermore, when referring to the USA most researchers use the Family and Medical Leave Act (FMLA), which was enacted in 1993 and demanded a minimum 12 weeks of unpaid maternity leave for around 50% of all women working in the US (Rossin, 2011). However, we do not focus on this policy as we believe that it is necessary to have monetary compensation, i.e. paid maternity leave and not just unpaid maternity leave in general to induce births. Just being able to stay at home might not motivate woman to have children, when they do not know how to provide for it afterwards. Additionally, the FMLA did not cover the majority of the working women but just a little more than half of them (Rossin, 2011). This is why we decided to focus on the Paid Family Leave (PFL), which was introduced in 2002 by the State of California. By this California became the first US State to offer a paid maternity leave program (California Work and Family Coalition, 2016). So, after cautious investigation, we came to the conclusion that up to now academic research lacks a generalist paper on the question if paid maternity leave leads to higher birth rates. As the topic is extremely relevant for the above mentioned reasons, this paper tries to fill this scientific gap.

Our research hypothesis within this paper is: the policy of paid maternity leave does lead to higher birth rates. For reviewing our hypothesis we made use of the state-specific differences in the US-American maternity leave policies. We used California, which is endowed with the PFL, which was introduced in 2002 with contributions granted from January 2004 on (State of California Employment Department, 2016) and Nevada, a Californian neighboring state without any protections beyond FMLA. We chose those two states, because of several reasons. Firstly, as they are neighbors we can assume that they are similar with regard to climate, mentality of the people, history and culture. During our research we did not find any facts, which contradict this assumption. Secondly, they possess a similar population percentage with around, a similar age structure, a similar gender structure, a similar education level and a similar median income per household (Index Mundi). These equalities with regard to the states preconditions and yet the inequality with regard to the maternity leave policy creates an ideal environment for a difference-in-difference analysis.

Data Description

For this analysis we used Integrated Public Use Microdata Series (IPUMS-CPS). It consists of harmonized data provided by the Current Population Survey (CPS) in United States of America every March from 1962 to the present. Our data (Minnesota Population Center) provides us with detailed observations on individual persons. We started with the entire data set for Nevada and California, all other states were excluded. As we are only interested in the effects of maternity leave we dropped men. Moreover, we kept only women, which are in a biological age for pregnancy, i.e. women aged 15 to 54. People, who are not citizen of the USA were excluded, too. This way we made sure that we do not include women, who are not able to get the compensation due to their citizenship. After all these data preparations we have a remaining data set of 52,058 appropriate observations.

Methodology and Model

To examine the impact of paid maternity leave on the number of children we chose the difference-in-differences methodology. We decided to explore our discovered natural experiment. To do so we created the control group out of the state, where there is no maternity leave, Nevada, and the treatment group out of the state, with maternity leave, California. The main requirement for this methodology is that these states must be as similar as possible. As stated above California and Nevada fulfill these criteria. To secure the outcome of this methodology we followed two crucial steps. Firstly, we used the neighboring state of California as control group and secondly, we compared the before-after change in the outcome for the treatment group California to the before-after change in the outcome for the control group Nevada.

Another important factor is the assumption of a common trend. To control it, we checked if common trends were present for the two states before the policy was introduced. We came to the conclusion that they should have had an equal trend and have faced the same economic fluctuations. However, this is the main weakness of our methodology, because even if the trends are parallel in the before-policy period, there still might be some group specific shocks, which occurred after the policy and that violates this assumption.

California introduced the PFL in 2002. Only knowing that contributions will be paid from 2004 on can already have led to an effect, because some women might postpone their pregnancy if they can then receive paid maternity leave. This is why we divided our dataset into the period before California introduced the new policy, from 1996-2000, and period after 2007-2012. We chose five year gaps, because it seems logical that becoming pregnant can take some time. Moreover, people need to get to know about the new policy and thus the effect can easily be carried out to a five year period.

To set up our model we made use of demographic variables, which are likely to have an effect on our research question. These are: the age of the person in years, the race of the person, the marital status, the employment status, the level of education, the total family income and the number of own children in a household. We transformed race into a dummy variable and simplified it to 0 if the person is white and 1 if the person is non-white. We also simplified the variable marital status and created the dummy variable married, was_married. Married is equal to 1 if the person is currently married, was_married is equal to 1 if person is divorced, separated or widowed and single or never married people are our reference group. Regarding employment we created a dummy variable equal to 1 if the person currently works. For all other cases like being unemployed, unable to work etc. we set assigned 0. For education we created two dummy variables – HSchool equal to 1 if the person has a high school diploma and clg_degree, which is equal to 1 if the person has some college degree. All educational levels lower than high school diploma level were taken as reference group. Variable ftotval stands for total family income. We decided to include total family income instead of personal income, because it takes the whole income into account. Regarding the decision of having a child the entire income seems to us highly relevant. The income is given in USD.

Additionally, we created another variable – sq_age, age squared. We take the number of children as endogenous variable. For our model estimation we chose the ordinary least square method, which is in our case the best option. To discover the impact of the policy we created two variables: After equal to 1, if the relevant period is 2007-2012 and 0 if it is 1996-2001 and Treat equal to 1 if the relevant state is California and 0 if it is Nevada. We also created the interaction of After and Treat in order to find out if there is an effect of the policy. The theoretical model is given in *Equation 1*. When we tested the model we discovered a heteroskedasticity problem. We solved it by using robust standard errors.

Equation 1

$$\textbf{nchild} = \textbf{cons} + \alpha_1\textbf{*race\_cat} + \alpha_2\textbf{*ftotval} + \alpha_3\textbf{*age} + \alpha_4\textbf{*After} + \alpha_5\textbf{*Treat} + \alpha_6\textbf{*Treat\_After} + \alpha_7\textbf{*sq\_Age} + \alpha_8\textbf{*married} + \alpha_9\textbf{*was\_married} + \alpha_{10}\textbf{*empl} + \alpha_{11}\textbf{*HSchool} + \alpha_{12}\textbf{*clg\_degree}$$

Results

Table 1 displays our results. We can see that the Treat_After coefficient is negative. This means, that after PFL was implemented, people have even less children than before the policy implementation. This effect is not statistically significant as the p-value is 0.101.

Moreover we find that with higher age, people have more children by 0.25 and this coefficient is statistically significant. However, the coefficient of sq_age indicates, that with increasing age women have more children, but this effect grows by a decreasing rate with an increasing age of the mother. The coefficient of ftotval is positive. This implies that with increasing family income people tend to have more children. This coefficient is statistically significant, as the p- value is equal to 0.01. The coefficient of After is positive, which means that in period 2007-2012 we have a higher number of children than in period 1996-2001. Additionally, the coefficient of Treat tells us, that women from California tend to have more children than women from Nevada. Both of these variables are statistically significant.

Table 1

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Linear regression                                   Number of obs =   52058
                                                    F( 12, 52045) = 3181.80
                                                    Prob > F      =  0.0000
                                                    R-squared     =  0.3395
                                                    Root MSE      =  .98755
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nchild	Coef.	Robust HC3 Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	.249868	.0032517	76.84	0.000	.2434946	.2562414
ftotval	1.53e-07	5.95e-08	2.57	0.010	3.63e-08	2.69e-07
After	.1276102	.0239734	5.32	0.000	.0806221	.1745984
Treat	.1096425	.0204461	5.36	0.000	.069568	.149717
Treat_After	-.0423198	.0257732	-1.64	0.101	-.0928355	.0081958
sq_Age	-.0033991	.000045	-75.59	0.000	-.0034872	-.003311
race_cat	.0048353	.0106954	0.45	0.651	-.0161277	.0257984
married	.9925267	.0125767	78.92	0.000	.9678762	1.017177
was_married	.5915572	.0171351	34.52	0.000	.5579722	.6251422
empl	-.1862693	.0103548	-17.99	0.000	-.2065647	-.1659739
HSchool	-.4426278	.0149365	-29.63	0.000	-.4719034	-.4133522
clg_degree	-.7379585	.0179875	-41.03	0.000	-.7732141	-.7027028
_cons	-3.269863	.0452206	-72.31	0.000	-3.358496	-3.18123

The coefficient of race_cat is positive. This means that non-white women have by 0.005 more children than white, but the coefficient is not statistically significant. The coefficient of empl is negative and statistically significant. This displays that if a woman works, she has less children by 0.186. The coefficient of married tells us, that married people have more children than single people by 0.993 and the coefficient of was_married tells us, that people who are divorced, separated or widowed have more children than single or never married women by 0.59. Both these coefficients are statistically significant. The coefficient of HSchool is negative and significant. It tells us that women with high school diploma have less children by 0.443 than women with lower education. The coefficient of clg_degree depicts that women with some college degree have less children by 0.738 than women with lower education, i.e. lower than high school diploma. This coefficient is also significant. According to the F-test our model is significant as a whole. R squared is equal to 0.33. This means that the independent variables can explain 33 percent of the dependent variable variation.

Discussion

In our model the treatment-after effect is negative, which is the opposite of what we expected. The result would imply that paid maternity leave leads to a lower birth rate. Due to this unexpected outcome we wanted to explore the question further. We decided to make a sensitivity analysis, because the prevailing result is based on all children living in a household. However, only women with children born from 2004 on will be receiving paid maternity leave. This is why we decided to do a sensitivity analysis, which can be found in the appendix. In the sensitivity analysis, too, the Treat_After was negative. Therefore the problem of negative impact of this policy is not caused by the chosen age group of women or the dependent variable. In order to be sure on the result we drove the experiment further and made several sensitivity analyses with different variables displaying the age of the children and various age groups of women. The outcome stayed always the same. Therefore the outcome seems to be robust. In some of the models the Treat-After is significant, but not in all cases. All models are significant according to the F-statistic.

There could be a lot of other explanations for the discovered outcome. The most logical explanation is a problem with endogeneity. This can be caused by reverse causality or by omitted variables. Reverse causality means that the policy was implemented, because there was a too low birth rate, i.e. the policy was influenced by the birth rate and not the birth rate by the policy. The problem of omitted variables states that there are some hidden factors that influence both the dependent variable and independent variable Treat_After.

Another reason could be a probable trend of having less and less children. In this case the paid maternity leave can have zero or a positive impact, yet if this positive impact is lower than the trend, it still would lead to a negative outcome like in this paper. However, this trend has to be a shock trend and has to have a different impact in the treated and non-treated region in order to have such an effect.

Additionally, there is a chance that the characteristics of the researched maternity policy is a too low extrinsic motivation to persuade women to bear children. More attractive characteristics, i.e. more money or a longer leave period could maybe change the results.

To conclude, further research should include these parameters of maternity leaves. The above mentioned explanations should be taken into account when continuing to study this highly relevant topic. Further research will show under which conditions our result holds true and in which cases the initial hypothesis can be confirmed. When it comes to research and policy we give the same recommendation: Focus more on the details of paid maternity leave.

Appendix

Sensitivity Analysis

For the sensitivity analysis we set Number of own children under the age of 5 in household (nchlt5) as endogenous variable. The data sample was restricted only to women from 25 to 45 years old, because we defined this as the most likely age to bear children. The number of affected women is 24, 713. All our variables, except clg_degree and race_cat, are robust and their impact on nchlt5 has thus the same sign and significance. Most important is the fact that the variable Treat_After stays negative, but is significant in this model, which is displayed by *Table 2*.

Table 2

Linear regression

Number of obs	=	24713
F(12, 24700)	=	375.86
Prob > F	=	0.0000
R-squared	=	0.1599
Root MSE	=	.57353

nchlt5	Coef.	Robust HC3 Std. Err.	t	P>|t|	[95% Conf.	Interval]
After	.078557	.0186666	4.21	0.000	.0419693	.1151446
Treat	.0378759	.0149413	2.53	0.011	.00859	.0671618
Treat_After	-.0549189	.0202556	-2.71	0.007	-.0946211	-.0152167
age	.0903408	.0095534	9.46	0.000	.0716156	.109066
ftotval	1.33e-07	5.91e-08	2.24	0.025	1.68e-08	2.48e-07
sq_Age	-.0017439	.000133	-13.11	0.000	-.0020047	-.0014832
race_cat	-.0057872	.0087619	-0.66	0.509	-.022961	.0113866
married	.3974206	.0088939	44.68	0.000	.379988	.4148531
was_married	.1615672	.0101395	15.93	0.000	.1416931	.1814412
empl	-.1955094	.0088931	-21.98	0.000	-.2129403	-.1780785
HSchool	-.0262246	.0137488	-1.91	0.056	-.0531732	.0007239
clg_degree	.0348915	.0148967	2.34	0.019	.0056931	.0640898
_cons	-.793125	.1695677	-4.68	0.000	-1.125488	-.4607621

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