The Effect of Russia’s Maternity Capital Program on Birth Rates and Real Earnings

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I. Introduction

From the late 1980s to the year 2000, Russia's fertility rate plummeted. The country recorded a total fertility rate (TFR) of 2.2% in 1987 and an astonishing 1.195% in 2000. The dramatic decrease in fertility can be attributed mostly to the dissolution of the Soviet Union from 1988 to 1991. Following this collapse, the newly independent Russian state found itself in a disarray, economically and politically to say the least. With much turmoil and many unknowns for what the future may bring, the number of births saw a steady decline for each passing year. As fertility fell, Russia's population naturally aged, hinting at a disaster in the making - fertility rates below replacement levels causing a dying population that promised little economic security for Russia's future.

To counteract, or lessen the effect, of this fertility issue, Russian leaders devised multiple avenues that could be taken. For the purpose of this paper, only one main approach will be discussed, and that is the Maternity Capital Program (MCP). The MCP was implemented in 2007 and is a pro-natalist policy that provides monetary assistance, or maternity capital (MC), to women who give birth to an additional child. The financial support was a one-time subsidy of 250,000 rubles, or approximately $10,000, and was distributed to *mothers* - women who already had at least 1 child - if they had an additional child. Thus, the focus of this program was to increase births through the channel of family size.

It seemed questionable as to why the MCP only included women who had children; why not include all women to stimulate fertility even more? Upon further investigation and knowledge of human behavior, a common trend became apparent - the decision to have the first child is more significant, broadly speaking, than the decision to grow one's family. A substantial change in livelihood, including finances, travel, work, living conditions, and so forth, may transpire to welcome a newborn into the world. In regards to having an *additional* child, much of these burdens have already been confronted and resolved, disregarding finances since having an additional child will unmistakably impact this factor. Thus, the MCP emphasizes increased births for mothers, because many of these individuals have already undergone much of the more difficult changes.

MC is distributed in the form of a certificate entitling its holder to receive the allotted amount, as mentioned previously, of approximately $10,000. Guidelines of this policy include that the child must be at least 3 years of age in order for the certificates to be claimed. Also, the recipient can not spend this money aimlessly, rather only a limited number of options for ways of spending are outlined. In general, those receiving this money can spend it on: "1) acquiring housing, 2) paying for children's education, or 3) investing in the mother's retirement fund. [Also,] women can apply for MC funds only once in their lifetimes" (Slonimczyk and Yurko, 2014). Despite issuing over four million MC certificates, many holders are in no hurry to claim and spend the money. As noted by Slonimczyk and Yurko in their discussion paper, only 37.4% of the issued certificates have been claimed - 32.9% fully claimed - and of these claimed MC certificates, an overwhelming amount (+90%) have been used on acquiring and or improving housing conditions.

With knowing some general information about Russia's MCP, whether the program was effective in increasing fertility can be focused on. Using the Russia Longitudinal Monitoring Survey, 1994-2019, a difference-in-differences (DID) empirical model method will be used to determine the effectiveness of the MCP regarding fertility and the decision to have an additional child.

This paper is structured as follows. The next section (II) discusses the initial DID set-up. Here, variables will be introduced and definitions will be provided. Section III contains information specific to pre-treatment, or pre-policy implementation, for both the control and treatment groups. Section IV outlines the DID empirical model and discusses how the policy effect is estimated. Section V covers an Oaxaca-Blinder decomposition of the between-group gap in the log of real earnings. Lastly, section VI summarizes the research results, possible complications of the model, and key takeaways.

II. Difference-In-Differences Set-Up

The decision to have a child or to not have a child is a binary measurable outcome that will be investigated. Real earnings, a continuous measurable outcome, will also be analyzed. Other possible outcomes that may be researched will be further discussed in Appendix C and Appendix D - employment and hours of work, respectively. To use the DID method, two groups must be generated. These groups are often referred to as the treatment group, or the group that is being affected, and the control group, or the group that remains untouched. For the purpose of this paper, the treatment group will capture females between the ages of 15 and 45 who have at least one child and the control group will be composed of females between the ages of 15 and 45 who do not have children. Data on the number of children a female has is only available beginning in the year 2004. Since the policy was implemented in 2007, the years 2004 to 2006 which were prior to the policy's implementation, will be used as the pre-policy time period (t_0). Due to the delay in conceiving and birth, and the delay in eligibility to claim MC because of the child's age, as well as the prior planning for having a child, the post-policy year chosen includes the year range 2014 to 2016. Two binary variables are created for the treatment vs. control groups (*treat*) and for before vs. after the policy (*post*).

Tabulating the data, the share of the treatment group can be observed in Table 1. Both before and after the policy is implemented, the frequency of females with at least one child is larger than the frequency of those without children. The percent of women who do not have children decreases as the share of women with children increases in regards to before and after policy implementation; 36.76% to 33.06% and 63.24% to 66.94%, respectively. However, both groups saw an increase in the actual observations accounted for from before to after the policy was implemented; possible immigration trends may be researched. The mean number of births, or average birth rate, for women with no children decreased from before to after policy implementation and the average birth rate for women who have at least one child increased from before to after policy implementation, as described in Table 2.

In terms of real earnings, details are provided in Table 3 and Table 4. At each percentile in the earnings distribution, an increase in real earnings is observable from before the MC policy implementation to after the MC policy implementation. The mean real earnings increased from 2860.01 rubles to 4425.18 rubles between the two time periods. There are significant differences, however represented by the large standard deviation and thus the median earnings is best to be looked at. The median earnings value increased from 2145.36 rubles to 3709.55 rubles, pre- to post-policy respectively. This potentially indicates other economic reforms presented alongside the MC policy, as well as potential aid, via the MC policy, for women allowing increased work and or support by way of the incentive that can be applied to child care and housing (i.e. relocating, etc.). Looking at specific groups and real earnings, both the treatment and control group individuals saw an increase in both mean and median real earnings.

Table 1: Estimation Samples

Period	**Control** ($women\ w/o\ children$)	**Treatment** ($women\ \geq 1\ child$)	**Total**
t_0, **Pre-Policy Observations**	3,630	6,245	9,875
%	36.76	63.24	100.00
t_1, **Post-Policy Observations**	4,199	8,501	12,700
%	33.06	66.94	100.00
Total	7,829	14,746	22,575
%	34.68	65.32	100.00

Table 2: Pre-and Post-Policy Tabulations for Birth Rate Means, Standard Deviations, and Frequencies

	Control ($women\ w/o\ children$)	**Treatment** ($women\ \geq 1\ child$)	**Total for Time Period**
Pre-Policy Tabulations			
Mean	0.07432897	0.03328817	0.04806144
Standard Deviation	0.26235065	0.17940541	0.21390934
Frequency	2906	5167	8073
Post-Policy Tabulations			
Mean	0.06466513	0.05350477	0.05711882
Standard Deviation	0.24596954	0.22505335	0.23208036
Frequency	3464	7233	10697
Total Overtime			

Tabulations			
Mean	0.06907378	0.04508065	0.05322323
Standard Deviation	0.25359947	0.2074894	0.2244843
Frequency	6370	12400	18770

Table 3: Pre-Policy Real Earnings Distribution (Rubles)

	Percentiles	Smallest Values		
1%	0	0		
5%	533.1466	0		
10%	778.6488	0	**Obs.**	5,692
25%	1340.848	0	**Sum of Wgt.**	5,692
50%	2145.357		**Mean**	2860.011
		Largest Values	**Std. Dev.**	2480.714
75%	3593.764	43338.96		
90%	5690.125	44514.55	**Variance**	6153943
95%	7370.849	61825.77	**Skewness**	2.987135
99%	12284.75	63422.6	**Kurtosis**	22.04083

Table 4: Post-Policy Real Earnings Distribution (Rubles)

	Percentiles	Smallest Values		
1%	0	0		
5%	1083.474	0		
10%	1582.74	0	**Obs.**	7,888
25%	2473.031	0	**Sum of Wgt.**	7,888

50%	3709.546		**Mean**	4425.179
		Largest Values	**Std. Dev.**	3378.042
75%	5417.37	43338.96		
90%	7742.94	44514.55	**Variance**	1.14e+07
95%	9892.123	61825.77	**Skewness**	4.233727
99%	16104.2	63422.6	**Kurtosis**	44.39968

III. Summary Statistics

The Kuznets ratio of real earnings for the two groups during the pre-treatment period allows for the discovery of possible inequality that existed before the policy was implemented and is represented by Table 5 and Table 6. From the data, females with children at the 90th percentile of the earnings distribution earn about 7.46 times more than females with children at the 10th percentile pre-treatment. Females with children at the 90th percentile of the earnings distribution earn about 5.16 times more than females with children at the 10th percentile post-treatment. Most of the divergence in earnings takes place at the lower percentiles for both groups and for both time periods. Females with children earn 2.93 times more at the 50th percentile compared to the 10th percentile and 2.55 times more at the 90th percentile compared to the 50th percentile pre-treatment, and females with children earn 2.45 times more at the 50th percentile compared to the 10th percentile and 2.11 times more at the the 90th percentile compared to the 50th percentile post-treatment. For women without children and prior to the MC policy, women earned about 6.55 times more at the 90th percentile compared to the 10th percentile. During the post-policy time period, women without children earned 3.79 times more at the 90th percentile compared to the 10th percentile. Again, more of this divergence in earnings is found at lower percentiles. Pre-policy, women without children earn 2.68 times more at the 50th percentile compared to the 10th percentile and women earn 2.45 times more at the 90th percentile compared to the 50th percentile in the earrings distribution. Post-policy, women without children earn 2.02 times more at the 50th percentile compared to the 10th percentile and earn 1.87 times more at the 90th percentile compared to the 50th percentile in the earrings distribution. Therefore, from these results, it appears that females with children experience more inequality in earnings compared to women without children both pre-and post-policy implementation.

Inequality in earnings between the two groups has been observed. It is important to also analyze all control variables for the treatment and control group during the pre-treatment time period; the unadjusted group differences exist between the groups prior to the policy. Table 7 shows the averages for each control variable observed pre-policy for both groups. It is important to note that a balancing technique was not used. Similar individuals within the treatment group were not similarly matched with those in the control group on the basis of observed characteristics; a mean bias of 24.6% and median bias of 8.5% results (see Table 7). Much of this bias is explained by differences in age and marriage status, as seen in Figure 1. Age is significantly different between groups; a p-value of essentially zero with the average age for the treatment group being almost 34 years and the average age for the control group being approximately 22 years. Thus, females with at least one child are, on average, older than females without children. All variables between the two groups are significant, indicating unadjusted group differences before the policy. Being Russian (*ethrus*), and having bad (*hlt_selhlt_4*) and very bad (*hlt_selhlt_5*) health are significant, but less so with p-values of 0.052, 0.032, and 0.059, respectively.

Table 5: Kuznet Ratios for Treatment Group, women with at least 1 child

Kuznet Type	Pre-Policy Kuznet Ratio	Post-Policy Kuznet Ratio
90/10	7.462083	5.1648
50/10	2.927738	2.45128
90/50	2.548754	2.106981

Table 6: Kuznet Ratios for Control Group, women without children

Kuznet Type	Pre-Policy Kuznet Ratio	Post-Policy Kuznet Ratio
90/10	6.545119	3.785065
50/10	2.676484	2.021719
90/50	2.445416	1.872201

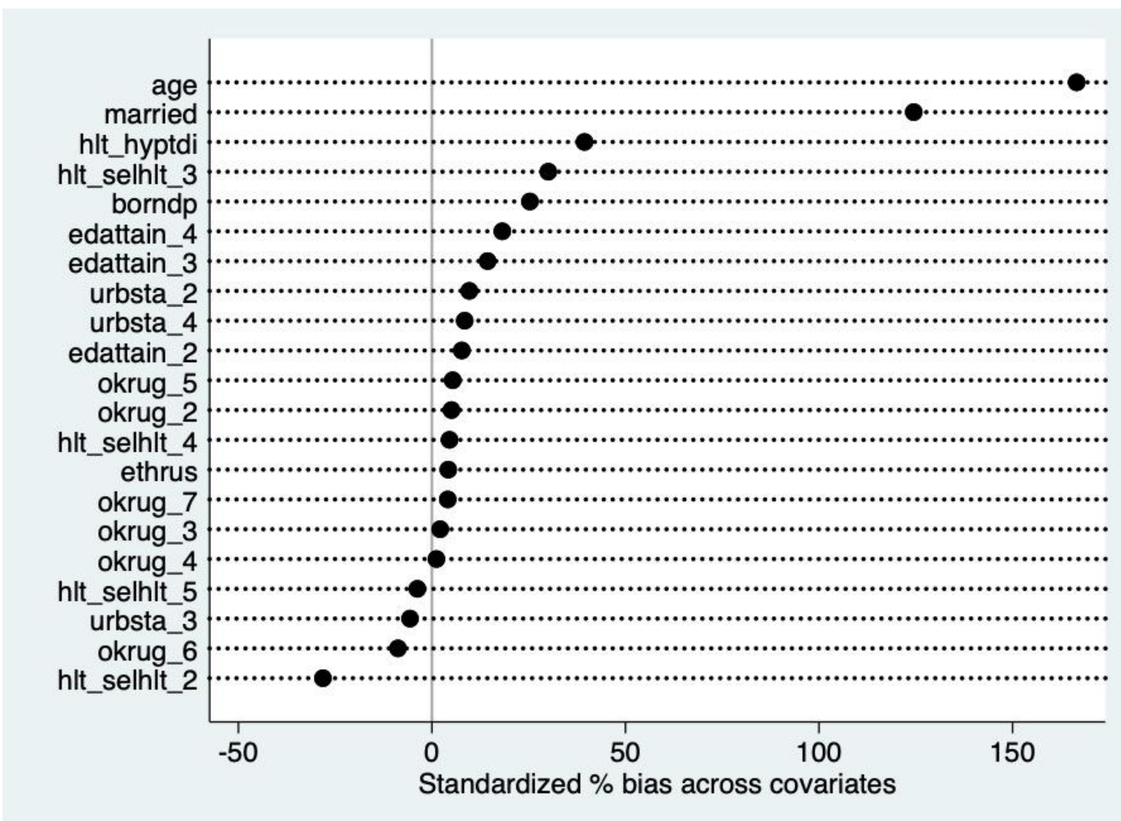
Table 7:T-test for Differences in Groups, Pre-Policy

	Mean			**t-test**			
Variable	**Treated**	**Control**	**%bias**	***t***	$p > \|t\|$	**V(T)/V(C)**	
age	33.656	22.345	166.6	79.07	0.000	1.15*	
married	.65672	.13935	124.5	57.32	0.000	.	
Is Russian	.86466	.84991	4.2	1.95	0.052	.	

Born elsewhere	.46222	.33918	25.3	11.99	0.000	1.11*	
Education, secondary completed	.36003	.32342	7.7	3.69	0.000	.	
Education, associate degree	.32239	.2573	14.4	6.83	0.000	.	
Education, university completed	.23158	.15978	18.2	8.55	0.000	.	
Urban, other city	.29015	.24738	9.7	4.60	0.000	.	
Urban, township	.0562	.06997	-5.7	-2.75	0.006	.	
Urban, village	.26421	.22782	8.5	4.02	0.000	.	
Region, North West	.11273	.09725	5.1	2.40	0.016	.	
Region, South	.17214	.16419	2.1	1.02	0.310	.	
Region, Volga	.23299	.2281	1.2	0.56	0.579	.	
Region, Urals	.06677	.05399	5.4	2.54	0.011	.	
Region, Siberia	.1297	.16061	-8.8	-4.26	0.000	.	
Region, Far East	.05076	.04215	4.1	1.94	0.053	.	
Health, good	.33917	.47626	-28.2	-13.58	0.000	.	
Health, Neither good/bad	.60016	.45168	30.1	14.42	0.000	.	
Health, bad	.04607	.037	4.5	2.15	0.032	.	
Health, very bad	.00225	.00442	-3.8	-1.89	0.059	.	
High blood	.25607	.10697	39.4	18.03	0.000	.	

pressure							
* if variance ratio outside [0.95; 1.05]							
Ps R2	**LR chi2**	**p > chi2**	**MeanBias**	**MedBias**	**B**	**R**	**%Var**
0.439	5194.40	0.000	24.6	8.5	195.2*	1.11	100
* if B>25%, R outside [0.5; 2]							

Figure 1: Percent Bias for Covariates, Summary Statistics



IV. Difference-In-Differences Model

To estimate the effectiveness of the MC policy in increasing family size, and thus birth rates, the difference-in-differences (DID) method will be used. Typical DID models take advantage of randomization; individuals placed into subsequent groups are randomly selected. For the DID model being discussed, the randomization of groups was not possible. This is because a woman can not be assigned to a group - either treatment or control - for this would mean that the woman must have a child or cannot have a child. The usage of randomization would be unethical and unreasonable in this case. Without randomization, possible issues in estimates may arise due to differences in characteristics before policy implementation. A balancing method using weighted propensity scores for individuals belonging to each group may be used to account for differences in groups, but is not present in this research due to time constraints. Another hindrance to using this model that may prove difficult in analysis as to whether this policy is truly effective is the inability to separate the effect of this policy from the effect of other policies that may be implemented during the post-policy time period used. For instance, maternity leave reforms were passed post-2007, which may lead to an increase in births since working mothers now feel a sense of comfort being able to stay home for an extended period of time with their newborn. Further criticisms of this method will be discussed in Section VI.

The DID model used to estimate the difference in differences between the groups and the groups pre- and post-policy can be denoted by Equation 1,

$$Y_{it} = \alpha + \beta X_{it} + \lambda_1 T_i + \lambda_2 P_t + \lambda_3 (T_i * P_t) + \varepsilon_{it} \quad 1$$

and terms in Eq. 1 can be defined as follows, beginning with the broad definitions and then the terms together summarized in Table 2. The sample is constrained to only include females ages 15 to 45.

Y_{it} represents the outcome of the policy, or what the policy affects. Here, the binary outcome is giving birth and the continuous outcome is real earnings. Additional outcomes, including employment and hours worked, are reviewed in Appendix C and Appendix D. The outcome indicator variable uses subscripts, i and t, where i indicates the treatment status of the individual and t indicates the time period the individual is observed in - before and after the treated groups receive treatment.

X_{it} represents the vector of control variables. These variables are those that we wish to be represented by both groups so that the groups have similar characteristics. The control variables used here include age (*age*), being married (*married*), being Russian (*ethrus*), if born in another city (*borndp*), education attainment (*edattain*), urban setting that is resided in (*urbsta*), Federal district (region in Russia, *okrug*), health self-evaluation (*hlt_selhlt*), and if having high blood pressure (*hlt_hyptdi*). Further variable descriptions and summary statistics can be found in Appendix A.

T_i represents the groups being used. These groups have been referred to thus far as the treatment and the control group, or more specifically, women with at least one child and women with no children. $T_i = 1$if an individual belongs to the treated group and $T_0 = 0$ if an individual belongs to the control group.

P_t represents the time periods used for the policy. P_t will allow comparison before the policy is implemented to after the policy is implemented. $P_t = 1$ to indicate the post-policy period and $P_t = 0$ to indicate the pre-policy period. A specific year before and after the policy is not used, rather a time period from 2004-2006 is used for the pre-policy time and a time period from 2014-2016 is used for the post-policy time.

$T_i * P_t$ represents the interaction between the groups and policy period. This interaction is important for estimating and interpreting the difference-in-differences. The term captures the effect on the outcome of one variable dependent on the other.

ε_{it} is also known as the error term. This term accounts for any unobserved characteristics that may exist. These unobserved characteristics may include personal desires, and so forth.

Table 8: DID OLS Model Terms

	Pre-Policy	Post-Policy	Post-Pre Difference
Treatment Group	$\alpha + \beta X_{it} + \lambda_1$	$\alpha + \beta X_{it} + \lambda_1 + \lambda_2 + \lambda$	$\lambda_2 + \lambda_3$
Control Group	$\alpha + \beta X_{it}$	$\alpha + \beta X_{it} + \lambda_2$	λ_2
T-C Difference	λ_1	$\lambda_1 + \lambda_3$	λ_3

There are several assumptions of the model. To predict policy effect, it is assumed that the control variables, denoted by X_{it}, are uncorrelated with ε_{it}, or $Cov(X_{it}, \varepsilon_{it}) = 0$. Another assumption made is that $Cov(T_i, \varepsilon_{it}) = 0$. More specifically, $T_i$is independent of unobserved characteristics such that the selection into the treatment group is uncorrelated with epsilon. Lastly, the third assumption made is the parallel-trend assumption, $Cov(T_i * P_t, \varepsilon_{it}) = 0$. The parallel-trend assumption assumes that in the absence of the policy or treatment, the two groups will follow the same or very similar trend. Here, this assumption can be interpreted as: if the MC policy was not implemented, women with at least one child and women without children would follow a similar trend in terms of probability of giving birth and real earnings.

Using the DID model, Eq. 1, the policy effect can be estimated for both outcomes of interest - births and real earnings. The Ordinary Least Squares regression method is used first to estimate the probability of giving birth for women who already have a child and for women who do not have a child. From the OLS method with estimates captured in Table 9, conditional on all other controlled variables, pre-policy women without children had more births - approximately 6.3 percentage points more - compared to women who had at least one child. Childless women's birth rate decreased by almost 1.5 percentage points from before the policy to after the policy time period. The gap in birth rates closed significantly, indicated by a p-value of essentially zero. The gap in birth probability closed by 3.3 percentage points, or in other words, after the policy the gap for the probability of giving birth between groups became 3 percentage points, roughly (6.3% - 3.3%). This can also be interpreted as the treatment group, or women with at least one child, improved birth rates post-policy by about 3.3 percentage points. The Probit model provides similar results and can be found in Appendix B. Of importance, the predicted probability of giving birth post-policy for women with at least one child is 3.3 percentage points greater than childless women post-policy and the predicted probability of a woman with at least one child giving birth is greater than the predicted probability of a woman without children post-policy

Table 9: DID Estimates, Giving Birth

Number of obs	18,104
F(24, 18079)	10.65
Prob > F	0
R-squared	0.0189
Root MSE	0.22407

		Robust				
birth	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
1.treat	-0.0634263	0.0077265	-8.21	0.000	-0.0785709	-0.0482816
1.post2	-0.0154163	0.0067569	-2.28	0.023	-0.0286605	-0.0021721
treat#post2						
1 1	0.0328182	0.0077432	4.24	0.000	0.0176408	0.0479956
age	-0.0013434	0.0002606	-5.15	0.000	-0.0018543	-0.0008326
married	0.0502989	0.0045932	10.95	0.000	0.0412959	0.059302
Is Russian	0.0034144	0.0053603	0.64	0.524	-0.0070923	0.0139211
Born elsewhere	0.0052206	0.0036469	1.43	0.152	-0.0019275	0.0123688
Education, secondary completed	0.0213627	0.0052673	4.06	0.000	0.0110383	0.0316871
Education, associate degree	0.0110761	0.0052507	2.11	0.035	0.0007843	0.0213679
Education, university completed	0.031497	0.0057033	5.52	0.000	0.0203179	0.042676
Urban, other city	-0.0011655	0.0042415	-0.27	0.783	-0.0094793	0.0071483
Urban, township	0.0052105	0.0073354	0.71	0.478	-0.0091676	0.0195886
Urban, village	0.0102234	0.0047968	2.13	0.033	0.0008212	0.0196255

Region, North West	0.0061824	0.006284	0.98	0.325	-0.0061347	0.0184995
Region, South	0.0015708	0.0055827	0.28	0.778	-0.0093718	0.0125134
Region, Volga	0.0084913	0.0049793	1.71	0.088	-0.0012685	0.0182512
Region, Urals	0.0196007	0.0080733	2.43	0.015	0.0037761	0.0354252
Region, Siberia	0.0056754	0.0056289	1.01	0.313	-0.0053577	0.0167085
Region, Far East	-0.0012054	0.008761	-0.14	0.891	-0.0183778	0.015967
Health, good	0.0245178	0.0105248	2.33	0.020	0.0038881	0.0451475
Health, Neither good/bad	0.0191026	0.0106458	1.79	0.073	-0.0017642	0.0399694
Health, bad	0.0147134	0.0131026	1.12	0.261	-0.010969	0.0403958
Health, very bad	0.0247416	0.0388255	0.64	0.524	-0.05136	0.1008433
High blood pressure	0.0020514	0.0044067	0.47	0.642	-0.0065861	0.010689
_cons	0.0561102	0.0135528	4.14	0.000	0.0295454	0.082675

Using the Ordinary Least Squares regression method, the DID for the real earnings outcome is estimated and can be seen in Table 10. Conditional on all other control variables, prior to policy implementation, women without children earn about 14% more than women who do have children. Real earnings for women without children increased 40% from pre-policy (2004-2006) to post-policy (2014-2016). The gap between real earnings for women with children and women without children closed by approximately 8.9%. This was positive and significant at an alpha level of 0.05, inferring that success in closing the gap is evident. Post-policy, the gap between real earnings for the two groups decreased from 14% to 5.1%.

Table 10: DID Estimates, Real Earnings

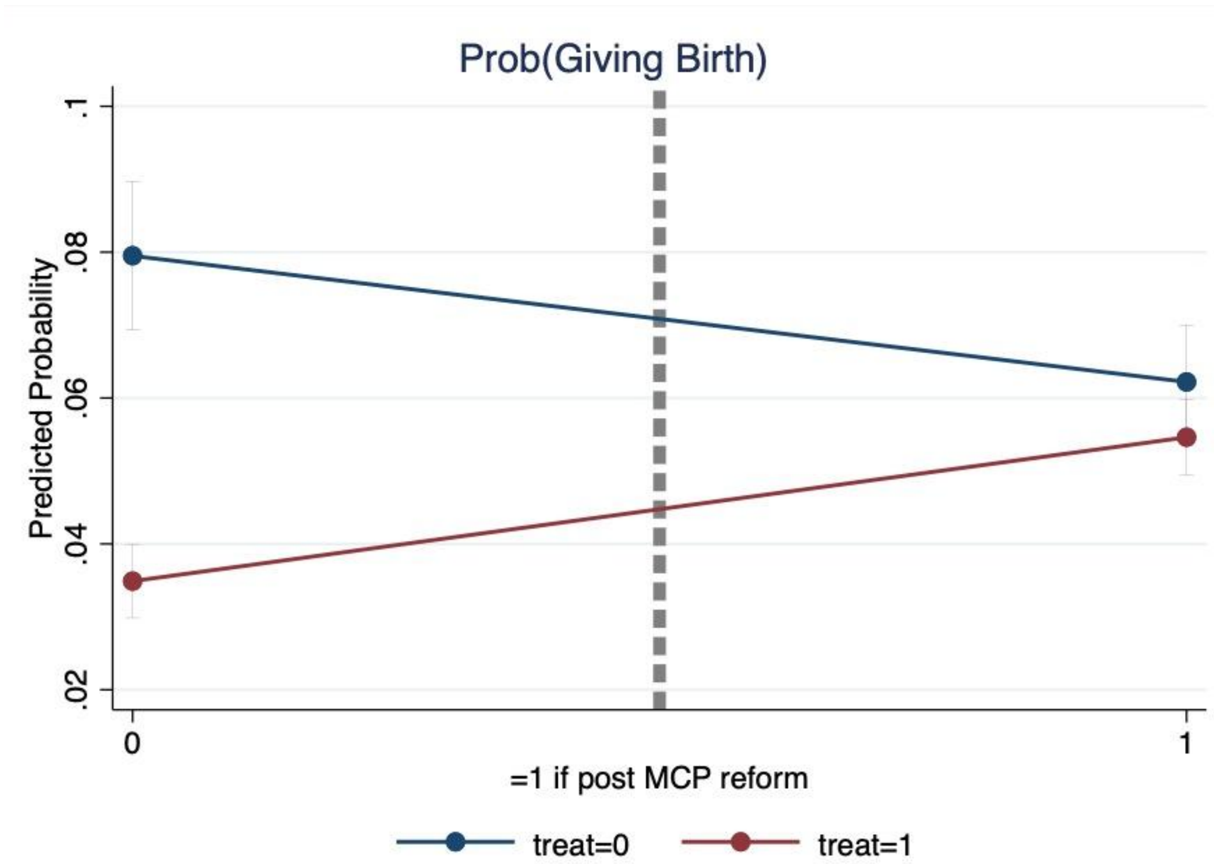
Number of obs	13,020
F(24, 12995)	257.12
Prob > F	0
R-squared	0.3349
Root MSE	0.60211

		Robust				
lnearnings	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
1.treat	-0.1399422	0.0224553	-6.23	0.000	-0.1839579	-0.0959264
1.post2	0.3990508	0.0212248	18.8	0.000	0.3574471	0.4406546
treat#post2						
1 1	0.0887272	0.0246565	3.6	0.000	0.0403968	0.1370576
age	0.0125576	0.0009175	13.69	0.000	0.0107591	0.0143561
married	-0.0551557	0.011387	-4.84	0.000	-0.0774758	-0.0328356
Is Russian	-0.0105076	0.0169099	-0.62	0.534	-0.0436535	0.0226383
Born elsewhere	0.0387875	0.0111918	3.47	0.001	0.0168499	0.060725
Education, secondary completed	0.0673051	0.0228631	2.94	0.003	0.0224901	0.1121201
Education, associate degree	0.1746023	0.0227053	7.69	0.000	0.1300967	0.219108
Education, university completed	0.4511131	0.0223663	20.17	0.000	0.4072719	0.4949543
Urban, other city	-0.1355339	0.0135618	-9.99	0.000	-0.162117	-0.1089508
Urban, township	-0.2062019	0.0238528	-8.64	0.000	-0.2529569	-0.1594469
Urban, village	-0.4291288	0.0149824	-28.64	0.000	-0.4584966	-0.399761

Region, North West	0.1930685	0.0217244	8.89	0.000	0.1504855	0.2356515
Region, South	-0.2680447	0.0186323	-14.39	0.000	-0.3045668	-0.2315226
Region, Volga	-0.3353773	0.0161452	-20.77	0.000	-0.3670242	-0.3037304
Region, Urals	-0.2256682	0.0229921	-9.82	0.000	-0.2707361	-0.1806004
Region, Siberia	-0.2562527	0.0175296	-14.62	0.000	-0.2906133	-0.2218922
Region, Far East	-0.0473997	0.0277963	-1.71	0.088	-0.1018846	0.0070852
Health, good	0.0195285	0.0582508	0.34	0.737	-0.0946517	0.1337087
Health, Neither good/bad	-0.0270656	0.0583507	-0.46	0.643	-0.1414415	0.0873102
Health, bad	-0.1228532	0.0682226	-1.8	0.072	-0.2565795	0.0108732
Health, very bad	-0.1584296	0.1414585	-1.12	0.263	-0.4357089	0.1188498
High blood pressure	-0.0522158	0.0130557	-4	0.000	-0.0778069	-0.0266248
_cons	7.522835	0.0675954	111.29	0.000	7.390338	7.655331

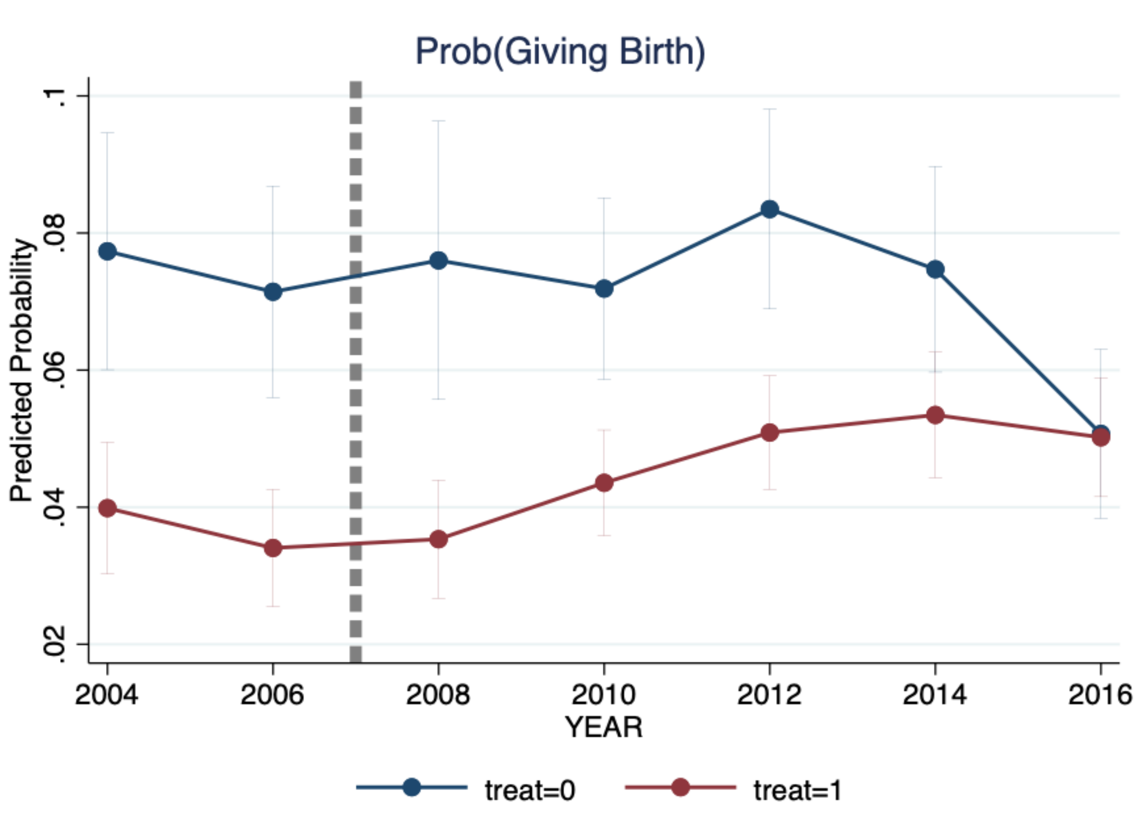
A Probit model is used to estimate marginal effects of the MCP on the probability of giving birth. The estimates are essentially the same as those captured by the OLS method in regards to the difference in differences. The marginal effects and predicted probability estimates can be found in Appendix B. A visualization of the DID estimates using the Probit model can be found below, where Figure 2 uses the before and after the policy indicator variable and Figure 3 is time-varying, showing the MCP effects on the probability of giving birth from 2004 to 2016.

Figure 2: Marginal Effects of MCP on Births



From Figure 2, an increase in the probability of giving birth can be observed amongst the treatment group that consists of women who have at least one child, meaning that these women are eligible to receive the one-time MC subsidy if having another child. From pre-policy to post-policy, women with no children see a decreasing trend; as time continues, the change in the predicted probability of birth rates decreases. The visualization of the marginal effects of the MCP on births supports the policy's success. It can also be seen that the parallel-trend assumption appears to be met from Figure 3; the trend for the probability of giving birth pre-policy seems similar. Possible outside factors, such as other policies aiming to stimulate fertility, could have been practiced prior to the 2007 MCP.

Figure 3: Time-Varying Policy Effect on Births



From Figure 3, a decreasing trend for both women with and women without children is apparent. There is a gradual increase in predicted probabilities for women with no children giving birth, but is inconsistent. The highest positive change in births for this group is seen in 2012, but then diminishes substantially. A consistent increase in predicted probabilities for giving birth is observed for women who have at least one child. For each passing year, the change in births increases until 2014, where the trend tapers off.

V. Oaxaca-Blinder Decomposition

The Oaxaca-Blinder decomposition statistical method is used to examine the difference in the mean of a dependent variable(s) between two groups. This is done so by 'decomposing' the gap, showing the differences in the mean values of the independent variable(s) within the groups and also the group differences in the effects of the independent variable. Other sources cite this decomposition as endowments and coefficients, or explained and unexplained effects respectively. Endowments may be referred to as the contribution of group composition or characteristics, whereas coefficients may be referred to as the contribution of market prices.

The Oaxaca-Blinder decomposition is performed using the log of real earnings as the dependent variable to allow the interpretation of the gap between earnings for women with at least one child and women with no children post-policy (2014-2016). The estimates can be found in Table 11. Assessing the mean gap for real earnings between these two groups post-policy, an overall gap of 7.35% is observed. If the two groups have the same composition and characteristics, the expected contribution of prices to the earnings gap is 8.76%. Of the variables used, the most significant contribution on behalf of coefficients is being married. Significant with a coefficient of 0.05787, the returns to being married are positive. If the market rewarded characteristics equally in terms of prices and the only difference is composition, then the expected earnings gap will be roughly (-) 1.41%. The most significant contribution to endowments is age and urban regions resided in. Holding constant prices and all other characteristics, and only accounting for the difference in average age, the earnings gap will be expected to be about (-) 9.2%. The negative coefficient can be interpreted as the control group - women with no children - have an average age less than the treatment group - women with at least one child. Again, holding constant prices and all other characteristics, but now only accounting for the difference in average share of women living in a city (*urbsta_2*), the earnings gap will be expected to be about 0.73%. If the only difference is in the average share of women living in a village (*urbsta_4*), the earnings gap is expected to be 3.92%. From the overall decomposition, most of the gap in earnings results from changes in prices and not group composition, based on the model created.

Table 11: Oaxaca-Blinder Decomposition for Between Groups, Post-Policy

		Robust				
lnearnings	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
overall						
group 1, Control	8.289559	0.0137272	603.88	0.000	8.262654	8.316464
group 2, Treatment	8.216051	0.0085985	955.52	0.000	8.199198	8.232904
difference	0.0735081	0.0161979	4.54	0.000	0.0417609	0.1052554
explained	-0.0140886	0.020804	-0.68	0.498	-0.0548636	0.0266865
unexplained	0.0875967	0.0237809	3.68	0.000	0.040987	0.1342063
explained						
age	-0.0919883	0.0149951	-6.13	0.000	-0.1213782	-0.0625985

married	0.0001638	0.0115889	0.01	0.989	-0.02255	0.0228776
Is Russian	-0.0007249	0.0007686	-0.94	0.346	-0.0022314	0.0007815
Born elsewhere	-0.0086873	0.0027343	-3.18	0.001	-0.0140464	-0.0033282
Education, secondary completed	-0.0024879	0.0028304	-0.88	0.379	-0.0080354	0.0030595
Education, associate degree	0.0021977	0.0022669	0.97	0.332	-0.0022454	0.0066407
Education, university completed	0.0216921	0.0066171	3.28	0.001	0.0087228	0.0346614
Urban, other city	0.0073242	0.002287	3.2	0.001	0.0028417	0.0118067
Urban, township	-0.0000706	0.0011	-0.06	0.949	-0.0022265	0.0020853
Urban, village	0.0391517	0.0057216	6.84	0.000	0.0279375	0.0503659
Region, North West	-0.0012117	0.0011269	-1.08	0.282	-0.0034203	0.0009969
Region, South	-0.0037847	0.0029142	-1.3	0.194	-0.0094963	0.001927
Region, Volga	0.0148745	0.0041302	3.6	0.000	0.0067795	0.0229696
Region, Urals	-0.0002058	0.002	-0.1	0.918	-0.0041258	0.0037141
Region, Siberia	0.0016826	0.0031748	0.53	0.596	-0.0045398	0.007905
Region, Far East	-0.0006678	0.0006576	-1.02	0.310	-0.0019567	0.000621
In good health	0.0002646	0.0004087	0.65	0.517	-0.0005364	0.0010655
High blood pressure	0.0083894	0.0040603	2.07	0.039	0.0004314	0.0163474
unexplained						
age	-0.0631664	0.0849796	-0.74	0.457	-0.2297234	0.1033905
married	0.0578726	0.0212117	2.73	0.006	0.0162985	0.0994467
Is Russian	0.0913445	0.0409998	2.23	0.026	0.0109865	0.1717026
Born elsewhere	0.0227998	0.0122359	1.86	0.062	-0.0011821	0.0467817
Education, secondary completed	-0.0008761	0.0188121	-0.05	0.963	-0.0377471	0.0359949
Education, associate degree	0.0100986	0.0194871	0.52	0.604	-0.0280954	0.0482925

Education, university completed	-0.0028276	0.0324459	-0.09	0.931	-0.0664205	0.0607652
Urban, other city	-0.0084917	0.0110762	-0.77	0.443	-0.0302006	0.0132172
Urban, township	-0.0023669	0.0034888	-0.68	0.498	-0.0092049	0.0044711
Urban, village	-0.0025371	0.010514	-0.24	0.809	-0.0231441	0.0180699
Region, North West	-0.0081918	0.0059084	-1.39	0.166	-0.019772	0.0033884
Region, South	-0.010193	0.0068058	-1.5	0.134	-0.023532	0.0031461
Region, Volga	-0.0110688	0.011532	-0.96	0.337	-0.0336711	0.0115335
Region, Urals	-0.0062988	0.0043674	-1.44	0.149	-0.0148587	0.0022611
Region, Siberia	-0.0123992	0.0067906	-1.83	0.068	-0.0257086	0.0009102
Region, Far East	0.0055639	0.0023881	2.33	0.020	0.0008832	0.0102446
In good health	-0.0209277	0.1089923	-0.19	0.848	-0.2345486	0.1926933
High blood pressure	-0.0055013	0.0089057	-0.62	0.537	-0.0229562	0.0119535
_cons	0.0547637	0.1581303	0.35	0.729	-0.2551661	0.3646934

VI. Conclusion

The Maternity Capital Program of 2007 showed a significant increase in births as captured in Eq. 1 of this paper. Difference-in-differences allowed for the observation of increasing trends for not only births from women with at least one child, but also increasing trends in real earnings. The DID model also recognized a statistically significant closing of the gap between pre- and post-policy women with at least one child.

Issues, however, do arise due to the structure of this model that may bias results. As noted previously, randomization of the selection into groups is not necessarily possible and can easily lead to differences in group characteristics. A woman's choice to have a child can easily be persuaded based on age, marriage status, employment status, residency, and so forth. As seen in the mean differences in group compositions before policy implementation, women without children are on average 11 years younger than women with at least one child. It can be inferred that this, in of itself, may lead to bias in the model - the control group may be comprised mainly of younger women who were already planning to have children in the future and thus the true effect of the policy would be less.

Simultaneous policies and events post-policy may lead to biases in results. The inability to separate the effect of the MCP from the effect of other policies and events that took place during the post-policy time period used may skew outcomes. As suggested before, several maternity leave reforms were passed post-2007, which may lead to an increase in births since working mothers now feel a sense of comfort being able to stay home for an extended period of time with their newborn. Also, events occurring in Russia post-policy included a financial crisis in 2014 along with the annexation of Crimea in 2014. This could affect the probability of a woman giving birth due to tremendous uncertainty and turmoil. In future research, using either of these events - especially the annexation of Crimea - as an instrumental variable to observe the magnitude of influence on births among these groups could prove worthwhile.

In conclusion, from the longitudinal representative survey dataset used along with the covariates, groups, and time periods selected, there is supporting evidence that the Maternity Capital Policy was successful in stimulating births among women who were already defined as mothers in the following years, but success long-term is questionable. This positive impact began to diminish post-2014, as seen in Figure 3, due to possible other demographic factors. The estimates for the policy effect are somewhat biased from not balancing the observed differences between groups prior to the policy and likely influenced by policies implemented and events occurring post-policy. Thus, further analysis on the true policy effect should be executed to determine, once accounting for group differences by using a reweighted DID model, more accurate estimates for the effect of the MCP on the probability of giving birth between groups.

Appendix A

Appendix A, Table 1: Covariate Descriptions and Summary Statistics

STATA	Variable	Obs	Mean	Std. Dev.	Min	Max
age	age	66,257	30.51525	8.541045	15	45
married	married	66,179	0.4827664	0.4997067	0	1
ethrus	Is Russian	64,747	0.876751	0.3287253	0	1
borndp	Born elsewhere	65,931	0.3800943	0.4858819	-5	1
edattain_2	Education, secondary completed	66,201	0.2856452	0.4517246	0	1
edattain_3	Education, associate degree	66,201	0.2550717	0.4359048	0	1
edattain_4	Education, university completed	66,201	0.2962191	0.4565923	0	1
urbsta_2	Urban, other city	66,257	0.2708091	0.4443811	0	1
urbsta_3	Urban, township	66,257	0.061669	0.2405551	0	1
urbsta_4	Urban, village	66,257	0.2446383	0.4298758	0	1
okrug_2	Region, North West	66,257	0.1001555	0.3002094	0	1
okrug_3	Region, South	66,257	0.1738533	0.3789862	0	1
okrug_4	Region, Volga	66,257	0.2239311	0.4168796	0	1
okrug_5	Region, Urals	66,257	0.0636159	0.2440693	0	1
okrug_6	Region, Siberia	66,257	0.1422038	0.3492617	0	1
okrug_7	Region, Far East	66,257	0.0428936	0.2026187	0	1
hlt_selhlt_2	Health, good	65,950	0.4699924	0.4991025	0	1
hlt_selhlt_3	Health, Neither good/bad	65,950	0.4720546	0.4992222	0	1
hlt_selhlt_4	Health, bad	65,950	0.0326459	0.1777095	0	1

hlt_selhlt_5	Health, very bad	65,950	0.0018347	0.0427947	0	1
hlt_hyptdi	High blood pressure	65,865	0.1683899	0.374215	0	1

Appendix B

Appendix B, Table 1: Probit Average Margins, Overtime Change in Births for Treated v. Control Groups

	Margin	**Delta-method Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
treat						
0	0.0847693	0.0057457	14.75	0.000	0.0735079	0.0960306
1	0.0419628	0.0020447	20.52	0.000	0.0379553	0.0459704
post2						
0	0.0494702	0.0024828	19.93	0.000	0.044604	0.0543363
1	0.0569234	0.0022519	25.28	0.000	0.0525098	0.061337
treat#post2						
0 0	0.0943471	0.0075346	12.52	0.000	0.0795795	0.1091147
0 1	0.0779747	0.0063514	12.28	0.000	0.0655262	0.0904232
1 0	0.0322504	0.0025723	12.54	0.000	0.0272088	0.037292
1 1	0.0488263	0.0027926	17.48	0.000	0.043353	0.0542996

Appendix B, Table 2: Probit Average Marginal Effects, Difference in Births for Post-Policy Treated v. Control Group

	Delta-Method					
	dy/dx	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
0.post2	(base outcome)					
1.post2						
treat						
0	-0.0163724	0.0076052	-2.15	0.031	-0.0312784	-0.0014664
1	0.0165759	0.0035616	4.65	0.000	0.0095954	0.0235565

Note: dy/dx for factor levels is the discrete change from the base level.

Appendix B, Table 3: Probit Average Marginal Effects, Difference in Births for Treated Group Pre- v. Post-Policy

	Delta-Method					
	dy/dx	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
0.treat	(base outcome)					
1.treat						
post2						
0	-0.0620967	0.0084162	-7.38	0.000	-0.0785921	-0.0456013
1	-0.0291484	0.0076705	-3.80	0.000	-0.0441822	-0.0141145

Note: dy/dx for factor levels is the discrete change from the base level.

Appendix B, Table 4: Probit Pairwise Comparisons of Average Marginal Effects Post-Policy Treated v. Control Group

	Contrast Delta-Method		Unadjusted	
	dy/dx	**Std. Err.**	**[95% Conf. Interval]**	
0.post2	(base outcome)			
1.post2				
treat				
1 vs 0	0.0329484	0.0083353	0.0166114	0.0492853

Note: dy/dx for factor levels is the discrete change from the base level.

Appendix C

There are various outcomes that can be analyzed for pre- and post-policy differences in the two groups. Births and real earnings have both been discussed thus far, but another outcome that may be estimated is being employed. The MCP allows for funds placed towards childcare and the child's education; a possible incentive for a woman to work is the alleviation of child responsibilities by way of daycare and or school.

Using OLS regression, coefficients can be directly interpreted and seen in the table below, Appendix C, Table 1. Before the policy, women without children were 5.06 percentage points more likely to be employed compared to women with children. Women without children saw a 1.83 percentage point decrease in the likelihood of being employed over the course of time observed. The employment gap between women without children and women with children expanded by a significant 4.62 percentage points after the policy. Therefore, despite the MCP suggesting positive effects on birth rates, the probability of women becoming employed was left behind. A possible reason for these findings is that employers may not wish to hire mothers who will be leaving their job to give birth, which would lead to less productivity.

Appendix C, Table 1 : DID Model Estimates, Employment

Number of obs	21,717
F(24, 21692)	375.73
Prob > F	0
R-squared	0.2191
Root MSE	0.43517

		Robust				
employed	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
1.treat	-0.0505621	0.0115176	-4.39	0	-0.0731375	-0.0279868
1.post2	-0.0182905	0.0098764	-1.85	0.064	-0.037649	0.001068
treat#post2						
1 1	-0.0461793	0.0123608	-3.74	0.000	-0.0704074	-0.0219513
age	0.0221454	0.000479	46.23	0.000	0.0212064	0.0230844
married	-0.0415056	0.0069724	-5.95	0.000	-0.0551721	-0.0278391
Is Russian	0.1024473	0.0094533	10.84	0.000	0.083918	0.1209765
Born elsewhere	0.0141805	0.0063209	2.24	0.025	0.0017911	0.02657
Education, secondary completed	0.1358798	0.0098668	13.77	0.000	0.1165401	0.1552194
Education, associate degree	0.2230759	0.0102893	21.68	0.000	0.2029081	0.2432437
Education, university completed	0.3073523	0.0102648	29.94	0.000	0.2872325	0.327472
Urban, other city	0.0162098	0.0075935	2.13	0.033	0.0013259	0.0310936
Urban, township	-0.0478335	0.0134084	-3.57	0.000	-0.074115	-0.0215519

Urban, village	-0.0484985	0.0084043	-5.77	0.000	-0.0649715	-0.0320255
Region, North West	0.0364145	0.0112287	3.24	0.001	0.0144054	0.0584237
Region, South	-0.0588483	0.0101896	-5.78	0.000	-0.0788206	-0.0388761
Region, Volga	0.0434435	0.0088211	4.92	0.000	0.0261535	0.0607336
Region, Urals	0.0462476	0.0132916	3.48	0.001	0.0201952	0.0723001
Region, Siberia	-0.0036776	0.009996	-0.37	0.713	-0.0232704	0.0159152
Region, Far East	-0.0242338	0.0162291	-1.49	0.135	-0.056044	0.0075763
Health, good	0.044067	0.0205619	2.14	0.032	0.0037641	0.0843698
Health, Neither good/bad	0.0486958	0.0208356	2.34	0.019	0.0078566	0.0895351
Health, bad	-0.1179462	0.0268267	-4.4	0.000	-0.1705284	-0.065364
Health, very bad	-0.3037117	0.0711628	-4.27	0.000	-0.443196	-0.1642275
High blood pressure	0.0059843	0.0080262	0.75	0.456	-0.0097476	0.0217163
_cons	-0.3281675	0.0249886	-13.13	0.000	-0.3771469	-0.2791881

Appendix D

Births and real earnings, as well as employment, have been discussed thus far, but another outcome that may be estimated is the number of hours worked. The MCP allows for funds placed towards childcare and the child's education, enabling a woman to work more. Another consideration may be the extra expense of having another child and therefore having to work more hours.

Using OLS regression, coefficients can be directly interpreted and seen in the table below, Appendix D, Table 1. The outcome variable is the log of hours worked in 30 days, or hours worked in a month. Before the policy, women without children worked 1.12% more hours in a month compared to women with children. Women without children saw a 2.35% increase in hours worked in a month over the course of the time observed. The gap between hours worked between women without children and women with children closed insignificantly by 2.36% after the policy. Therefore, along with the MCP suggesting positive effects on birth rates, women also saw an increase in hours worked from before to after policy implementation. As noted previously, possible reasons as to why hours worked for the treatment group increased are less constraints a woman faces due to available childcare using the one-time subsidy and or the need to work more hours due to increased expenses from having an additional child.

Appendix D, Table 1: DID Model Estimates, Hours Worked

Number of obs	12,011
F(24, 11986)	8.48
Prob > F	0.000
R-squared	0.0169
Root MSE	0.39836

lnhrsmonth	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
1.treat	-0.0111914	0.0145253	-0.77	0.441	-0.0396633	0.0172805
1.post2	0.0234602	0.0152504	1.54	0.124	-0.0064331	0.0533535
treat#post2						
1 1	0.023577	0.0172257	1.37	0.171	-0.0101882	0.0573422
age	0.0039153	0.0006371	6.15	0.000	0.0026666	0.005164
married	-0.0373296	0.0078512	-4.75	0.000	-0.0527192	-0.0219399
Is Russian	0.0341035	0.0132583	2.57	0.010	0.0081151	0.0600918
Born elsewhere	-0.0117296	0.0078864	-1.49	0.137	-0.0271882	0.0037291
Education, secondary completed	-0.032767	0.0164741	-1.99	0.047	-0.0650589	-0.0004751
Education, associate degree	-0.0519863	0.0160398	-3.24	0.001	-0.0834269	-0.0205457
Education, university completed	-0.0610913	0.0155907	-3.92	0.000	-0.0916515	-0.030531
Urban, other city	0.0007957	0.0089247	0.09	0.929	-0.016698	0.0182895

Urban, township	0.0437068	0.0157034	2.78	0.005	0.0129257	0.074488
Urban, village	-0.0432108	0.0109691	-3.94	0.000	-0.0647121	-0.0217095
Region, North West	-0.0152371	0.0135414	-1.13	0.261	-0.0417805	0.0113063
Region, South	0.0247585	0.0122869	2.02	0.044	0.0006742	0.0488428
Region, Volga	0.0388788	0.0101256	3.84	0.000	0.0190311	0.0587265
Region, Urals	0.0070493	0.0174812	0.40	0.687	-0.0272166	0.0413152
Region, Siberia	-0.0155397	0.0129602	-1.20	0.231	-0.0409438	0.0098644
Region, Far East	0.0242836	0.0222345	1.09	0.275	-0.0192997	0.0678668
Health, good	0.0557197	0.0414613	1.34	0.179	-0.0255511	0.1369905
Health, Neither good/bad	0.0371517	0.0416096	0.89	0.372	-0.04441	0.1187133
Health, bad	0.0246755	0.0484095	0.51	0.610	-0.070215	0.1195659
Health, very bad	-0.0122733	0.1157265	-0.11	0.916	-0.2391159	0.2145693
High blood pressure	-0.0041771	0.0092136	-0.45	0.650	-0.0222373	0.0138831
_cons	4.898345	0.048666	100.65	0.000	4.802952	4.993739

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