The Effect of Paid Maternity Leave on Fertility and Mother's Labor Force Participation

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Abstract

This study examines how paid maternity leave (ML) impacted fertility and mothers' labor force participation in Romania. The ML gives mothers the right to paid leave until the child turns one year old, and it offers 65% of monthly income before birth. I examine the effects of this policy change using a regression discontinuity design and census data. I show that mothers who are eligible for ML are 2.5 percentage-points more likely to have an additional child than those ineligibles. The effect is persistent for seven years after the policy was implemented. I find no significant results regarding the mother's labor force participation. These results have important implications regarding the shrinking working-age population and the ability to fund benefits programs.

Key Words: Paid Maternity Leave, Fertility, Women Labor Force Participation

JEL Classification: J08,J1,J13

1 Introduction

Low fertility rates in developed countries have been studied extensively in recent decades.[1] In these countries, shrinking working-age populations and growing elderly populations threaten the government's ability to fund benefit programs, such as pension or healthcare (Bloom, Canning, Fink, and Finlay (2010)). This problem is exacerbated in Eastern European countries, where European Union expansions and fewer restrictions on worker movement have led to negative net migration, decreasing the government's revenues.[2]

A country's population remains stable when the fertility rate is higher than the replacement rate of 2.1 children per woman. In 1970, most countries that are now member-states of the European Union had fertility rates above the replacement level. Since then, fertility rates have dropped significantly, below the replacement level—leading governments to implement pro-natalist policies to encourage births, including maternity, paternity, and parental leave; child subsidies; or child tax credit. Consequently, countries such as Romania, Bulgaria, and Slovenia have experienced increases in fertility rates from 1995 to 2018 (Figure 1). However, all countries in the European Union are still having fertility rates under the replacement level.

I examine how an extension of maternity leave (ML, hereafter), from 60 days to 1 year, in Romania in 1990, affected subsequent fertility and mother's labor force participation. I use a regression discontinuity design and 1992 Romanian census data to focus on mothers who gave birth 60 days before or after the reform. ML led to a 2.5 percentage-points increase in the probability of giving birth to an additional child over a 21 month period and had no significant effect on the mother's labor force participation. Moreover, I use the 2002 Romanian census data and a difference-in-differences estimation strategy to analyze the long-run effect of ML on the probability of giving birth to an additional

[1] See Sleebos (2003) for "stylised facts" and literature review

[2] United Nations Population Division. World Population Prospects: 2019 Revision

child within 7 years after the previous birth. I find that the policy's impact persisted for seven years after implementation. This suggests that the policy did affect the timing of additional births and the number of children.

This subsequent increase in fertility is driven by women under the age of 25 and by educated women. This is expected because the former group has the highest fertility rate (Table 1), and the latter group benefited more from the policy. That is, educated women are more likely to be employed and have higher incomes, and since the additional time off is an earning-dependent benefit this policy offers them higher payments. Analyzing the probability of having an additional child by birth order, I find statistically significant effects for women who had a second child after the reform was implemented.

In addition to 52 days of pre-birth ML, expectant mothers could work six hours per day—with no change in income—in the three months leading up to the pre-birth ML. The government subsidized the difference between their full-time wage and their six hours per day wage. Because women were eligible for two months of pre-birth and an additional three months wage subsidy, they had an incentive to give birth no later than five months after their previous ML expiration. Using regression discontinuity and difference-in-differences estimations, I find a significant positive effect of 1.3 percentage-points and 1.7 percentage-points, respectively, on subsequent fertility rates within 17 months after the previous birth. The ML can be automatically renewed when mothers are on leave with the previous child. The automatic renewal of ML, coupled with additional benefits, seems to be the mechanism driving my results.

The research literature identified two main sets of policies that might affect fertility rates. One strand of the literature looks at the effect of specific financial incentives on fertility, particularly on child cash transfers and child-related taxes. Milligan (2005), Riphahn and Wiynck (2017) and Laroque and Bernard (2014) show that the impact of child cash transfers on fertility increases with family size, while Cohen, Dehejia, and Romanov (2013) find a negative effect at low levels of income, and a positive effect at higher income levels. Studying family cap policies that suspends the incremental cash assistance for each additional child for families on welfare, Kearney (2004) finds no effect on higher-order births. According to González (2013), a one-time payment of €2,500 per child, in Spain, increased fertility mostly through a reduction in abortions. Research on child tax credit shows that increases in fertility rates are driven by less-educated women (Azmat and González (2010)) and married women (Brewer, Ratcliffe, and Smith (2011)). Junsen Zhang, Quan, and Van Meerbergen (1994) analyze tax exemption and child tax credits in Canada, which helped attenuate the large decrease in fertility.

The second strand of literature focuses on parental leave effect on fertility. Parental leave can vary in terms of benefits, duration, job protection, or availability for either parent. In cross-country analyses, fertility is positively correlated with the duration of the leave (Winegarden and Bracy (1995)), job protection (Shim (2014)) and benefits (Kalwij (2010); Adema, Ali, and Thévenon (2014)). In a recent study, Olivetti and Petrongolo (2017), show that the length and financial benefits of parental leave are negatively correlated with fertility rate, but this effect is driven by four Eastern European countries: Poland, the Czech Republic, Hungary, and Slovenia. Due to differences in institutional, political, and cultural settings, it is difficult to establish causality of parental leave policies across countries. For this reason, researchers focus on individual countries when analyzing these reforms.

When analyzing a specific parental leave policy within a country, there is little consensus of its effects across studies. Lalive and Zweimüller (2009) show that parental leave extension, from one year to two years, in Austria had a strong positive impact on subsequent fertility behavior, and Golightly and Meyerhofer (2022) show that access to paid family leave increases the fertility by 2.8 percent in California, U.S. Cygan-Rehm (2016) finds that the German parental leave reform that changed from means-tested to an earnings-related benefit affected the "timing" of births rather than the number of children, within five years after implementation. Tudor (2020) analyzes the impact of a policy change from earnings-dependent to fixed benefits in Romania and finds no effect on the short-term conceptions rates. Examining six expansions of ML in Norway between 1987 to 1992, in which each expansion increased ML by 2-3 weeks while retaining 100% income replacement, Dahl, Løken, Mogstad, and Salvanes (2016) find an insignificant effect on completed fertility.[3]

A newer type of leave is paid paternity leave, which is allocated only for fathers and which can contribute to fertility decisions by alternating the allocation of childcare between parents. Kotsadam and Finseraas (2011) show that fathers who were eligible for "daddy quota" (i.e., four weeks of paternity leave in Norway) are 50% more likely to divide the chores of washing clothes, and there are 11% lower conflicts over the household division of labor. Dahl, Løken, and Mogstad (2014) provide evidence that coworkers are more likely to take parental leave if one of their peers used it in the past. This result was driven by transmission of knowledge: employees knew how their employer would react to use of paternity leave. These studies find no measurable effect on fertility. However, a recent study by Farré and González (2019) find that introducing two weeks of paid paternity Leave in Spain decreased subsequent fertility. The authors provide evidence for two channels to explain this result. Firstly, fathers' involvement in childcare led to higher labor force attachment for women, increasing the opportunity cost of having an additional child. Secondly, fathers showed a lower desired level of fertility, which may be caused by increased awareness of the cost of having a child.

The fall of the Communist regime in December 25^{th}, 1989, led to dramatic changes in all aspects of life across the country. One significant change was the legalization of abortion and lifting the ban on birth control methods. In a study that analyzed the effects of these policies on fertility and compared data from 1988-1989 to 1991-1992, Pop-Eleches (2010) notes a decrease in fertility rate from 3.22 to 2.10 children among women with primary education and from 1.93 to 1.38 among women with secondary education. In

[3]Completed fertility represents the average number of children born for a particular generation of women through their fertile life

the present study, I focus on Romania's law regarding paid ML which was enacted on January 18^{th}, 1990, less than one month after the fall of the Communist regime. This law was unexpected and came into effect the next day, creating conditions for a quasi-natural experiment that allows me to establish causality.

1.1 Paid Leave Benefits in Romania

Maternity leave reform was first introduced in Romania in 1965 during the Communist period. It provided mothers with a total of 112 paid days: 52 days before birth and 60 days after birth. The eligibility and amount paid were based on the number of months worked before birth. Women would be eligible to receive 90% of their monthly income if they worked continuously for more than 12 months, 70% if they worked between 6 and 12 months, and 50% if the worked for less than 6 months. For each additional child after the second birth, mothers received 100% of their previous wage, regardless of the amount of time in the labor force (Law Nr. 880/1965 (1965))

The family policies mentioned in the Decree Nr. 31/1990 (1990) were divided into two categories: *Maternity Leave*-the time before and immediately after birth (112 days), related to pregnancy and recovery after birth—was awarded exclusively to birth mothers; and *Paid Parental Leave* —designed to facilitate the care of children—could be used at any time within the child's first year. All language referring to whom can benefit from paid parental leave is focused on the mother or adopting mother so that I will refer to this leave as maternity leave (ML) throughout the paper. A later reform, Law Nr. 120/1997 (1997) was ambiguous in regard to which of the parents could use the leave. It is a continuation of maternity leave for women, but at the same time specifies that either of the two parents can take the leave. The first time fathers had the right to take parental leave was stipulated clearly by Law Nr. 19/2000 (2000).

Although parental leave can be used by women and men, it is mostly taken by women. For instance, in 2010, the Romanian National Institute of Statistics (2018) reported that from the total number of parents with children under 15 years old who took parental leave, only 1.5% of fathers used the whole period of parental leave, while 73.5% of mothers used the entire duration of parental leave.

There were several pro-natalist policies that provided negligible benefits and failed to reach their objective according to The World Bank (1992). Mothers who have a child with disability receive a fixed child state allowance (1,000 lei/month, approximately $47/month) until the child is 18 years old. To receive this benefit, mothers had to be legal residents of Romania and children needed to live with their parents. Birth allowance was another benefit representing a one-time payment (1,500 lei, approximately $71) for each birth, excluding the first birth. Mothers with three or more children would receive a monthly payment for life (400 lei/month, approximately $19/month for three children and 500 lei/month, approximately $24/month for four or more children).[4] To put the magnitude of these benefits into perspective, the average income in 1990 was 3,381 lei/month, approximately $161/month. Other related benefits allowed mothers, during pregnancy, to work shorter workdays, six hours per day, for three months leading up to their two month pre-birth ML. Their income was not affected: the difference in wages was paid to the employer by the government. Moreover, mothers with children who have a disability could stay home and care for the child until the age of three, retaining their ML benefits during that time.

Decree Nr. 31/1990 (1990) was issued on January 18th, 1990 to regulate parental leave, and it came into effect the following day. This reform provides parents with additional leave, in addition to the 112 days of ML. The norm confers mothers the right to maternity leave any time until the child turns one year old, and it offers 65% of monthly income before birth. Eligibility was contingent on the mother working at the time they became pregnant and contributing to the social security system. There is no threshold for earnings, and the percentage of the benefit does not depend on how long the mother

[4]The official exchange rate stipulated by Decree Nr.44/1990 (1990) was 21 lei/US.

worked before birth. This reform was revoked on July 11^{th}, 1997. A new ML law, implemented in 1997, increased both the duration of parental leave from one to two years and the percentage of the subsidized portion of the mother's pre-birth monthly income from 65% to 85%. These changes in benefits did not come with changes in the eligibility criteria.

The remainder of the paper is organized as follows. Section 2 describes the data, Section 3 explains the empirical etrategy, and the results are reported in Section 4. The Section 5 presents the conclusion.

2 Data

Data come from a 15% sample of the Romanian census, collected between January 7^{th} and 14^{th}, 1992, two years after the reform was implemented. This dataset is part of census samples gathered by the **ICSPR**. The main scope of creating cross-nationally comparable data for European countries was primarily to study the social and economic conditions of older persons. The data provide socioeconomic and demographic information, such as gender, age, number of children, educational attainment, occupational status, and labor market outcomes. Data include the day, month, and year of birth, which are crucial for the identification strategy I use in the present study. The precision of the day of birth allows identifying children born immediately before or after the reform.

I generate a unique identification number (ID) for households, individuals, mothers, and fathers used in matching mothers with their children. Households with no mother ID's are dropped from the sample. The sample is restricted to the analysis of mothers who had childbirth 60 days before reform or 60 days after. Therefore, the sample consists of women for whom I could identify the date of birth for their children. I further refine the sample to women for whom the age and level of education are known.

Table 1 presents the birth rates and total fertility rate by mothers' level of education and age groups. The total fertility rate represents the average number of children that a woman would have over her childbearing years (age 15-44) based on age-specific birth trends. The total fertility rate was 2.3 in 1989, and it dropped to 1.85 in 1990. The number of births is lower for each age group and education category in 1990, compared to 1989. Most births, 21,003 in 1989 and 19,161 in 1990, are recorded in the age group 20-24. The birth rate falls by 26% (from 85 to 63 births per 1,000 women) for women with primary education, while for higher educated women, it falls by 20% (from 61 to 49 births per 1,000 women). Pop-Eleches (2010) finds that after the legalization of abortions and access to birth control, at the beginning of 1990, pregnancy rates across educational levels decreased similarly while the abortion rate increased more among women with primary education. This led to a differential impact on the fertility rate by educational groups.

2.1 Summary Statistics

In Table 2, panel A, I provide summary statistics of mother's characteristics for the whole sample. At the same time, in panel B, the outcomes and control variables used in this analysis are shown separately for the control and treatment group. The control group includes women who had their child 60 days before the date of reform implementation and were not eligible for maternity leave. In comparison, the treatment group includes women who had their child within 60 days after reform implementation and were eligible for maternity leave. The sample consists of $16,658$ mothers, of which $8,319$ gave birth within 60 days before the reform, while $8,339$ gave birth within 60 days after the reform.

The mean age of mothers is 27 years, and a high percentage of them, 54.9%, have at most a primary education (8 years of education), while only 3.8% have a college degree. The percentage of women with one child is 28.15%, meaning that most women in the sample have more than one child. There are 2,415 women who have at least five children.

In panel B of Table 2, I present a comparison of the means of age groups, education, number of children, marital status, and employment for control and treatment groups. The last column presents the P-value of the t-test for the mean differences between the two groups. All values are higher than 0.10, so the difference in means between control and treatment groups are statistically insignificant.

Figure 2 shows the spike in the number of births in 1966 when abortion became illegal and birth controls were restricted, followed by a negative birth rate trend. The blue line represents the legalization of abortion and birth control at the end of 1989. The number of births dropped from 58,364 in 1989 to 47,438 in 1990, a 18.72 % decrease.

I use a regression discontinuity design (RDD) because the probability of subsequent fertility changes for women who gave birth after the date the policy was implemented. Figure 3 depicts the linear fit on the probability of having an additional birth on each side of the cutoff. The circles represent the percentage average bin of mothers who have an additional child within 21 months after the previous birth.[5] Shaded areas represent 95% confidence interval. There is a large jump at the discontinuity, accompanied by a negative trend.

3 Empirical Strategy

3.1 Methodology

Estimating the effect of maternity leave on fertility using ordinary least squares (OLS) would yield biased estimates because of endogeneity. Olivetti et al. (2017), in a cross-country analysis, show that the length of paid family and financial benefits are negatively correlated with fertility rate. There might be reverse causality if low fertility rates led to the adoption of paid family leave. The ML reform was announced one day before being enacted, so women who gave birth near the reform's implementation date could not have planned this birth in response to the policy. Thus, comparing the total num-

[5] Due to the small window around the reform, the average outcome is computed for four-day bins.

ber of births shortly before and after the reform would not estimate the policy's impact, because these children would be born even in the absence of the reform. Similarly, if I compare the number of births for a more extended period before and after the policy, results may reflect the time trend because some women would give birth even without the ML policy.

An ideal experiment to overcome the endogeneity issues would be a randomized control trial (RCT). In an RCT, some women would be offered treatment (i.e., ML) randomly during their reproductive lifetime while some women would not be offered the treatment. I could subsequently compare the mean outcomes between groups. As this ideal experiment is not possible, I use a regression discontinuity design (RDD) to examine the subsequent fertility, which approximates a randomized control trial (RCT). This strategy allows me to compare the probability of having an additional child among mothers who gave birth after the policy was enacted and mothers who gave birth before.

Given that the policy was unannounced, and the timing of birth is unlikely to be manipulated, the assignment to treatment is random. RDD is a local estimation strategy, but it is unlikely to be a limitation because the cutoff's distance does not affect my outcome variables. Also, there is no significant difference in observables between the control and treatment groups, as shown in Table 2, panel B, which makes this strategy even more appealing.

I restrict the sample to mothers who gave birth within the 60 days before or after the reform; hereafter, I refer to this birth as the reference child. Additionally, I study the mothers' subsequent fertility decision within 21 months from previous birth and mother's labor force participation two years after the reform. The reform was enacted on January, 19^{th}, 1990, and data collection for the census began on January, 7^{th}, 1992. Even though the data were collected two years after the reform was implemented, I analyze subsequent fertility over 21 months from the previous birth for each woman to ensure that mothers have the same amount of time available for having an additional child. For instance, without any restriction on subsequent fertility, mothers who gave birth in November 1989 would have an additional four months to give birth to another child compared to mothers who gave birth child at the end of March 1990. Figure 5 graphically depicts the main time points.

I estimate the following equation:

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 f_1(d) + \beta_3 f_2(d) * T_i + \beta_4 X_i + \epsilon_i \tag{1}$$

where Y_i is either an indicator of whether the mother gave birth to an additional child within 21 months or an indicator for whether mother is employed two years after the reform. T_i is an indicator that is assigned the value 1 if the reference child was born within 60 days after reform and 0 if born within 60 days before. The running variable is normalized to 0 for January 19^{th}, 1990, and f is a polynomial in the running variable d (day). Maternal and time-related controls are included, such as polynomial of 3^{rd} order in mothers' age, and day of the week fixed effects corresponding to child's birth. Robust standard errors are clustered at the day of childbirth level to avoid the issues of using discrete running variable in the RDD framework (Lee and Card (2008)).[6] I only observe the eligibility criteria, date of birth, and not the actual take-up of ML, so the coefficient of interest, β_1, represents the Intention to Treat (ITT) effect.

A major challenge in RDD is setting the functional form for a parametric regression or the bandwidth for a non-parametric procedure. Having a finite sample, it is impossible to know which of these have a smaller bias. Instead of choosing the functional form, Hahn, Todd, and Van Der Klaauw (2001) suggests running local linear regressions to reduce the importance of bias. Choosing a bandwidth for the estimation involves a trade-off between precision and bias. The closer to cutoff, the smaller the bias would be, but this would increase the variance because fewer observations are analyzed.

[6] Kolesár and Rothe (2018) argue that clustering the standard errors by the running variable lead to poor coverage properties. The main results with no clustered standard errors are reported in Appendix, Table A1.

Aside from my main specification, I provide local polynomial estimates using the optimal bandwidth selection, as proposed by Calonico, Cattaneo, and Titiunik (2014). The local polynomial estimates have confidence intervals constructed using a bias-corrected RD estimator and standard error estimator. I also report local polynomial estimates developed by Imbens and Kalyanaraman (2012), who derive asymptotically optimal bandwidth under squared error loss. This estimate uses a data-driven approach to decide how to weight the bias term coming from misspecification and the variance term coming from excluding data from the regression.

More formally, the RDD estimate can be written as:

$$\tau_{RDD} = \mu_Y^+ - \mu_Y^-, \quad where$$

$$\mu_Y^+ = \lim_{d \downarrow c} \mu(d) \quad and \qquad \mu_Y^- = \lim_{d \uparrow c} \mu(d)$$

The value of μ_Y^+ and μ_Y^- are obtained from the following local linear regression:

$$(\hat{a}_y, \hat{c}_y) = \underset{(\hat{a}_y, \hat{c}_y)}{\operatorname{argmin}} \sum_{i=1}^{N} \{y_i - a_y - c_y(\chi_i - \tau)\}^2 (\frac{\chi_i - \tau}{h}) I[\chi_i \geqslant \tau] \tag{2}$$

Here, $K(.)$ is a uniform kernel function, which weights data equally regardless of the distance from the cutoff, h represents the bandwidth, and τ is the threshold of the running variable (day of birth).

The identifying assumption is that having a child before or immediately after January 19^{th}, 1990 is as good as random. One potentially important concern with this strategy is that women who were scheduled to give birth through C-section could manipulate the day of birth. This manipulation is more likely to occur when an earlier date is desired, but in this context, women likely prefer to give birth later, after the reform was implemented. To address this concern empirically, I perform the "Donut" RDD proposed by Barreca, Guldi, Lindo, and Waddell (2011). I exclude children born seven days before and after the reform and re-estimate the remaining sample's discontinuity in this specification. My results are not sensitive to the exclusion of births around the cutoff.

Moreover, this policy change could not have been anticipated, as the decree came into effect only one day after the president signed it. The reform was proposed by the new democratic government which came to power on December 25^{th}, 1989. Therefore, extensive discussions about this reform were not likely before the law was enacted. Thus, we can almost completely rule out mothers' manipulation of the delivery date. If this were not true, we would observe an increase in the number of births immediately after the reform. A graphical representation of the number of births per day (Figure 6) are provided. I use two different density tests for testing the manipulation of the running variable, McCrary (2008) (Figure 7)) and Cattaneo, Jansson, and Ma (2019) (Figure 8), which fail to reject the null hypothesis that there is no discontinuity at the threshold.

Finally, as a robustness check, I estimate a difference-in-differences specification, in which I restrict the sample to mothers who gave birth within 60 days before or after the reform was implemented as the treatment group, while for the control group, I use mothers who gave birth in the same months, but one year earlier.

$$Y_i = \alpha_0 + \alpha_1 Treat_i + \alpha_2 After_i + \alpha_3 Treat_i * After_i + \alpha_4 X_i + \epsilon_i \tag{3}$$

where Y_i is a dummy variable of whether a mother gave birth to an additional child within 21 months. $Treat_i$ is an indicator that is assigned a value of 1 if the mother gave birth within 60 days before or after the reform. $After_i$ is an indicator variable equal to 1 if the child is born in the months "after" the reform (January 19^{th} to March 19^{th}) in the treatment year, 1990, and control year 1989, $Treat_i * After_i$ is an interaction term between the previous two variables. X_i is a vector that includes the parental level of education, father's age, third-order polynomial in mother's age, mother's ethnicity (three dummies), and dummies for multiple births and for child's sex. The coefficient of interest is α_3, which refers to children born between January 19^{th} and March 19^{th} 1990, and identifies the Intention to Treat effect of ML on subsequent fertility.

3.2 Identification Assumptions

The regression discontinuity design uses births close to the cutoff to approximate a randomized experiment. This requires that giving birth, before or after the reform, is as good as random. A sufficient condition for regression discontinuity is the continuity of potential outcomes. This assumption may not be plausible if the running variable, date of birth, can be manipulated. In this section, I examine two diagnostics needed for RDD's validity, one based on the distribution of childbirth and one based on mean differences in observables between treatment and control groups.

Figure 6 shows the number of births per day in the 60 days before and 60 days after the reform was implemented. There is no visible jump or any other discontinuity at the threshold. However, there is a spike in the number of births registered 18 days before the reform. This corresponds to 1^{st} of January 1990, which is a Monday, and it is probably due to delays in reporting the births because some offices are closed on Sundays during the winter holidays. Offer, Mitrut, and Pop-Eleches (2018) notes that the spike in observations occurs on January 2^{nd} when January 1^{st} is a Sunday.

I formally test the discontinuity at cutoff in the running variable's density function, using the two sub-samples: the control group and the treatment groups. Thus, the null (H_0) and alternative (H_1) hypothesis are:

$$H_0 : \lim_{d \downarrow c} f(d) = \lim_{d \uparrow c} f(d) \ \ vs \ \ H_1 : \lim_{d \downarrow c} f(d) \neq \lim_{d \uparrow c} f(d)$$

Firstly, I use the test developed by McCrary (2008). In the first step, it computes the histogram of the running variable. By construction, none of the histogram bins includes observations that fall both before and after the discontinuity date. The second step is a local linear smoothing of the histogram, having bin frequencies as a dependent variable, and the midpoint of the histogram bins as an independent variable. This estimation is conducted separately on either side of the cutoff. The estimate of discontinuity in the density at threshold is provided by the log difference in height of coefficients on the intercepts from the two local regressions, which is 3% with a P-value of 0.21 (Table 3). I fail to reject the null hypothesis that the density of births is continuous at the cutoff. This is represented graphically in Figure 7, where the gray dots show the number of births in each bin, and the solid black lines show the two local linear smoothings of the histogram with the corresponding 95% confidence intervals (dashed lines).

Secondly, I use the approach suggested by Cattaneo et al. (2019), who proposes a manipulation testing based on their local polynomial density estimator. This method does not require the pre-binning of data and uses weighting schemes such as uniform or triangular kernel. The test statistic is computed using bandwidth choices of 23 days for control, respectively for treatment, leading to effective sample sizes of $N_{-} = 8,306$ and $N_{+} = 8,487$. The discontinuity estimate is -0.39, with a P-value of 0.69. Therefore, there is no statistical evidence of systematic manipulation of the running variable. Results are reported in Table 3 and the graphical representation in Figure 8, where confidence intervals of the two local linear regression overlap almost entirely at the threshold.

As an additional test of regression discontinuity design validity, I examine the smoothness of possible confounding variables. Table 4 shows the estimates from the main specification (Equation 1) on the parental and household characteristics, which may affect future fertility decisions. I also included the nationality, mother's native language, and religion of the child because they proxy the family values, which in turn may affect fertility decisions. Out of 14 regressions, none of the estimates are statistically significant at 90% percent level.

4 Results

4.1 Fertility

The main regression results are presented in Table 5. Panel A shows linear polynomial estimates, and panel B displays the estimates of quadratic polynomials across various windows. Mothers eligible for maternity leave are around 2.5 percentage-points more likely to give birth to an additional child within 21 months after childbirth. The column header specifies the windows that are spaced by seven days interval. CCT and IK columns show the estimates from a local linear polynomial regression using the bandwidth selection algorithm proposed by Calonico et al. (2014)[7] and Imbens et al. (2012), respectively. These coefficients are comparable with the coefficients from the main specification.

The "Donut" column in Table 5 shows the results of RDD estimation when seven days before and after the reform are excluded. This sub-sample analysis shows that mothers who benefit from ML are 2 percentage-points more likely to have an additional child within 21 months.

With more substantial effects among more educated women, my positive results on fertility align with findings from Kluve and Schmitz (2018) who study a reform change from means-tested to earning related benefits. The authors use a regression discontinuity design and show that mothers who benefit from the new paid leave are 5% less likely to have another child in Germany. This effect is almost exclusively determined by younger mothers, with some visible results among poor households. This reform change impacted fertility negatively among low-income families, who receive less money than before, while more affluent families benefit from this change as their income is high.

There is little scientific consensus regarding completed fertility. Lalive et al. (2009) documents that an expansion of paid parental leave, from one to two years, increased

[7] I adopted one common optimal bandwidth selector (mserd) and uniform kernel for CCT. Estimates were adjusted for mass points in the running variable.

completed fertility and led to a tighter birth spacing; however Dahl et al. (2016) find no significant effect on completed fertility 14 years after the reform. Cygan-Rehm (2016) uses differences-in-differences estimation to analyze the 2007 German reform and shows that the reform affected the “timing” of births, and there was no significant effect after five years on subsequent fertility.

4.2 Analysis by mother’s age and education level

Panel A in Table 6 shows the results stratified by maternal age, where linear polynomial regression is used for smaller windows and quadratic polynomial for the whole sample. Women under the age of 25 drive the results. This is expected because women under 25 years old had a 10.16% decrease in number of births from 1989 to 1990, while women over 25 years old register 26.13% fewer births over the same period. In the 1990s, women were giving birth at a younger age than nowadays, which might be another reason why there is no observable effect in the older group. Also, young women have a more fertile reproductive system that might have helped them give birth to an additional child quickly. Similarly, Farré et al. (2019) examining the context in Spain in 2007—find that a new paid paternity leave policy had negative impacts on fertility rates that were driven by women older than 30 years.

Furthermore, panel B in Table 6, classifies the results based on the mother’s level of education. Primary education refers to women who finished middle school, while the secondary and tertiary education category represents women with at least a technical degree. Maternity leave is an earning-dependent benefit, which means that it provides higher payments for more-educated women, who, on average, have higher income and are more likely to be employed. There are stronger results on subsequent fertility among women with at least a secondary degree and no effect for women with primary education. These estimates are ten times larger than estimates for the primary education category and statistically significant at 95% level. My results are similar to Raute (2019), who explores a change in maternity leave from means-tested to earnings-dependent benefit, and finds a 23% increase in fertility for tertiary-educated women. These results were mainly driven by women in the middle and upper end of the income distribution. To put my estimates into perspective, for highly educated women, a 4 percentage-point increase in the probability of giving birth to an additional child translates into a 38% increase.[8]

In census data, the birth order variable may have measurement error because it is constructed based on the members observed in the household. Children tend to live with their parents until they are at least 18 years old in Romania, and the sample is restricted to mothers who gave birth within two years before the data were collected. These factors partially mitigate the measurement error, because an age gap larger than 16 years among siblings is not common. Table 7 presents the effect of maternity leave on giving birth to an additional child by birth order. The most substantial results are present among second born children. Approximately 4 out of 100 women who were eligible for maternity leave gave birth to a second child and would not have done so in the absence of leave. The relative frequency of the third child is 15.98%, compared to the second child 32.45% and firstborn born child 28.07%, respectively.

4.3 Mother's Labor Force Participation

The policy's impact on mothers' participation in the labor force is ambiguous because it affects two categories of women who participate in the labor force. The first category consists of women who would have continued to work but are incentivized by the policy to stay at home longer (or possibly permanently). In the second category are women who would quit but ML incentivizes them to return to work (Rossin-Slater (2017)).

I analyze the effect of ML on the mother's labor force participation two years

[8] The outcome mean is 0.095, so 4 percentage points translates in 38%.
$(\frac{Coefficient}{Mean} = \frac{4}{0.103} = 38\%)$

after the reform, in 1992. Table 8 shows that there is statistically no difference in mother's employment between women who benefit from ML for the reference child and mothers who did not. The results are graphically depicted in Figure 4 where the Y-axis represents the percentage of mother employed two years after the reform. There is no discontinuity at the threshold. One drawback of using census data is the fact that employment history cannot be observed. Women's labor force participation was high in Romania, 62.5% of working-age women participated in the labor force between 1990 and 1992. They were mostly employed in the public health and education sectors and underrepresented in the construction and transport sectors (The World Bank (1992)).

In Table 9, I analyze the effect of ML on the mothers' participation in the labor force by skill. I categorize elementary, intermediate, and high skill based on International Standard Classification of Occupation (ISCO) codes. These codes organize jobs by the tasks and duties performed in each specific job, which is useful for international comparisons. The elementary skill category includes manufacturing and agricultural laborers, sales occupations, cleaners, domestic-related helpers, and other elementary occupations. The intermediate skill category contains managers, personal care (childcare or institution based personnel), and other service workers. The high skill category includes professionals (physicists, doctors, architects, lawyers, etc.), technicians, and associate professionals (civil engineering, computer and health assistants, etc.).[9]

A large proportion of mothers work in sectors that require intermediate skills, but it seems that their employment is not affected by ML. I find an insignificant effect of ML on mother's employment in all skill levels. Kluve et al. (2018) study a change in parental leave from means-tested to an earnings benefit and show that it has a positive effect on employment on mothers from the upper distribution of income. In contrast, mothers from lower distribution of income are not affected. Their results are driven by the fact that higher-income mothers have seen their benefits increased by €4700 compared to benefits

[9] This classification is similar to Pop-Eleches (2006)

under the previous reform, being the real ”winners” while lower-income mothers face a loss of approximately €3000, being the ”losers”.

Baum (2003) provides evidence that women who benefit from Family and Medical Leave Act (FMLA) are 30% more likely to return to their previous jobs than women who had no leave, while Klerman and Leibowitz (1999) find that among mothers who worked full-time before birth, 60% of them returned to the same employer. However, Klerman et al. (1999) argue that the FMLA's effect on job continuity is small because this job continuity was present before the implementation of the FMLA. Studies that focus on FMLA impact on wages and employment find insignificant effects (Baum (2003); Waldfogel (1999); Klerman et al. (1999)). It is difficult to see a large impact on labor outcomes because it offers short unpaid leave, and not all workers are eligible for job protection due to FMLA's strict requirements.

4.4 Robustness Checks

In Table 10, I report the results of difference-in-differences specification (Equation 3) where the columns specify the cutoffs used in the regression. The cutoff, January 19 1990 (i.e., the date that the reform was implemented), confirms previous results from the regression discontinuity design from Table 5. Mothers who benefit from maternity leave for the reference child are 2.1 percentage-points more likely to have an additional child. Using placebo cutoffs for two and three years(respectively) before reform yields insignificant results.

I also run the main specification, Equation 1 using placebo cutoffs, same day and month of the reform (i.e., January 19), but different years: 1989 and 1991. The results for 1991 are undoubtedly insignificant because data were collected in 1992 and women have a larger gap than twelve months between children. Table 11, panel A shows that all estimates are statistically negligible from 0 using January 19, 1989 as a cutoff. Similar, in panel B, none of the estimates are significant at 90% level using January 19, 1991 as the cutoff.

Finally, a falsification test is performed, and it shows that the ML policy estimates become statistically indistinguishable from zero under placebo cutoffs. Figure 9 illustrates the local linear estimates using Imbens et al. (2012) optimal bandwidth along with 95% confidence intervals at different cutoffs. The blue point reflects the policy's estimate along with the confidence interval. This is statistically significant at the 95% level. The red line represents the estimates before the reform, while the green line represents estimates after the reform, yielding confidence intervals that substantially cover zero. There are only 8 out of 100 different days as cutoff, which yields significant results.

4.5 Long Run Effects on Fertility

ML was reformed seven years later in 1997, offering mothers two years of leave with 85% of their monthly income before birth. Using the 2002 Romanian census data, I analyze the ML policy's effect, implemented in 1990, on fertility over seven years from previous childbirth, so that the mothers would have identical ML for the additional child.

These data include information on the individual's month and year of birth, but not of the day of birth. Because the policy was implemented in the middle of January, I drop all children born in January because it cannot be identified if they were affected by the policy. Moreover, regression discontinuity does not perform well with a few mass points for the running variable (in this case, month of birth). Therefore, I adopt the difference-in-differences approach (Equation 3) to estimate the policy's causal impact on subsequent childbirth.

Table 12 shows the effect of ML on the probability of giving birth to an additional child within 11 months through 21 months after a previous birth using regression discontinuity and 1992 census data in panel A, while in panel B, a difference-in-differences estimation with 2002 census data. The latter estimation, compared to regression discontinuity, requires more assumptions for a causal interpretation. Still, the similarity of coefficients between these two panels suggests that difference-in-differences is suitable for analyzing the long term effects.

In Equation 3, Y_i is an indicator of whether the mother gave birth to an additional child within 7 to 84 months, representing the cumulative probability of giving birth to an additional child within a specific number of months after the previous birth. The estimates of maternity leave effect on subsequent fertility are plotted in Figure 10 along with 95% confidence intervals. Coefficients for giving birth to an additional child within 21 months are similar to regression discontinuity and difference-in-differences estimates using 1992 Romanian census data. This is an additional robustness check of the coefficients from the main regression, Equation 1.

In months 7 to 14 after the reform, there was no observable impact on additional birth after a previous birth . This is expected because it is biologically challenging for women to give birth within such a short period. The effect is positive and statistically significant, starting with month 15, a few months after the ML expired. The most considerable effect occurs in month 25. There is an increase of 2.9 percentage-points in the probability of giving birth to an additional child for women with ML for the reference child than women who did not benefit from this policy. The estimates are statistically significant at 90% level over the seven years.

Completed fertility, the average number of children born for a particular generation of women through their fertile life, is difficult to observe in data. The positive effect of ML on higher-order birth over such a long period suggests that the policy affected the timing of subsequent fertility and the number of births. Any incentive to encourage women to have a child earlier may translate into a higher number of births, as they avoid potentially adverse shocks to marriage or health (Lalive et al. (2009)).

The key identification for this estimation is the absence of time and cohort effects. I present additional robustness checks using placebo cutoffs in Figure 11. The top panel shows the coefficients using January 1987 as a cutoff, while the bottom panel illustrates the estimates using January 1993 as a placebo cutoff. For the latter cutoff, I analyzed subsequent fertility for up to four years because the reform was revoked in 1997, and mothers must face identical ML for the additional child.

4.6 Theoretical Consideration and Mechanisms Behind Fertility

The theory of demand for children implies that with higher income, families would increase expenditure on their children, and they would also have more children (Becker (1960)). Consequently, policies that reduce the net cost of children would increase fertility. However, Becker and Lewis (1973) emphasize the trade-off between quantity-quality of children.[10] This means that by having more children, resources are divided among them, so there is less money to be spent on education or other expenses leading to lower human capital. By having fewer children, more money can be spent on each child, which can help these children acquire higher educational attainment. The trade-off would lead to an ambiguous effect of ML on fertility.

The main channel for ML's positive effects on subsequent fertility is the automatic renewal coupled with pre-birth benefits. Extending ML until the child turns one year old, along with the extra 52 days of paid leave before birth, offers the opportunity to receive ML without going back to work. Thus, to take advantage of automatic renewal, women need to give birth by the end of month 14 after the previous childbirth. Figure 10 shows that the estimate for month 14 is statistically insignificant. Perhaps, the short period makes it difficult for women to take advantage of the automatic renewal. However, pregnant women can choose to work only six hours per day for three months, without changes in their income, after which they can take 52 days off before giving birth. Consider a mother who gives birth on January 19^{th}, 1990. She is eligible for ML until January 19^{th}, 1991, after which she can benefit for almost two months of pre-birth ML if pregnant again. Therefore, to qualify for ML renewal, she would have to give birth by

[10]"quality of children" refers to the expenditure per child

June 19^{th}, 1991. Because the reduced work benefit starts five months before childbirth, women may still want to have an additional child within 17 months, avoiding full-time work between births. In Table 12, regression discontinuity and difference-in-differences estimations show a significant positive effect of 1.3 percentage-points and 1.7 percentage-points,respectively, on subsequent fertility within 17 months after the previous birth.

It may be challenging for women who work full time while having a newborn to conceive an additional child. In Figure 10, I note a significant positive effect of having an additional child in month 17. In Table 12, estimates from regression discontinuity design, using the 1992 census data, are reported in panel A, and difference-in-differences estimations using the 2002 census data are presented in panel B. These results align with findings of Lalive et al. (2009) who examine an extension of parental leave from one year to two years in Austria.

Moreover, ML is associated with improvements in depressive symptoms, physical health (Dagher, McGovern, and Dowd (2014)) and maternal mental health (Staehelin, Bertea, and Stutz (2007), Borrell, Palència, Muntaner, Urquía, Malmusi, and Campo (2014)). These would facilitate having a child sooner for mothers who have ML for the reference child.

Lastly, this policy may persuade some individuals with no children, who originally intended to wait longer to have a child, to conceive their first child earlier, which would allow them to have more time to plan for additional children. There are significant risks for maternal age greater than 35 years old. In a systematic review of the effects of advanced maternal age on maternal and child health, Khoshnood, Bouvier-Colle, Leridon, and Blondel (2008) conclude that older age among mothers poses increased risks for maternal mortality, preterm delivery, fetal growth retardation, and anomalies. Also, women who benefit from ML for the current child and for whom fertility would have been completed in the absence of the reform may decide to have another child once they experience the lower cost of having a child (Barbos and Milovanska-Farrington (2019)).

5 Conclusion

This paper assesses how the extension- from 60 days to one year- in paid maternity leave in Romania affected the subsequent fertility and mother's labor force participation. The unexpected policy implementation generates a quasi-natural experiment that allows me to estimate unbiased coefficients. I use a regression discontinuity design and the 1992 Romanian census, with the date of birth as an assignment to treatment, the cutoff being the day that the policy was implemented: January 19, 1990.

The sample is restricted to mothers who gave birth within 60 days before or after the reform was enacted and I study their subsequent fertility over 21 months. I find approximately 2.5 percentage-points increase in fertility for mothers who benefit from ML, with more substantial effects among younger and more educated mothers. Analyzing the mother's employment in 1992, almost two years after birth, yields insignificant negative effects. This is similar to Waldfogel (1999), who studies shorter periods of parental leave in the United States. To estimate a long-run effect of the policy, I use a difference-in-differences estimation strategy and the 2002 Romanian census. I show that the policy's impact is persistent for up to seven years. The effect of ML likely caused a life-time fertility impact.

The mechanism behind the increase in subsequent fertility is the automatic renewal of ML, which is offered to new mothers who are still on leave from a previous child, coupled with the benefits before childbirth. Mothers who gave birth within 17 months after the previous birth can work fewer hours before using a new ML. Another mechanism that deserves to be investigated further is maternal stress and postpartum depression. I could not analyze this channel due to data limitations, but it is likely that not having to work while taking care of a newborn would improve the mother's mental state (Staehelin et al. (2007), Borrell et al. (2014)). An exciting avenue for future research would be to examine ML's effect on children's health and educational attainment in the cases in which mothers spend more time with their children.

My findings show that ML, which aims to reduce the opportunity cost of having children and facilitates both child-rearing and mother's career, increases subsequent fertility. Lalive et al. (2009) argue that an increase in subsequent fertility translates into higher completed fertility because women avoid adverse shocks to marriage or health. From a policy perspective, higher fertility rates in developed countries increases tax revenues, making pensions and healthcare economically viable.

Table 1: Descriptive Statistics of Fertility by Education and Age

Variable	Births	Women	Fertility rate
Panel A. Fertility for 1989			
Women's Age			
Age 15-19	5,638	144,819	0.038
Age 20-24	21,003	138,249	0.151
Age 25-29	12,558	88,288	0.142
Age 30-34	8,871	108,752	0.081
Age 35-39	4,563	113,889	0.040
Age 40-44	1,534	105,065	0.014
Total	54,167	699,062	**2.330**
Women's Education			
Primary Education	29,956	353,487	0.085
Secondary Education	22,118	311,073	0.071
Tertiary Education	2,093	34,502	0.061

Variable	Births	Women	Fertility rate
Panel B. Fertility for 1990			
Women's Age			
Age 15-19	4,773	147,864	0.032
Age 20-24	19,161	149,904	0.128
Age 25-29	9,852	86,368	0.114
Age 30-34	6,187	103,588	0.060
Age 35-39	3,159	115,715	0.027
Age 40-44	1,135	107,321	0.011
Total	44,267	710,760	**1.859**
Women's Education			
Primary Education	23,399	370,618	0.063
Secondary Education	19,245	307,000	0.063
Tertiary Education	1,623	33,142	0.049

Note: Data represent 15% sample from the 1992 Romanian census.

Table 2: Descriptive Statistics. 1992 Romanian census

Variable	Observations	Mean	Std. Dev.	Min	Max
Panel A. Mother's Characteristics					
Education					
Relative frequency of Primary Education	8,997	54.01	-	0	1
Relative frequency of Secondary Education	7,029	42.19	-	0	1
Relative frequency of Tertiary Education	632	0.04	-	0	1
Age Category					
Age less than 25 years old	7,180	22.07	1.75	14	24
At Least 25 years old	9,478	31.31	5.08	25	53
Age	16,658	27.33	6.08	14	53
Number of children					
Relative frequencies of one child	4,676	28.07	-	0	1
Relative frequencies of two children	5,406	32.45	-	0	1
Relative frequencies of three children	2,655	15.94	-	0	1
Relative frequencies of four children	1,506	9.04	-	0	1
Relative frequencies of five plus children	2,415	14.50	-	0	1
Panel B. Mothers's Characteristics by Group	Control		Treatment		Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	P-value
Demographics					
Age 15-19	18.35	0.87	18.39	0.87	0.58
Age 20-24	22.49	1.32	22.44	1.29	0.12
Age 25-29	26.82	1.39	26.85	1.41	0.59
Age 30-34	31.86	1.41	31.84	1.40	0.69
Age 35-39	36.72	1.39	36.70	1.43	0.71
Age 40-44	41.36	1.23	41.45	1.26	0.38
Age over 44	47.50	2.50	46.79	2.50	0.12
Schooling Degree	1.50	0.57	1.50	0.57	0.82
Number of children	2.71	1.91	2.67	1.88	0.30
Marital status	0.97	0.16	0.97	0.17	0.15
Dependent Variables					
Additional child	0.11	0.32	0.12	0.33	0.19
Employment	0.59	0.49	0.59	0.49	0.65
Observations	8,319		8,339		

Note: Data represent 15% sample from the 1992 Romanian census. Sample for analysis is restricted to mothers who gave birth within 60 days before or after January 19, 1990. Education is a categorical variable that was assigned the following values: 1 for primary education, 2 for secondary education, and 3 for tertiary education.

Table 3: Local Linear Polynomial Density Estimator

McCrary (2008)		Cattaneo et al (2019)	
Coefficient	0.03	Coefficient	-0.39
P- value	0.21	P- value	0.69
Bin size	2.28	Bandwidth left	23
Bandwidth	16.90	Bandwidth right	23

Note: Local linear polynomial density estimator of the discontinuity at the threshold using two different tests. Sample for the McCrary test is one year before and after the policy implementation date, while for the Cattaneo test, it is two months before and after the same date.

Table 4: Results for Other Characteristics

	Mother						Father
VARIABLES	Age	Education	Marital Status	Sector	Age at First Birth	Occupation	Age
RDD Effect	0.339	0.000	0.004	0.004	0.164	-3.829	0.145
	(0.206)	(0.006)	(0.006)	(0.016)	(0.102)	(5.788)	(0.122)
Observations	16,658	16,658	16,246	9,587	16,658	16,473	15,588

	Father	Child				Household	
VARIABLES	Education	Nationality	Mother tongue	Gender	Religion	# of supported people	Home Ownership
RDD Effect	0.001	0.004	0.006	-0.010	-0.003	-0.043	-0.008
	(0.006)	(0.008)	(0.008)	(0.016)	(0.009)	(0.027)	(0.011)
Observations	15,588	16,658	16,658	16,658	16,658	16,658	16,658

Note: The table presents estimates from the main equation: $Y_i = \beta_0 + \beta_1 T_i + \beta_2 f_1(d) + \beta_3 f_2(d)) * T_i + \beta_4 X_i + \epsilon_i$, where $f_i(d)$ is the value of a linear polynomial in the running variable d (day). Each coefficient comes from a different regression. Robust standard errors are clustered at the day of birth. The dependent variable is given in column header. Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 5: The Effect of Maternity Leave on Subsequent Fertility

Panel A. Linear Polynomial

DV: Additional Child	14 days	21 days	28 days	35 days	42 days	49 days	56 days	CCT	IK	Donut (-7 Days)
RDD Effect	0.047**	0.029*	0.028**	0.027**	0.025**	0.020**	0.025***	0.039*	0.022**	0.020**
	(0.021)	(0.017)	(0.013)	(0.011)	(0.011)	(0.010)	(0.009)	(0.024)	(0.010)	(0.010)
Bandwith										
Observations	3,748	5,657	7,747	9,715	11,643	13,688	15,630	16,658	16,658	14,983

Panel B. Quadratic Polynomial

DV: Additional Child	14 days	21 days	28 days	35 days	42 days	49 days	56 days	CCT	IK	Donut (-7 Days)
RDD Effect	0.0423	0.0429**	0.0424*	0.0339*	0.0359**	0.0379**	0.0276*	-	-	0.027*
	(0.030)	(0.021)	(0.022)	(0.020)	(0.017)	(0.015)	(0.015)	-	-	(0.015)
Observations	3,748	5,657	7,747	9,715	11,643	13,688	15,630			14,983

Note: Each coefficient comes from a different regression. The sample includes mothers who gave birth in a specific window, specified in the column header, around January 19, 1990. Controls include indicators for the mother's level of education and the day of the week, third-order polynomial in age. $f_i(d)$ is the value of a linear polynomial, in panel A, and quadratic polynomial in panel B, in the running variable d (day). The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. The "Donut" column excludes 7 days before and after the reform. The columns CCT and IK show estimates based on a data-driven approach. Robust standard errors are clustered at the day of birth. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 6: Heterogeneity by Maternal Age and Education

Window	14 days	28 days	35 days	42 days	49 days	60 days
Panel A. By Maternal Age						
Under 25 Years						
RDD Effect	0.072**	0.065***	0.048**	0.045**	0.036**	0.055**
	(0.030)	(0.020)	(0.019)	(0.017)	(0.016)	(0.023)
Observations	1,623	3,358	4,193	5,028	5,910	7,180
At Least 25 Years						
RDD Effect	0.029	0.01	0.011	0.011	0.008	0.003
	(0.025)	(0.017)	(0.016)	(0.014)	(0.014)	(0.019)
Observations	2,125	4,389	5,522	6,615	7,778	8,875
Panel B. By Mother's Level of Education						
Primary Education						
RDD Effect	0.036	0.011	0.009	0.014	0.011	0.011
	(0.029)	(0.018)	(0.015)	(0.014)	(0.013)	(0.018)
Observations	2,594	5,311	6,670	8,003	9,392	11,362
Secondary and Tertiary Education						
RDD Effect	0.063**	0.063***	0.061***	0.047***	0.037**	0.056***
	(0.024)	(0.018)	(0.017)	(0.016)	(0.015)	(0.021)
Observations	1,154	2,436	3,045	3,640	4,296	5,296
Linear Trend	Y	Y	Y	Y	Y	Y
Quadratic Trend	N	N	N	N	N	Y

Note: Each coefficient comes from a different regression. The sample includes mothers who gave birth in a specific window, specified in the column header, around January 19, 1990. Controls include indicators for mother's level of education, third- order polynomial in age and day of the week fixed effects for childbirth. The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 7: The Effect of Maternity Leave on Subsequent Fertility by Birth Order

Window	14 days	28 days	35 days	42 days	49 days	60 days
Second Child						
RDD Effect	0.074**	0.069***	0.043**	0.046**	0.038***	0.057**
	(0.033)	(0.023)	(0.022)	(0.020)	(0.019)	(0.025)
Observations	1,334	2,724	3,416	4,111	4,834	5,907
Third Child						
RDD Effect	0.069***	0.041**	0.034	0.012	0.012	0.032*
	(0.018)	(0.018)	(0.014)	(0.016)	(0.015)	(0.019)
Observations	1,105	2,290	2,841	3,350	3,937	4,828
Fourth Child or Higher Order						
RDD Effect	-0.004	-0.018	0.003	-0.012	-0.024	-0.007
	(0.036)	(0.024)	(0.022)	(0.022)	(0.021)	(0.026)
Observations	1,309	2,733	3,458	4,182	4,917	5,923
Linear Trend	Y	Y	Y	Y	Y	Y
Quadratic Trend	N	N	N	N	N	Y

Note: Each coefficient comes from a different regression. The sample includes mothers who had a child in a specific window, specified in the column header, around January 19, 1990. Controls include indicators for mother's level of education, third- order polynomial in age and day of the week fixed effects for childbirth. The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 8: The Effect of Maternity Leave on Labor Force Participation

Panel A. Linear Polynomial									
DV: Employment	14 days	21 days	28 days	35 days	42 days	49 days	56 days	CCT	Donut (-7 Days)
RDD Effect	-0.031	-0.006	0.013	0.001	-0.001	-0.010	-0.012	-0.046	0.003
	(0.029)	(0.023)	(0.022)	(0.019)	(0.018)	(0.016)	(0.015)	(0.036)	(0.019)
								14.59	
Observations	3,748	5,657	7,747	9,715	11,643	13,688	15,630	16,658	14,983

Panel B. Quadratic Polynomial									
DV: Employment	14 days	21 days	28 days	35 days	42 days	49 days	56 days	CCT	Donut (-7 Days)
	-0.092*	-0.044	-0.035	-0.005	-0.007	0.005	0.001	-	0.033
RDD Effect	(0.046)	(0.035)	(0.030)	(0.027)	(0.024)	(0.023)	(0.022)	-	(0.039)
Observations	3,748	5,657	7,747	9,715	11,643	13,688	15,630		14,983

Note: Each coefficient comes from a different regression. The sample includes mothers who gave birth in a specific window, specified in the column header, around January 19, 1990. Controls include indicators for the mother's level of education and the day of the week, third-order polynomial in age. $f_i(d)$ is the value of a polynomial (specified by Linear Trend and Quadratic Trend rows) in the running variable d (day). The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. The "Donut" column excludes 7 days before and after the reform. The column CCT shows an estimate based on a data-driven approach. Robust standard errors are clustered at the day of birth. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 9: The Effect of Maternity Leave on Mother's Labor Force Participation by Skill Level

DV: Employment	14 days	21 days	28 days	35 days	42 days	49 days	60 days
Panel A: Elementary Skill							
RDD Effect	-0.119*	-0.007	0.013	0.055	-0.013	-0.020	0.001
	(0.067)	(0.065)	(0.056)	(0.062)	(0.062)	(0.055)	(0.067)
Observations	151	213	297	392	480	573	685
Panel B: Intermediate Skill							
RDD Effect	0.003	-0.002	0.010	-0.009	-0.012	-0.006	0.000
	(0.024)	(0.017)	(0.016)	(0.013)	(0.012)	(0.011)	(0.014)
Observations	1,830	2,737	3,784	4,732	5,660	6,659	8,152
Panel C: High Skill							
RDD Effect	-0.041	-0.029	-0.019	-0.0408*	-0.027	-0.040*	-0.037
	(0.032)	(0.029)	(0.025)	(0.024)	(0.023)	(0.022)	(0.027)
Observations	347	537	737	951	1,133	1,319	1,635
Linear Trend	Y	Y	Y	Y	Y	Y	Y
Quadratic Trend	N	N	N	N	N	N	Y

Note: Each coefficient comes from a different regression. The sample includes mothers who gave birth in a specific window, specified in the column header, around January 19, 1990. Controls include indicators for mother's level of education and for day of the week; and third-order polynomial in age. The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 10: The Effect of Maternity Leave on Subsequent Fertility using DID Estimation

DV: Additional child	*Cutoff 1990, 19th of January*	*Placebo Cutoff 1988, 19th of January*	*Placebo Cutoff 1987, 19th of January*
Treatment	-0.050	-0.015	-0.035
	(0.006)	(0.005)	(0.006)
After	-0.008	0.001	-0.003
	(0.007)	(0.009)	(0.010)
Treatment * After	0.021***	0.011	0.001
	(0.007)	(0.008)	(0.008)
Observations	31,274	32,573	31,161

Note: Each coefficient comes from a different regression using a difference-in-differences approach. The dependent variable is the probability of giving birth to an additional child within 21 months (column 1). The sample includes mothers who gave birth within 60 days before or after the reform, around January 19, 1990, as the treatment group, while for the control group, I use mothers who gave birth in the same months, but 1 year earlier. Placebo cutoffs are 19of January, 1988 and 1987. Controls include the parental level of education, father's age, third-order polynomial in mother's age, mother's ethnicity (three dummies), indicators for urban and regions of the child's birthplace, dummies for multiple births, and child's sex. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 11: Maternity Leave Effect on Subsequent Fertility using Placebo Cutoffs

Panel A: Placebo Cutoff 19^{th} *of January, 1989*								
DV: Additional Child	14 days	21 days	28 days	35 days	42 days	49 days	56 days	CCT
RDD Effect	0.002	0.006	0.006	-0.004	0.006	0.007	-0.011	0.004
	(0.020)	(0.017)	(0.017)	(0.012)	(0.018)	(0.016)	(0.015)	(0.024)
Linear Trend	Y	Y	Y	Y	Y	Y	Y	Y
Quadratic Trend	N	N	N	N	N	Y	Y	Y
Bandwidth								14.820
Observations	4,082	6,005	6,005	9,937	11,762	13,694	15,719	16,846

Panel B: Placebo Cutoff 19^{th} *of January, 1991*								
DV: Additional Child	14 days	21 days	28 days	35 days	42 days	49 days	56 days	CCT
RDD Effect	-0.005	-0.008	-0.006	-0.007	-0.003	-0.002	-0.003	-0.007
	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)
Linear Trend	Y	Y	Y	Y	Y	Y	Y	Y
Quadratic Trend	N	N	N	N	N	Y	Y	Y
Bandwidth								21.126
Observations	2,981	4,502	5,961	7,341	8,803	10,284	11,793	12,623

Note: Each coefficient comes from a different regression. The sample includes mothers who gave birth in a specific window, specified in the column header, around January 19^{th}, 1989 for top panel, and January 19^{th}, 1991 bottom panel. Controls include indicators for mother's level of education, third- order polynomial in age and day of the week fixed effects for childbirth. The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 12: The Impact of Maternity Leave on Subsequent Fertility. Robustness Check

Panel A: 1992 Census Data- Regresssion Discontinuity

DV: Additional Child	11 months	12 months	13 months	14 months	15 months	16 months	17 months	18 months	19 months	20 months	21 months
RDD Estimate	0.000	0.001	0.006	0.008	0.006	0.006	0.0132*	0.0132*	0.0151*	0.0171**	0.0205**
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
Observations	16,658	16,658	16,658	16,658	16,658	16,658	16,658	16,658	16,658	16,658	16,658

Panel B: 2002 Census Data- Differences in Differences

DV: Additional Child	11 months	12 months	13 months	14 months	15 months	16 months	17 months	18 months	19 months	20 months	21 months
Treatment	-0.00489***	-0.0119***	-0.0182***	-0.0256***	-0.0331***	-0.0399***	-0.0494***	-0.0569***	-0.0630***	-0.0665***	-0.0651***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)
After	-0.00339**	-0.00367*	-0.005	-0.00917***	-0.0142***	-0.0182***	-0.0245***	-0.0296***	-0.0335***	-0.0373***	-0.0364***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
DID Estimate	-0.002	0.000	-0.001	0.002	0.00859*	0.0110**	0.0173**	0.0249***	0.0262***	0.0290***	0.0258***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
Observations	26,018	26,018	26,018	26,018	26,018	26,018	26,018	26,018	26,018	26,018	26,018

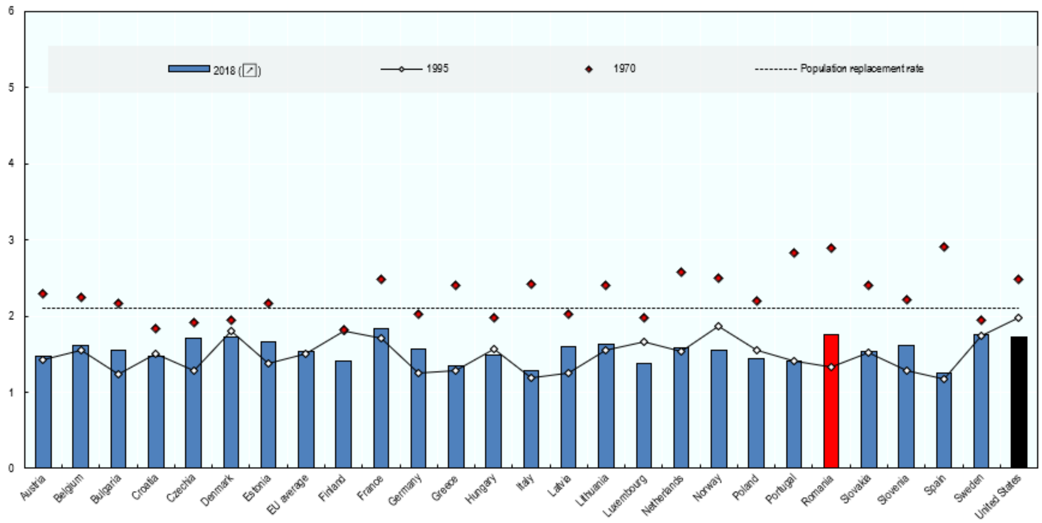
Each coefficient comes from a different regression. The sample includes mothers who gave birth within 60 days before or after January 19th, 1990 and the columns header represent the months after the previous birth.

Panel A: Regression discontinuity using 15% of 1992 census data, controls include indicators for mother's level of education and day of the week; and third-order polynomial in age. The linear trend in date of birth is interacted with the policy indicator. Robust standard errors are clustered at the day of birth.

Panel B: Differences in differences using 10% of 2002 census data, controls include the parental level of education, father's age, third-order polynomial in mother's age, mother's ethnicity (three dummies), dummies for multiple births, and child's sex. Robust standard errors are clustered at the month of birth.

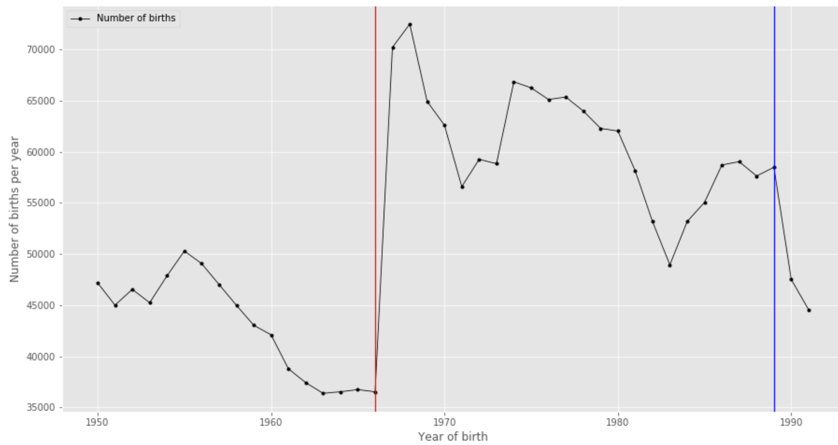
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Figure 1: Fertility Rates



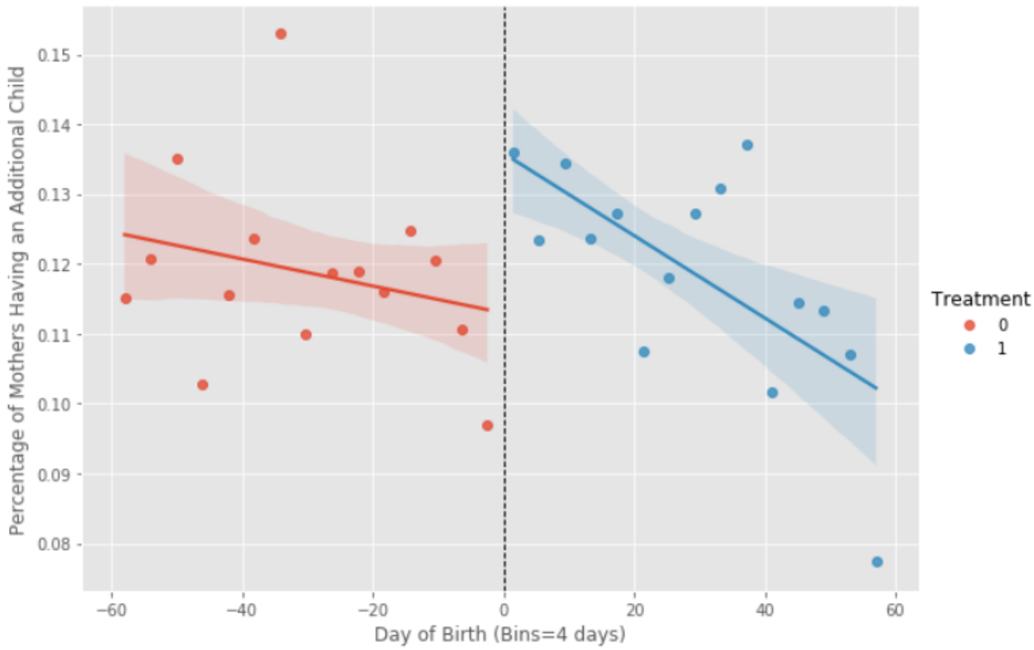
Fertility rates for European Union countries and the United States of America. Source: OECD Family Database

Figure 2: The Number of Births per Year



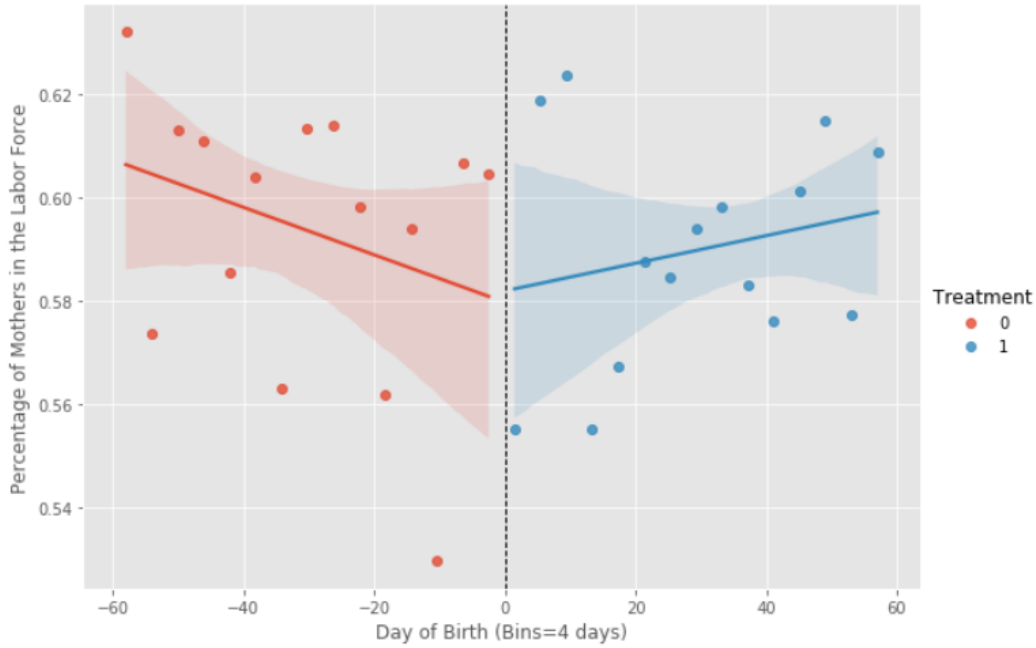
Pro-natalist policies characterize the period between red (1966) and blue vertical (end of 1989) lines. Source: Calculated by the author using 15% sample from the 1992 Romanian census

Figure 3: Linear Fit for the Subsequent Fertility



The lines are linear fit, and the circles represent the averages within each bin. The Y-axis represents the percentage of women who have an additional child within 21 months. The day of the reform is normalized to 0, and the shaded areas are 95% confidence intervals.

Figure 4: Linear Fit for the Mother's Labor Force Participation



The lines are linear fit, and the circles represent the averages within each bin. The Y-axis represents the percentage of women employed two years after the reform. The day of the reform is normalized to 0, and the shaded areas are 95% confidence intervals.

Figure 5: Time-line of the Reform Implementation and Data Collection

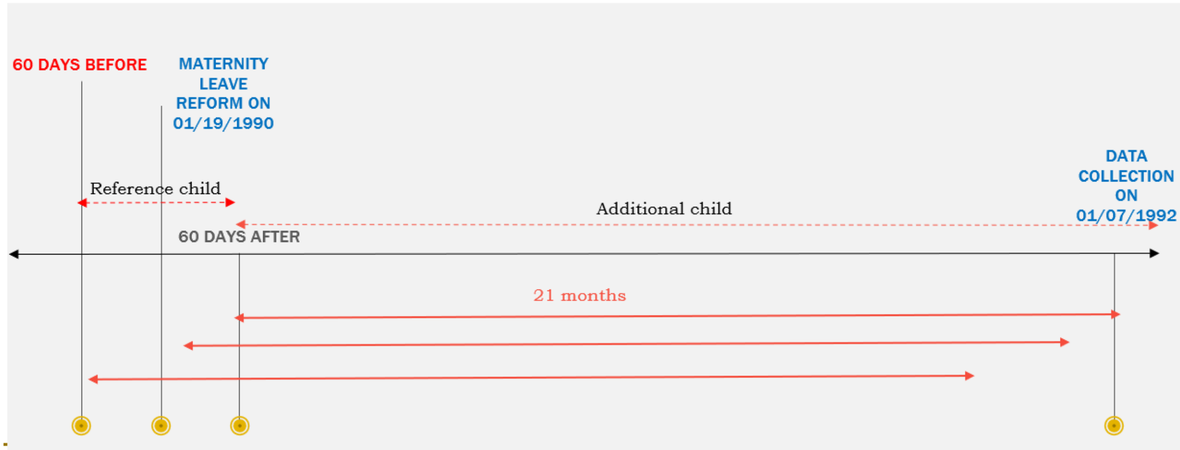
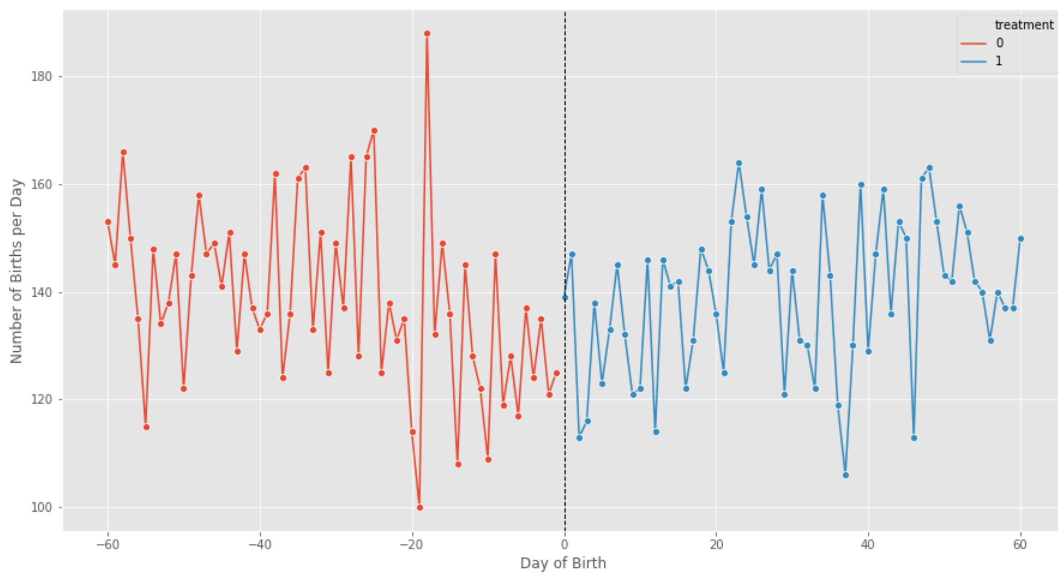
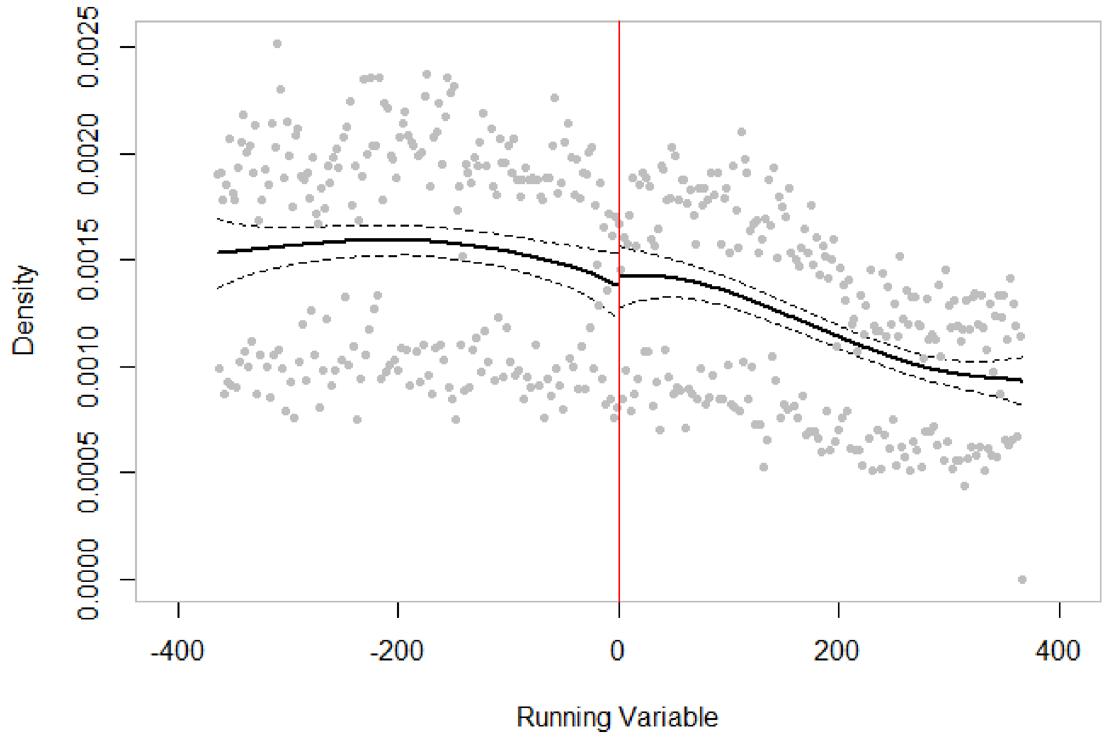


Figure 6: The Number of Births per Day



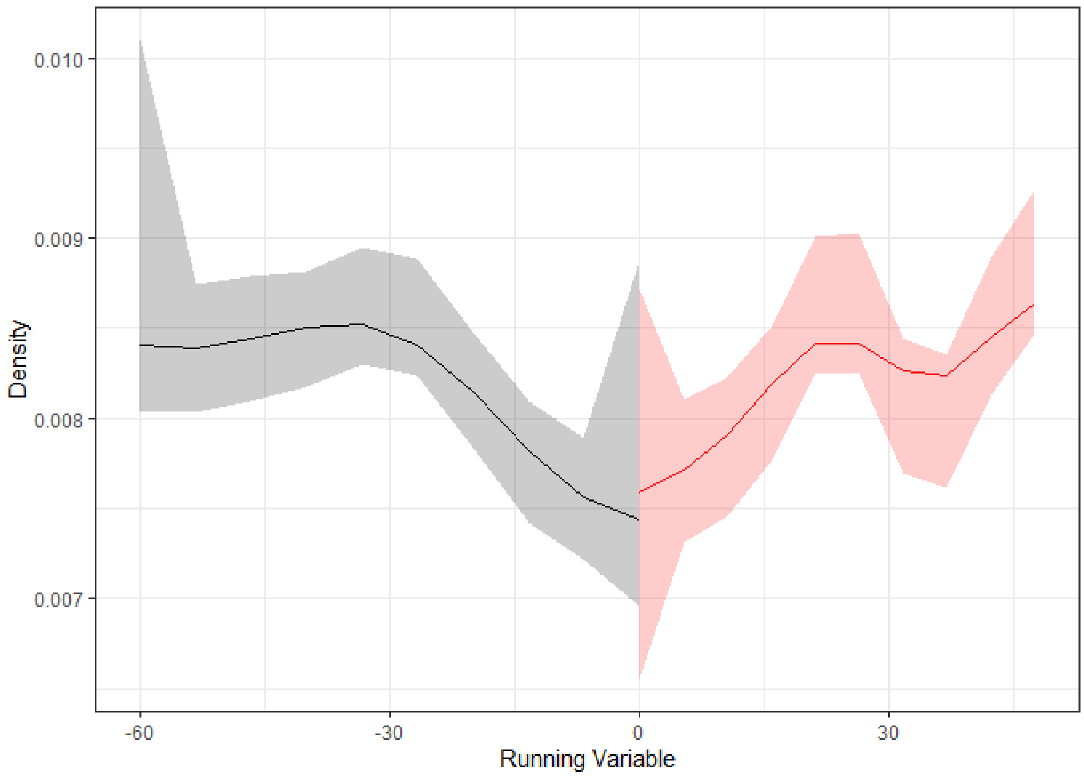
The number of births per day, around the reform date, which is normalized to 0.

Figure 7: Local Linear Estimator- McCrary



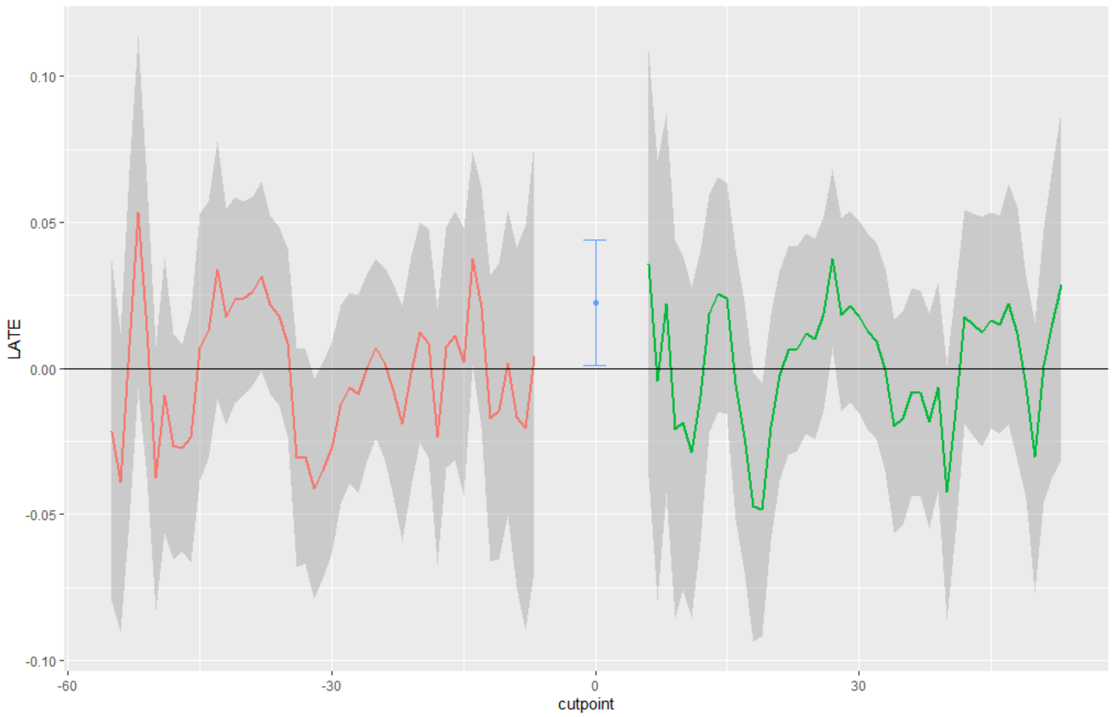
It computes equally spaced bins of the running variable (day of birth), and frequency counts are calculated within those bins. These frequency counts are then used as the dependent variable and midpoint of the bins as the independent variable in a local linear smoothing of the histogram, which is conducted separately on each side of the threshold. Each gray dot represents the number of births in a bin, and the solid black lines show the two local linear smoothings of the histogram with the corresponding 95% confidence intervals. The number of births per day, around the reform date, which is normalized to 0.

Figure 8: Local Linear Estimator- Cattaneo



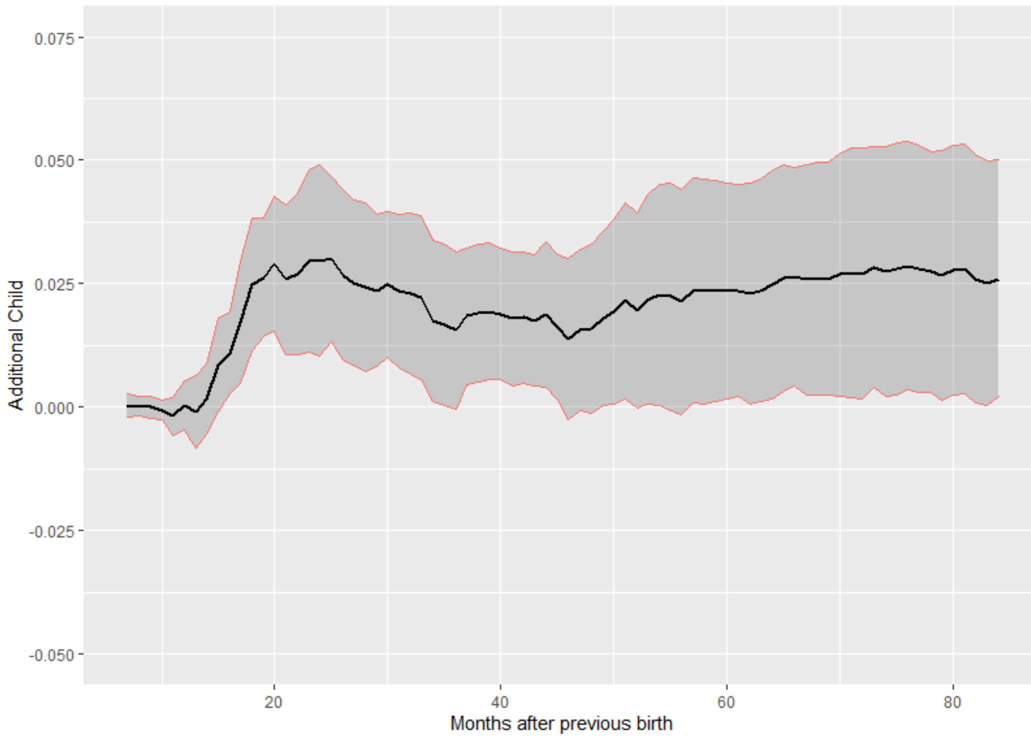
Local Linear Estimator- Cattaneo et al. (2019). This method does not require the pre-binning of data, and it uses a kernel-based density estimator employing local polynomial methods.

Figure 9: Placebo Cutoffs. Local Linear Estimation



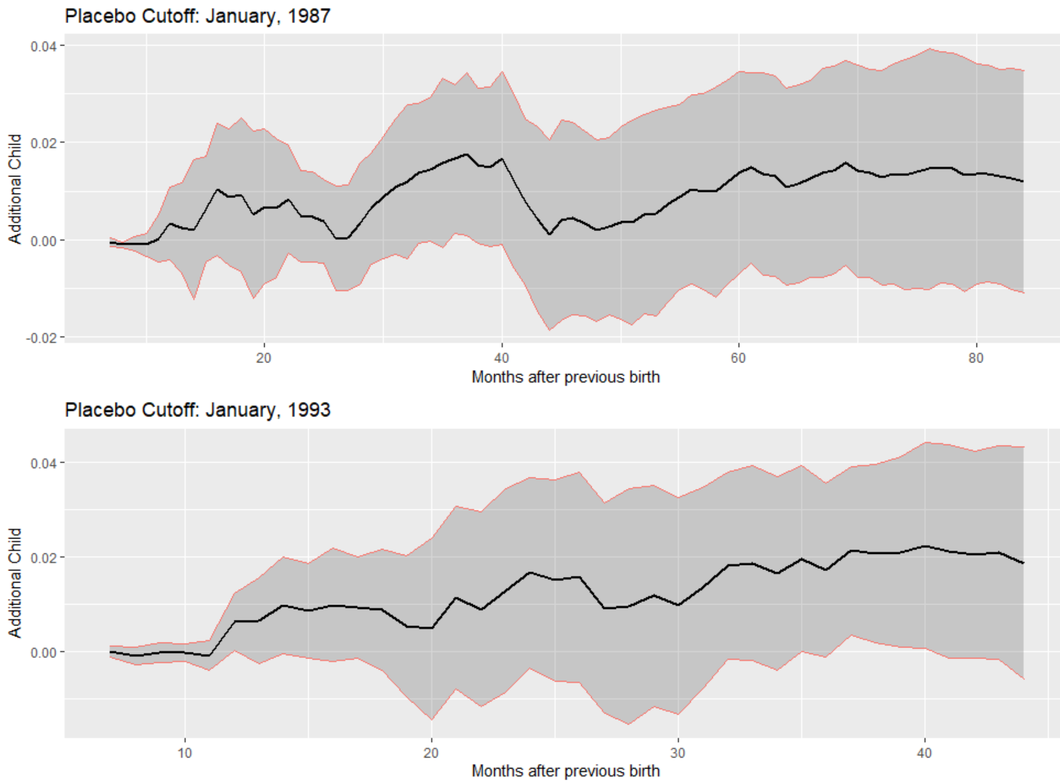
Reestimate the ML policy effect on placebo cutoffs using local linear estimation. The blue dot represents policy effect, effects at earlier cutoff in red, and effects at later cutoffs in green. The 90% confidence intervals bound all estimates. Data: 1992 Romanian census.

Figure 10: Long Run Effect of Paid Maternity Leave on Fertility



Long-Run Effect of paid maternity leave on the cumulative probability of having a next child within 7 to 84 months after a previous birth. The black line represents coefficients from the difference-in-differences approach, while the gray area shows 95 % confidence intervals. Data: 2002 Romanian census.

Figure 11: Long Run Effect of Paid Maternity Leave on Fertility using Placebo Cutoffs



Long-Run effect of paid maternity leave on the cumulative probability of having a next child within 7 to 84 months after a previous birth using placebo cutoffs. The black line represents coefficients from the difference-in-differences approach, while the gray area shows 95 % confidence intervals. Data: 2002 Romanian census.

Appendices

Table A1: The Effect of Maternity Leave on Subsequent Fertility

Panel A. Linear Polynomial							
DV: Additional Child	14 days	21 days	28 days	35 days	42 days	49 days	56 days
RDD Effect	0.047**	0.029*	0.028*	0.027**	0.025**	0.020*	0.025**
	(0.022)	(0.017)	(0.015)	(0.014)	(0.012)	(0.011)	(0.011)
Observations	3,748	5,657	7,747	9,715	11,643	13,688	15,630

Panel B. Quadratic Polynomial							
DV: Additional Child	14 days	21 days	28 days	35 days	42 days	49 days	56 days
RDD Effect	0.042	0.043*	0.042*	0.043**	0.036**	0.038**	0.028*
	(0.033)	(0.026)	(0.022)	(0.020)	(0.018)	(0.017)	(0.016)
Observations	3,748	5,657	7,747	9,715	11,643	13,688	15,630

Note: Each coefficient comes from a different regression. The sample includes mothers who gave birth in a specific window, specified in the column header, around January 19, 1990. Controls include indicators for the mother's level of education and the day of the week, third-order polynomial in age. $f_i(d)$ is the value of a linear polynomial, in panel A, and quadratic polynomial in panel B, in the running variable d (day). The linear (and quadratic) trend in the date of birth is interacted with the policy indicator. Robust standard errors (Kolesár and Rothe (2018)).
Data: 1992 Romanian census.
Significance levels: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

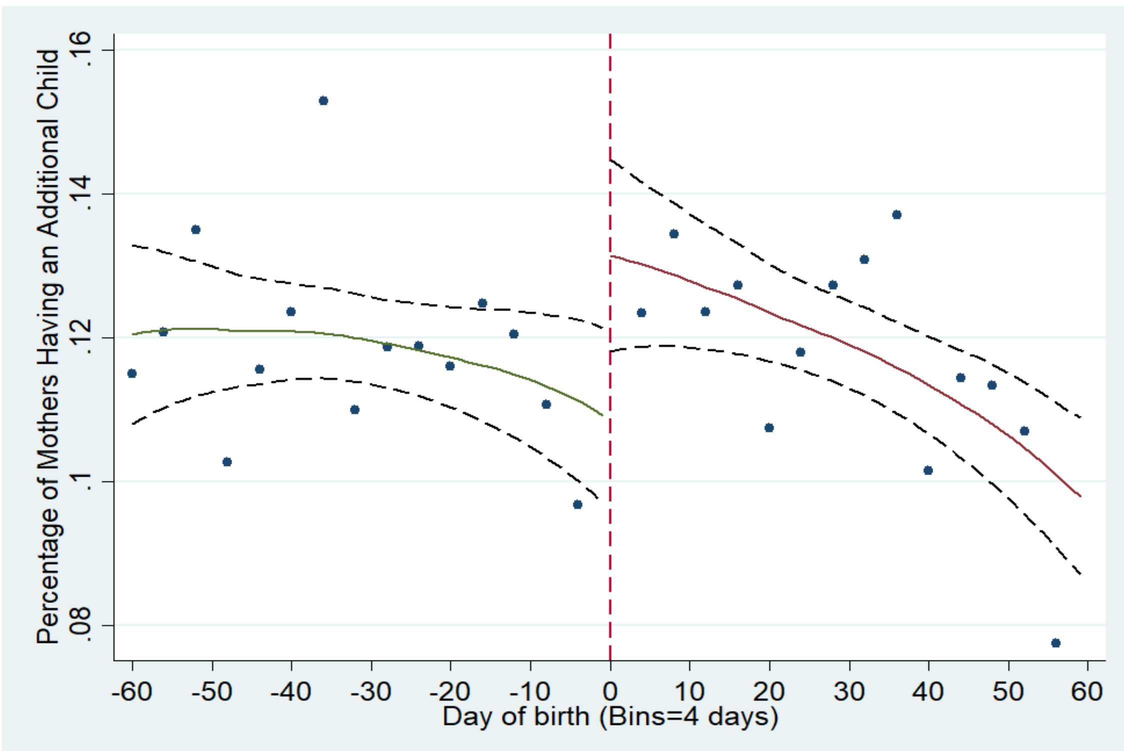


Figure A1: The solid lines are local linear fit, and the circles represent the averages within each bin. The Y-axis represents the percentage of women who have an additional child within 21 months. The day of the reform is normalized to 0, and the dotted lines are 95% confidence intervals. Data: 1992 Romanian census.

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