Wage Penalties for Motherhood and Child-rearing in Post-Soviet Russia

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Abstract

This paper studies the motherhood wage penalty, a wage gap that favors women who are not mothers to working mothers, using a Russian longitudinal data set spanning the years 1994-2012. Whether women experience a wage penalty when their household has children in it, regardless of individual motherhood status, is also studied. Fixed Effects, Heckman Selection, and a quantile analysis approach to the Oaxaca Blinder decomposition are used to study the two groups. The findings support the prevalence of a wage penalty against mothers, but are not as clear regarding a wage penalty faced by women with children in their households.

Introduction

Wage discrepancies favoring childless women over women with children are globally observed phenomena, met by a growing body of literature measuring the extent and persistence of these wage gaps, and discussing the political, social, and institutional conditions supporting the difference in wages. This paper will focus on the wage gap between women with children and those without children, often called the motherhood wage penalty, as it applies to women of different earning quantiles in the Russian Federation.

Classic economic theories behind the motherhood wage penalty postulate that a woman's human capital depreciates when she leaves the formal job sector in favor of child rearing (Mincer 1958). As well as experiencing skill depreciation while out of the workforce, she forgoes work experience and loses tenure. These may be especially influential factors in wage determination in a country like Russia, with generous maternity leave benefits allowing women to stay out of the labor force for up to three years (Gerber and Harris 2012). During this time, their jobs are secure, but avoiding a negative impact on their earning trajectory is not guaranteed.

Another classic theory stems from Gary Becker's (1985) work effort hypothesis, which proposes that individuals carry out work and home responsibilities from a fixed endowment of effort . Mothers must spend much of this effort at home, depleting from the total endowment and leaving less available to be spent on their work compared to non-mothers. Consequently, mothers earn lower wages than women who do not have to dip generously into their endowment of effort outside of the workplace (Becker 1985; Budig and England 2001). The presence of compensating differentials is also argued to contribute the wage gap, if women who plan on becoming mothers, or those who already are, select into part time or lower paying jobs that are more conducive to family life in terms of offering such benefits as flexible hours and limited travel requirements. Bridging the gap between supply and demand side explanations, is the theory that a working mother has an actual or perceived weak attachment to the labor force. This may lead employers to engage in statistical or taste discrimination. Cultural attitudes, family structures, and parental leave legislation are also shown to have a strong impact on the size and persistence of the motherhood wage penalty (Molina and Montuenga 2009; Budig et al. 2012).

Examining the factors which influence labor market outcomes for Russian women, particularly those that are different for mothers or women with children in their households, is policy relevant to a country has long experienced sub-replacement fertility rates . Following the collapse of the Soviet Union, declining birth rates have contributed to Russia's crippling population crisis. Additionally, Russia saw a steep drop in life expectancy in the early 1990s (World Health Organization[1]). When paired with persistently low fertility rates, the steady growth of Russian life expectancy in recent years (and decreasing mortality rates) raises concern for the future dependency ratio, where the number of

1 See Appendix for graph mapping the changes in life expectancy at birth and total fertility rates in Russia as reported by the World Heath Organization starting in 1990.

working age, tax paying individuals will not be enough to sustain the needs of the retired generation.

In turn, the country's low fertility level has been of key concern to policymakers. Compared to an approximate birth rate of 2% in 1990, shortly before the Soviet Union's dissolution, Russia's 2006 birth rate was an estimated 1.17% (World Health Organization). That year President Putin introduced a policy to encourage population growth by offering Russian mothers approximately $10,000 (250,000 rubles) if they are to have a second child[2] (Avdeyeva 2011; Weir 2011). Nearly a decade after the "baby bonus" was instituted, Russian birth rates remain low and fertility rates are below replacement level at approximately 1.7 (World Health Organization). Early research into the baby bonus suggests that it "actually reduces the number of second births" (Fomenko 2010). In the discussion of effective policy solutions to a nation's fertility problem, motherhood wage penalties are important to address as mothers' expected earnings in the labor market undoubtedly influence family planning decisions.

Using a Fixed Effects and a Heckman Selection model, this paper asks whether motherhood, or simply having children in the household, impact a woman's wages while controlling for time-invariant, individual specific characteristics and the sampling bias resulting from creating a sub sample of survey respondents who are part of the formal labor market, respectively. As well as looking into the nature and determinants of the motherhood wage penalty for the mean female worker, this paper asks whether and how the wage gap differs from high to low income earners, by taking a quantile regression approach to the Oaxaca-Blinder decomposition. Decomposing earning gaps for women with and without children by quantiles is an important analysis in uncovering the nature of the wage gap between the two groups, as the contributing factors could impact women at varying points of the earning distribution differently. The nature of the wage gap itself changes at different points of the income distribution. For instance, high income earners experience different returns to education than low income earners, and returns to education have significantly different effects between mothers and

2 The payment is received as a state-issued certificate, which can by claimed once the second child turns three, that can be used for improving housing conditions, towards pension savings, or for the child's education (Avdeyeva 2011).

non-mothers at opposite ends of the earning distribution. Policies offering financial incentives for motherhood have to carefully consider which portion of the population they are targeting and know that demographic well.

Finally, this paper considers not only the case of wages earned by mothers and non-mothers, but for women with and without children in their households. Evidence for the motherhood wage penalty in Russia turns out to not be straightforward, with FE results producing a significant, negative coefficient on the motherhood dummy, while the Heckman Selection results show that motherhood has a negative impact on a woman's decision to join the labor force, but not directly on her wages. However, both regressions yield significant, negative coefficients on the caregiver dummy, despite the fact that caregivers' mean earnings are lower than non-caregivers'. Lastly, a wage gap favoring non-mothers and non-caregivers over mothers and caregivers, respectively, is found at each earnings percentile using RIF in conjunction with the Oaxaca Blinder decomposition.

The results may lend credence to the work effort hypothesis where women with children in their households dip into a fixed store of effort to care for children at home, leaving a smaller amount of effort reserved for the workplace than women without childcare responsibility. The results also hint at the existence of social expectations that women with children in their households contribute to child rearing responsibilities, regardless of their motherhood status. As stated by Budig et al. “culture plays a role not only through policy, but also more broadly in terms of the norms and expectations that shape mothers' employment and earnings, as well as the gendered division of household labor” (Budig et al. 2012). The key contributions of this paper are (1) decomposing the wage penalty by quantiles and (2) studying the caregiver wage penalty, as well as the traditional motherhood wage penalty.

Literature Review

With exception to several Nordic and Scandinavian countries, some degree of a wage penalty faced by mothers has been largely observed in industrialized nations (Molina and Montuenga 2009). Thus the overarching questions tend to not deal with whether the penalty exists, but rather the size and persistence of the motherhood wage penalty, as well as inquiries into the causes and nature of the wage gap. One largely discussed explanatory factor contributing to the extent of the motherhood wage penalty is the nature of parental leave benefits. In Russia, mothers can take up to three years off work after having a child. From 1990 to 2009, women received full pay for up to 112 days of the leave (in 2009, the full-pay period was then extended to 140 days), partial pay up to a year, and mothers have the security of being able to return to their previous employment at the end of the three years (Gerber and Harris 2012). Research on the impact of maternity leave policies on women's labor market outcomes shows mixed results. Some works have shown that long leaves decreased employment continuity and earnings, while moderate leaves reduce pay gaps, by ensuring that women remain attached to their workplaces while their children are infants (Budig et al. 2012; Buligescue et al. 2009; Morgan and Zippel 2003; Pettit and Hook 2005). Gerber and Perelli-Harris found that Russian women who took long leaves from work for the birth of a first child were likelier to conceive a second child after returning to work, concluding that Russia's parental leave policies positively impact women's labor force attachment and increase fertility (2012). As well as being a question of policy, parental leave benefits reflect cultural attitudes. The implication of a three year maternity leave may be that a woman should or will prioritize her non-market, child-rearing labor over active labor force participation. Though, at present, this paper does not look directly at the impact of maternity leave and relevant policies on the motherhood page penalty, Russia's maternity leave policy is worth taking note of as a reflection on cultural attitudes towards a mother's central role in child rearing. Cultural attitudes can, in turn, play a notable role in wage discrimination favoring women who do not have child rearing responsibilities outside of the workplace.

Evidence for a motherhood wage penalty in Russia is not straightforward. Budig et al. (2012) produced undramatic results, concluding that Russian mothers do not exhibit wage penalties once individual-level factors are controlled for. Nivorozhkina and Nivorozhkin (2008) found a relatively small motherhood wage penalty of 4% in Russia. However when they examined the wage penalty by job sector, Nivorozhkina and Nivorozhkin saw an 8% percent penalty for women working in the public sector, contrasted with a small motherhood wage premium for women in the private sector (2008). They note the importance of studying wage penalties faced by Russian mothers, as the government policies put in place to increase the birthrate "[pay] little attention … to the issues of poor labour protection for mothers and the existence of a wage gap" (Nivorozhkina and Nivorozhkin 2008).

Like Russia, Ukraine has been a country in transition since the fall of the Soviet Union and is experiencing comparable trends in low fertility and consequent policy to Russia. To stimulate fertility, the Ukrainian government offers baby bonuses for the first, second, and third child of 12,250 Hryvnias[3], 25,000 Hryvnias, and 50,000 Hryvnias, respectively (Nizalova and Sliusarenko 2013). Despite the monetary incentive, Ukrainian mothers experience a 4% wage penalty for each year taken out of the labor force for child rearing, showing that the country's family support policies and anti-discrimination laws are inadequately enforced (Nizalova and Sliusarenko 2013). The difference in the wages of working mothers and childless women in Ukraine started at 6.5% and grew with the the addition of a second child (Nizalova and Sliusarenk 2013). However, when the sample was divided by education, Nizalova and Sliusarenko saw the wage penalty to be very small for women with vocational or professional educational attainment (2013). Furthermore, Ukrainian women with low educational

3 At the current exchange rate, 12,250 Ukrainian Hryvnias translate to approximately 1,051 US Dollars, a notable figure given that the world bank lists Ukraine's 2012 per capita gross national income as $3,500. It is also worth noting that the exchange rate between the Hryvnia and the USD has fallen significantly in recent months given the country's political turmoil.

attainment received a 15% wage premium if they had their first child after age 30 (2013).

The econometric methodology employed in the study of the motherhood wage penalty is chosen (or developed) with the issues of sample selection and unobserved heterogeneity in mind. Buligesar et al. use a censored Tobit participation model to deal with both heterogeneity and simultaneity in their German data, finding a 10%-14% wage penalty experienced by mothers returning to work after taking maternal leave, but the penalty dissipates by five years in the labor force (2008). In studying Spanish panel data, Molina and Montuenga used pooled ordinary least squares (OLS) and Fixed Effects (FE) estimation, but through a sequential process of progressively including new explanatory variables (2009). Ultimately, seeing significant wage gap arising with the birth of the first child and growing with subsequent children (Molina and Montuenga 2009). Livermore et al. went a bit further and compared results from a selectivity corrected Fixed Effects model, pooled OLS, and Heckman corrected pooled OLS, finding larger wage gaps present with the FE and Heckman corrected OLS model then with the regular OLS, finding that the data was impacted by both unobserved heterogeneity and selection bias (2011).

For the preliminary results presented in this paper, the Heckman selection model and Fixed Effects regression are both used, but (currently) without attempt to correct for unobserved heterogeneity in one or selection bias in the other. As well as the aforementioned methods, this paper employes the Oaxaca Blinder decomposition, a methodology that is well represented in wage gap literature, but not heavily among motherhood wage penalty works.

The importance of decomposing by quantiles rather than measuring solely a gap in mean wages is that women along varying points in the earning distribution differ in how explanatory variables impact their labor market outcome. The magnitude of the wage gap itself changes along the wage distribution. A homogenous policy aimed at increasing family size would not have a consistent impact on all women, or even be effective on the average woman. Understanding trends at key points of the wage distribution would allow for more targeted fertility incentives.

Data

The data used in this paper comes from the Russian Longitudinal Monitoring Survey (RLMS), an extensive household-based survey created in the early years of post-Soviet Russia in order to "measure the effects of Russian reforms on the economic well-being of households and individuals" (RLMS). With exception to 1997 and 1999, annual data from 1995 is available for use. The set surveys over 10,000 individuals from at least 4,000 households each year.

This paper will consider two sets of women for wage comparison: women with and without children in their households (hereafter referred to as caregivers and non-caregivers, respectively[4]) and women who are or are not mothers. Caregivers are not necessarily mothers, but may nevertheless have childcare responsibilities at home. In turn, mothers may not actually have children who need care in their households. Data explicitly specifying whether or not an individual is a mother is available starting in 2004, whereas general demographic data specifying whether children are present in the household is available for each year of the survey. As presented, making a direct comparison between the log wages of caregivers and non-caregivers to women with or without children of their own is not advised, since only one of the sample groups contains all the years of data.[5]

The following tables show variable descriptions and selected variable means[6].

4 This terminology is assigned primarily to condense the language. The underlying assumption of the term caregiver is that women are responsible for providing care to children in their households, whether or not those children are their own.

5 Additional analysis results, which are appropriate for direct comparison, are presented in the Appendix.

6 For a table of variable means tailored for direct comparison between mothers and caregivers, see Appendix.

Variable	Variable Description
Log Hourly Wage	natural log of hourly wage
	demographic characteristics
Mother	motherhood dummy, available starting in round 13
Caregiver	Dummy indicating that children <18 years old are part of female respondent's household
Russian	Nationality or ethnicity dummy
Married	marriage dummy
Age	respondent's age
Urban	Urban dummy
	work experience
Pregnancy Leave	pregnancy leave taken in the last 12 months, dummy
Experience	years respondent has been working at current job
Age*Experience	age * experience intercept term
	household characteristics
Young Kids	number of children under age 7 in household
Older Kids	number of children between the ages of 7 and 18 in household
Working Age Females	number of working age females in household
Working Age Males	number of working age males in household
Older Females	number of post-working age females in household
Older Males	number of post-working age males in household
Retirees	Number of post-working age female and male members of the household
	education
Higher education	Higher education dummy, indicates attainment of post-high school degree
Technical education	Technical education dummy, indicates completion of technical school program
High school education	High school education dummy, indicates attainment of high school diploma

Table 1: Variable descriptions

	Male 1994-2012	Female 1994-2012	Mother 2003-2012	Non-Mother 2003-2012	Caregiver 1994-2012	Non-Caregiver 1994-2012
Log Hourly Wage	4.207	3.939	3.900	3.981	3.984	3.923
Number of Kids	1.752	1.740	1.740	.	1.701	1.758
Russian	0.498	0.507	0.590	0.541	0.533	0.498
Married	0.585	0.458	0.515	0.141	0.596	0.413
Age	40.624	45.211	50.124	29.504	36.978	48.124
Urban	0.659	0.678	0.676	0.715	0.677	0.678
Pregnancy Leave	0.713	0.855	0.855	0.795	0.871	0.849
Experience	21.525	22.714	25.633	15.291	16.811	24.707
Higher Education	0.315	0.443	0.509	0.353	0.468	0.434
Technical Education	0.356	0.209	0.210	0.118	0.228	0.203
High School Education	0.796	0.817	0.933	0.866	0.869	0.799
Young Kids	0.265	0.253	0.307	0.091	1.176	.
Older Kids	0.523	0.485	0.426	0.455	0.463	0.491
Adult Males	1.179	0.825	0.846	0.818	1.128	0.742
Adult Females	0.953	1.026	0.952	1.363	1.418	0.918
Older Males	0.215	0.147	0.154	0.099	0.086	0.163
Older Females	0.347	0.487	0.528	0.378	0.299	0.539

Table 2: Selected variable means

Mean hourly wages are approximately 8% higher for non-mothers than for mothers, despite the fact that mothers exhibit a lot of characteristics that would be associated with a higher wage – they are older, have more work experience, and higher educational attainment than non-mothers. Mean wages for caregivers, on the other hand, are about 6% lower than for non-caregivers. Despite this, subsequent analysis results will associate caregiver status with decreased expected wages. Non-caregivers are older and much more likely to have a retired man in their household than caregivers – in turn, the lower pay to non-caregivers may reflect that non-caregivers are often older women who may be working in semi-retired positions.

Both mothers and caregivers exhibit higher educational attainment than their counterparts. Mothers, however, tend to have significantly more work experience than non-mothers, whereas the opposite holds true for caregivers and non-caregivers (caregivers having an average of 8 years less work experience than non-caregivers). Likewise, mothers and non-caregivers are older than non-mothers and caregivers, respectively. Predictably, mothers are more likely to be married than non-mothers; the same holds true for caregivers and non-caregivers. Non-caregivers have slightly more children than do caregivers on average. A likely explanation is that non-caregivers are older women who's children have left their homes. The household compositions for the groups are varied.

Model Specifications and Methodology

All of the models in this paper follow first from the general wage equation in which individuals' log hourly wages are a function of their demographic characteristics, work experience, household characteristics, and educational attainment.

$$\mathbf{lnW_i = \gamma_i + ß_1(demographic\ characteristics_i) + ß_2(work\ experience_i) + ß_3(household\ characteristics_i) + ß_3(education_i) + \varepsilon_i}$$

The y-intercept term, γ_i , signifies the wages an individual would receive in the absence of educational attainment, work experience, and the like. The betas are coefficients on the explanatory variables, and ε_i is the error term.

In order to address unobserved heterogeneity, selectivity, and measure the wage gap, this paper employes three regression methods towards examining the data: Fixed Effects (FE), the Heckman Selection model, and the Oaxaca-Blinder Decomposition. A relatively novel variation is taken on the latter, through decomposing wages by quantiles and not strictly at the mean.

The FE approach is appropriate because the data comes from a longitudinal panel survey set and it is safe to assume the presence of unobserved heterogeneity among the surveyed individuals. The underlying idea behind unobserved heterogeneity is that there are time invariant, individual specific characteristics that are absent from the data. These unobserved characteristics impact the outcome variable and are correlated with the control variables. In the case of wages, for example, consider that the data has no personality type measure. It may be that extroverts earn more than introverts, all else being equal. Furthermore, extroversion can be assumed to be constant over time and influential over independent variables that are present in the data, such as marital status, job tenure, and number of children. As the data does not include a measure for extroversion, then the model must exclude this unobserved, heterogeneous characteristic that impacts individuals' wages. As these unobserved variables are individual specific and do not change over time, it follows that changes in wages will come from changes in education level, experience, and other observed, fluid characteristics, and not because the person fluctuated in, for example, their extroverted nature. The wage equation for Fixed Effects identifies individual specific (i) variables at time (t). A_i are the individuals' time invariant characteristics and their coefficients, δ_i .

$$\mathbf{lnW_{it} = \gamma_i + \beta_i X_{it} + \delta_i A_i + \varepsilon_{it}}$$

The Heckman Selection Model is a two-part model designed to correct for selectivity issues with the data. By first estimating the probability that an individual selected into a particular group, then using the generated probability variable to correct for selection bias when running the second stage regression. The selection bias addressed in this paper comes from the fact that only women earning wages are observed; meaning all of the women in the sample have selected into the formal job market and form a non-randomly determined population sample. Observing wages for only for women who have had their reservation wages met or exceeded in the formal labor market, excludes women who were unable to earn their reservation wages. In turn, the returns to education, job tenure, and other determinants of labor market outcomes are likely to be higher for the sample of working women than for the entire female population.

Finally, the Oaxaca-Blinder decomposition works by first estimating the two group specific regression models, then decomposes the mean differences in log hourly wages into the part that can be explained by differences in two groups' regressors, such as education and work experience, and an unexplained portion that can not be determined by said differences. In order to assess how much of the estimated log hourly wage gap is determined by the variation in working mothers' and non-mothers' explanatory variables, the Oaxaca-Blinder methodology considers the counter-factual – what happens when group differences in the x variables for one group are weighed by the coefficients of the other group (Jann 2008). Conversely, the unexplained (coefficient) effect, is calculated by weighing differences in the coefficients of one group by the other group's means (Jann 2008). The coefficient effect is often used as a measure of discrimination, as the results are not elucidated by the regressors.

While the FE and Heckman Selection methodology is used in their traditional capacities, this paper uses a relatively novel approach to the Oaxaca-Blinder decomposition by combining it with the Recentered Influence Function (RIF) regression in order to decompose the log wages of working mothers and non-mothers by earning quantiles, rather than merely at the mean. RIF estimates " the impact of changing the distribution of explanatory variables, X, on the marginal quantiles of the outcome variable, Y, or other functional of the marginal distribution of Y" (Firpo et al. 2007).

Empirical Results

This paper considers two sets of women: (1) mothers and non-mothers and (2) women with and without children in their households, also referred to as caregivers and non-caregivers. In the case of the Fixed Effects and Heckman Selection estimation, a motherhood or caregiver dummy is included as an independent variable in the estimation equation. These regressions are not explicitly measuring a wage gap; rather they assess whether and how motherhood or the presence of children in the household impacts women's wages. The actual wage gap is estimated later using the Oaxaca Blinder decomposition.

First, the FE estimation results are presented for a model that includes mothers, a supplementary model that replaces the motherhood dummy with a continuous variable reporting the number of children a parent (mother or father) has, and a model replacing the motherhood dummy with a caregiver indicator variable[7]. The results show that motherhood, the number of children an individual has, and caregiver status each has a negative impact on log hourly wages, at the 10%, 5% and 1% significance level, respectively.

7 Mother and caregiver dummies are taken from an all female sample, whereas the *number of kids* variable is taken from a population of men and women.

	(1)	(2)	(3)
Dep. Variable	Log-Wage	Log-Wage	Log-Wage
Mother Status	-0.124*		
	(0.069)		
Number of Kids		-0.063**	
		(0.027)	
Caregiver2			-0.155***
			(0.024)
Russian	-0.030*	-0.018	-0.042***
	(0.018)	(0.016)	(0.015)
Married	-0.003	0.034	-0.178***
	(0.030)	(0.026)	(0.031)
Age	0.007	-0.001	0.0469***
	(0.005)	(0.004)	(0.0033)
Urban	0.624***	0.653***	0.522***
	(0.090)	(0.069)	(0.066)
Pregnancy Leave	-0.042*	-0.044**	-0.102***
	(0.025)	(0.021)	(0.027)
Experience	0.214***	0.203***	0.0808***
	(0.008)	(0.008)	(0.005)
Age*Experience	-0.0001	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)
Higher Education	0.0860**	0.0801**	0.236***
	(0.038)	(0.035)	(0.035)
Technical Education	0.006	0.002	-0.033
	(0.024)	(0.020)	(0.024)
High School Education	0.010	0.025	0.077*
	(0.068)	(0.050)	(0.044)
Young Children in HH	-0.009	-0.027	0.048*
	(0.028)	(0.023)	(0.026)
Adult Males in HH	0.026	0.034**	0.045**
	(0.019)	(0.017)	(0.019)
Adult Females in HH	0.032	0.045**	-0.022
	(0.021)	(0.019)	(0.019)
Older Males in HH	0.016	-0.090**	-0.015
	(0.052)	(0.044)	(0.047)
Older Females in HH	-0.041	0.026	0.024
	(0.031)	(0.028)	(0.029)
Constant	-1.366***	-1.396***	-0.558***
	(0.199)	(0.191)	(0.135)
Observations	9,714	13,082	16,379
R-squared	0.340	0.310	0.270
Number of Individuals	4,409	5,982	7,150

Standard Errors in parentheses
***p<0.01,**p<0.05,*p<0.1

Table 3: Three specifications of the Fixed Effects estimation for Log-hourly Wage

Many of the results are expected. Urban areas have higher wage earners, on average, than do urban-type settlements and rural areas. Higher wages also accompany the attainment of a post-high school, non-technical diploma (e.g. a university diploma), and wages increase with experience. Having taken pregnancy leave within the past year has a negative impact on wages for all three groups. Marriage appears to only impact wages individuals in the iteration of the regression that includes caregivers. An explanation for the negative coefficient on marriage for this group is that caregivers who are married are likelier to also be parents than caregivers who are unmarried. We have already seen that motherhood comes with lower average wages, the effect of which is picked up explicitly in the first two regressions, but indirectly by the negative coefficient on marriage in the last regression. Age is not a significant factor on wages in all but one of the models, but when it is, predictably, shown to have a positive impact on wages.

Other results, or lack thereof, are less expected. In the case of age, for instance, wages are only shown to increase with age at any notable level of significance in the third model, although anticipating that wages will increase with age at a significant level across the board is reasonable. Furthermore, wages are not shown to increase (with significance) for with the attainment of a technical diploma, nor does household composition show a strong pattern of impacting wages. Having young children in the house or other adult of various age and gender groups, does not impact wages in the model with the motherhood indicator at all. The model with the continuous variable reporting the number of kids an individual has shows that wages increase with the number of working age males and the quantity of working age females (potential caregivers) in the house, while they decrease with the number of retired males in the household, all at a 5% level of significance. Individuals who are able to share household and childcare responsibilities with other adults would have more time, energy, and schedule flexibility to allocate towards their jobs, which may lead to higher wages than women who must shoulder their home front and work responsibilities without a strong household support network. Having retirees in the household may mean having extra help in the home, allowing a person to focus more on their career, or, conversely, having more people that need care for at home, detracting from the working adult's store of time and, perhaps, effort that they have to spend in the labor market. The FE estimation results indicate the latter. The caregiver model variant also predicts that wages will increase with working age males, as well as with children ages 7 and under in the household. The other two variants of the model have a negative sign on the coefficient for the number of young children in the household, but those results are not significant at even a 10% level. Lastly, identifying as Russian (rather than any other nationality) has a significant, negative impact on wages for both mothers and caregivers – a peculiar result as the Heckman Selection Method results will show a strong positive correlation between identifying as Russian and wages.

The Heckman Selection method is again run on three, nearly identical equations with one containing a motherhood dummy, the next containing a variable reporting how many children the parent has in it's place, and the third replacing the motherhood or number of kids variable with a caregiver dummy. The variable for the number of post-working age female members of the household, shown to be insignificant in the determination of wages in the FE model, is taken out of the of the second stage of the Heckman, and added only into the selection process as an exclusionary variable. Although having older women in the household might not impact wages directly, it may impact the choice of whether or not a working age individual selects into the labor force. She may enter the labor force because she has free, in-home childcare provided by older members of the household. On the other hand, if an older member of the household requires care themselves, a working age woman may elect to stay out of the labor force in order to provide that care. As will be seen, the likelihood that a person participates in the labor market is negatively impacted impacted by the number of post-working age female members of the household, but not always at a significant level. More importantly, however, Heckman's lambda is significant in all three model variations. This value tells us how the selection effect impacts wages, and the fact that it's significant means that the wages of people who have self selected into the labor force are indeed different than the wages of a sample of people drawn at random from the general population. Presented next are the Heckman Selection Model results:

	(1)		(2)		(3)	
Variable	Log-W	Select	Log-W	Select	Log-W	Select
Mother	-0.038	-0.0825*				
	(0.04)	(0.05)				
Number of Kids			0.015	-0.105***		
			(0.03)	(0.02)		
Caregiver2					-0.117***	0.019
					(0.02)	(0.03)
Russian	0.460***	0.023	0.455***	0.011	0.070***	-0.028
	(0.021)	(0.029)	(0.025)	(0.025)	(0.020)	(0.021)
Married	-0.021	-0.063*	0.083***	-0.034	-0.094***	-0.102***
	(0.026)	(0.033)	(0.030)	(0.028)	(0.030)	(0.024)
Age	-0.006	0.015***	-0.013**	0.021***	-0.002	0.0162***
	(0.004)	(0.003)	(0.006)	(0.003)	(0.004)	(0.002)
Urban	0.295***	0.149***	0.310***	0.179***	0.236***	0.229***
	(0.036)	(0.031)	(0.056)	(0.026)	(0.051)	(0.022)
Pregnancy Leave	0.018	-0.086**	-0.060**	-0.007	-0.101***	-0.122***
	(0.030)	(0.040)	(0.030)	(0.030)	(0.035)	(0.031)
Experience	0.004	-0.002	0.000	0.00721**	0.0143***	0.003
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)
Age*Experience	0.000	0.000	0.000	-0.0002***	-0.0003***	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Higher Education	0.341***	0.036	0.274***	0.003	0.359***	0.088***
	(0.022)	(0.031)	(0.026)	(0.026)	(0.027)	(0.022)
Technical Education	-0.013	0.060*	0.014	0.059**	-0.029	0.031
	(0.027)	(0.036)	(0.032)	(0.028)	(0.024)	(0.025)
High School Education	0.471***	-0.021	0.425***	-0.092*	0.526***	0.059
	(0.047)	(0.067)	(0.056)	(0.052)	(0.038)	(0.037)
Young Kids in HH	0.230**	-0.455***	0.212***	-0.201***	0.345***	-0.418***
	(0.108)	(0.029)	(0.068)	(0.025)	(0.099)	(0.022)
Adult Males in HH	0.040**	-0.056**	0.074***	-0.048**	0.068***	-0.022
	(0.018)	(0.023)	(0.021)	(0.019)	(0.016)	(0.017)
Adult Females in HH	-0.061**	0.106***	-0.039	0.065***	-0.085***	0.116***
	(0.027)	(0.025)	(0.027)	(0.021)	(0.028)	(0.018)
Older Males in HH	-0.032	0.006	-0.066**	0.065**	0.023	0.045*
	(0.022)	(0.034)	(0.030)	(0.030)	(0.024)	(0.026)
Older Females in HH	-0.042	-0.122***	-0.012			
	(0.056)	(0.047)	(0.040)			
lambda	-0.994**		-1.423**		-1.268***	
	(0.505)		(0.684)		(0.472)	
Constant	3.113***	0.506***	3.609***	0.263**	2.909***	0.104
	(0.260)	(0.122)	(0.420)	(0.115)	(0.328)	(0.085)
Observations	11,849	11,849	16,037	16,037	20,744	20,744

Standard Errors in parentheses
***p<0.01,**p<0.05,*p<0.1

Table 4: Three specifications of the Heckman Selection estimation for Log-hourly Wage

The results show that motherhood impacts a woman's decision to enter into the labor force (negatively), but not her wages. The caregiver indicator, however, carries a significant, negative coefficient in the estimation of log hourly wages. The significant, positive coefficients on the urban dummy mirror the FE estimation results, as do the signs on the higher education variable coefficient. The Heckman estimation results further show that wages increase with the attainment of a high school diploma, significant results that were not present in the FE estimation output. Marriage again has a negative impact on wages in the caregiver model variant, as well as the decision to enter the labor force. In the model which includes the number of kids variable, the marriage dummy has a positive coefficient. Having taken pregnancy leave within the past year has a negative effect on wages and/or the decision to reenter the labor force. In the model variant that includes the caregiver indicator, wages increase with experience, but decrease with the Age*Experience interaction variable. I chose to include this interaction term, but not an experience squared variable, as the two would reflect much of the same information A negative coefficient on the Age*Experience variable tells a similar story as a negative coefficient on an experience squared variable – if wages increase with experience, they do so at a decreasing rate.

Unlike the Fixed Effects results, the Heckman estimation outcome showed a significant, positive impact of the Russian dummy on wages for all three groups. While Russia is ethnically diverse, the country historically and contemporaneously receives attention for issues stemming from racism, nationalism, and xenophobia (Leviyeva 2005; Holdsworth 2007; Verkhovsky 2007). In turn, the positive coefficient on the Russian indicator variable may reflect pro-Russian discrimination.

The Heckman results offer more insight into the impact of household demographics on wages than does the Fixed Effects estimation. For example, the Heckman estimation results show that wages increase with the number of young children in a household (furthermore, this result is shown at a 1% or 5% significance level in all three estimations). However, the likelihood that an individual selects into the labor force to begin with decreases with the number of young children in the household. Thus, given the condition that an individual has chosen to enter the formal labor market, that person's wages increase with the number of young children that they have in their household. Seemingly, an individual's reservation wage increases with the number of children they have. Again, wages increase with the number of adult males in the household, but tend to decrease with the number of adult females. The decision to enter the labor force, given the amount of adult males and adult females in the households are the opposite – decreasing with the number of males and increasing with the number of females. For most cases, retired aged adults do not impact wages significantly.

The final estimation conducted in this paper is the Oaxaca Blinder decomposition, analyzing several key earning percentiles with the help of the Recentered Influence Function regression. The results below show two charts, one for mothers and the other for caregivers, each of which consist of five rows, each of which reports the estimates with the standard errors below. In the top chart, the first two rows predict the log hourly wages for mothers and non-mothers, respectively. The predictions are organized by columns for 10th, 25th, 50th, 75th, and 90th percentile earners. The third row shows the difference in the two groups' predicted log hourly wages, with positive values indicating that non-mothers earn more than mothers in the given quantile. Next the explained effect estimates the average change in mothers' wages if they had the same characteristics (e.g. age, educational attainment, and work experience) as non-mothers. Lastly, the unexplained effect indicates the change in the hourly log wages for mothers if they had non-mothers' coefficients applied to their characteristics. The second chart is read the same way, only for non-caregiver and caregivers rather than non-mothers and mothers.

Percentile	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Non-Mother	2.217	2.687	3.167	3.608	4.045
	(51.06)**	(67.94)**	(73.82)**	(74.75)**	(71.25)**
Mother	2.070	2.488	2.944	3.397	3.822
	(98.80)**	(126.90)**	(139.95)**	(145.01)**	(134.80)**
Difference	0.147	0.199	0.224	0.211	0.223
	(3.06)**	(4.52)**	(4.68)**	(3.93)**	(3.51)**
Explained	0.178	0.133	0.104	0.117	0.153
	(3.26)**	(2.60)**	(1.90)	(1.91)	(2.07)*
Unexplained	-0.031	0.066	0.12	0.094	0.07
	(0.43)	(1.00)	(1.67)	(1.15)	(0.72)

Standard Errors in parentheses
***p<0.01,**p<0.05,*p<0.1

Table 5: Decomposition of the mean Log-wage for mothers and non-mothers by percentile

Percentile	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Non-Caregiver	1.535	2.093	2.705	3.281	3.755
	(64.29)**	(101.38)**	(133.04)**	(144.27)**	(138.84)**
Caregiver	1.257	1.770	2.339	2.889	3.331
	(60.50)**	(90.69)**	(114.72)**	(123.82)**	(121.24)*
Difference	0.278	0.323	0.366	0.393	0.424
	(8.78)**	(11.36)**	(12.71)**	(12.05)**	(10.99)**
Explained	0.235	0.265	0.313	0.377	0.391
	(9.73)**	(10.92)**	(12.25)**	(12.90)**	(11.36)**
Unexplained	0.043	0.058	0.053	0.016	0.033
	(1.12)	(1.64)	(1.47)	(0.39)	(0.7)

Standard Errors in parentheses
***p<0.01,**p<0.05,*p<0.1

Table 6: Decomposition of the mean Log-wage for caregivers and non-caregivers by percentiles

The predicted wages for mothers are higher than the predicted wages for non-mothers at each percentile. The same holds true for the predicted wages of non-caregivers relative to the predicated wages of caregivers. This confirms that working women in Russia face a a wage penalty given motherhood or caregiver status. In most cases, the unexplained or residual coefficient is small relative to the explained difference in wage estimations. Much of the literature will treat this residual coefficient as the discrimination factor. Given that the explained portion shows how much of the difference in predicted wages arises from differences in group characteristics (such as age, educational attainment, and work experience), the rest of the discrepancy between the two groups' wages may arguably be a factor of employer discrimination. As seen in the charts, mothers earn from 15% less in the lowest quartile, to approximately 24% less, in the highest wage quartile, than non-mothers. This wage gap is larger than found in previous literature on Russia's motherhood wage penalty, but not out of the bounds found in general wage penalty literature. The difference in non-caregivers' and caregivers' predicted wages, however, are much more dramatic, culminating in caregivers earning over 50% less than non-caregivers among 90th percentile earners and, consequently, needs refinement.

Presented next is a more detailed chart containing the decomposition results by each independent variable. Much of the difference in mothers' and non-mothers' wages are shown to come from group differences in nationality, urban versus rural living, and household composition (i.e. the number of young children in the household and the number of working age females). Caregivers' and non-caregivers' explained difference in estimated wages came from similar differences in the nationality and rural dummies, and household demographic differences. The impact of pregnancy leave and having attained a post- high school diploma are also significant explained factors.

	Percentile	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Explained	Russian	0.017	0.020	0.019	0.018	0.017	(0.002)	(0.001)	0.001	0.001	0.002
		(2.95)**	(2.99)**	(2.95)**	(2.90)**	(2.78)**	(1.000)	(0.990)	(0.890)	(0.970)	(0.980)
	Married	0.029	0.026	0.014	0.041	0.045	0.011	0.032	0.030	0.029	0.029
		(1.450)	(1.410)	(0.690)	(1.810)	(1.640)	(1.460)	(4.36)**	(3.88)**	(3.24)**	(2.74)**
	Age	(0.053)	(0.132)	(0.214)	(0.216)	(0.212)	0.061	0.092	0.147	0.165	0.135
		(0.790)	(2.20)*	(3.36)**	(3.02)**	(2.45)*	(1.930)	(3.02)**	(4.46)**	(4.32)**	(3.02)**
	Urban	0.047	0.038	0.039	0.032	0.030	0.025	0.031	0.024	0.028	0.025
		(6.54)**	(6.33)**	(6.25)**	(5.25)**	(4.39)**	(6.06)**	(7.09)**	(6.21)**	(6.40)**	(5.42)**
	Pregnancy Leave	0.004	0.007	0.007	0.006	0.010	0.006	0.007	0.008	0.007	0.009
		(1.180)	(2.09)*	(1.960)	(1.630)	(2.10)*	(2.84)**	(3.03)**	(3.11)**	(2.94)**	(2.91)**
	Experience	(0.047)	(0.009)	(0.028)	(0.039)	(0.075)	0.035	0.069	0.094	0.088	0.143
		(0.690)	(0.150)	(0.410)	(0.500)	(0.780)	(0.890)	(1.690)	(2.13)*	(1.730)	(2.26)*
	Age× Experience	0.013	0.025	0.086	0.070	0.119	(0.016)	(0.091)	(0.150)	(0.146)	(0.170)
		(0.140)	(0.300)	(1.000)	(0.710)	(1.000)	(0.220)	(1.250)	(1.97)*	(1.680)	(1.630)
	Higher Education	0.007	0.006	0.006	0.005	0.005	0.022	0.022	0.019	0.020	0.019
		(1.340)	(1.330)	(1.330)	(1.320)	(1.300)	(5.05)**	(5.21)**	(5.01)**	(4.89)**	(4.48)**
	Technical Education	(0.001)	(0.001)	(0.002)	(0.006)	(0.011)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
		(0.450)	(0.190)	(0.810)	(1.670)	(2.24)*	(0.570)	(1.640)	(1.320)	(1.440)	(1.97)*
	High School	0.000	0.000	0.000	0.000	0.000	0.003	0.003	0.003	0.003	0.002
		(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(1.320)	(1.360)	(1.360)	(1.350)	(1.300)
	Young Kids in HH	0.095	0.106	0.122	0.138	0.150	0.085	0.100	0.136	0.188	0.212
		(8.24)**	(9.13)**	(9.42)**	(9.39)**	(8.62)**	(5.58)**	(6.96)**	(8.60)**	(10.15)**	(9.48)**
	Adult Males in HH	0.012	0.006	0.014	0.013	0.025	0.006	0.004	0.002	0.001	0.002
		(1.670)	(0.990)	(1.98)*	(1.620)	(2.47)*	(1.670)	(1.160)	(0.480)	(0.340)	(0.350)
	Adult Females in HH	0.057	0.043	0.043	0.057	0.048	(0.015)	(0.016)	(0.016)	(0.019)	(0.025)
		(3.76)**	(3.03)**	(2.82)**	(3.34)**	(2.35)*	(3.84)**	(4.27)**	(4.02)**	(4.23)**	(4.48)**
	Older Males in HH	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.010)	(0.016)	(0.017)	(0.015)	(0.012)
		(1.120)	(1.280)	(1.700)	(1.600)	(1.280)	(2.41)*	(3.86)**	(3.90)**	(3.26)**	(2.18)*
	Older Females in HH	0.000	0.000	0.003	0.002	0.003	0.025	0.031	0.035	0.031	0.026
		(0.110)	(0.190)	(1.090)	(0.920)	(1.030)	(3.88)**	(4.84)**	(5.13)**	(3.95)**	(2.88)**
Un-explained	Russian	0.018	(0.002)	0.015	0.004	(0.009)	(0.004)	0.030	0.037	0.046	0.036
		(0.490)	(0.060)	(0.370)	(0.080)	(0.170)	(0.130)	(1.270)	(1.500)	(1.660)	(1.080)
	Married	(0.005)	(0.037)	(0.048)	(0.033)	(0.015)	(0.069)	0.010	(0.009)	(0.010)	(0.002)
		(0.180)	(1.550)	(1.830)	(1.100)	(0.410)	(1.97)*	(0.320)	(0.300)	(0.290)	(0.040)

Age	(0.214)	0.006	(0.225)	(0.280)	(0.458)	0.190	(0.030)	(0.416)	(0.324)	(0.280)
	(0.610)	(0.020)	(0.740)	(0.820)	(1.130)	(0.670)	(0.110)	(1.530)	(1.040)	(0.760)
Urban	(0.142)	(0.022)	0.015	(0.027)	(0.056)	0.079	0.011	0.108	0.076	0.093
	(1.380)	(0.250)	(0.160)	(0.250)	(0.450)	(1.360)	(0.220)	(2.25)*	(1.410)	(1.450)
Pregnancy Leave	0.011	0.114	0.111	(0.028)	0.043	0.097	0.145	0.212	0.205	0.259
	(0.110)	(1.270)	(1.150)	(0.260)	(0.330)	(1.340)	(2.16)*	(3.05)**	(2.61)**	(2.74)**
Experience	(0.232)	(0.091)	(0.045)	(0.071)	(0.122)	0.379	0.147	(0.260)	(0.136)	(0.198)
	(1.640)	(0.710)	(0.320)	(0.450)	(0.610)	(1.850)	(0.740)	(1.220)	(0.560)	(0.650)
Age× Experience	0.175	0.022	0.033	0.066	0.120	(0.488)	(0.229)	0.135	(0.014)	0.007
	(1.160)	(0.160)	(0.230)	(0.410)	(0.600)	(1.98)*	(1.010)	(0.570)	(0.050)	(0.020)
Higher Education	0.023	(0.013)	(0.036)	0.036	0.109	(0.115)	(0.081)	(0.055)	(0.050)	(0.036)
	(0.310)	(0.190)	(0.520)	(0.460)	(1.220)	(2.48)*	(2.01)*	(1.390)	(1.150)	(0.690)
Technical Education	(0.012)	(0.008)	(0.008)	0.004	0.015	(0.036)	(0.046)	(0.026)	(0.013)	(0.016)
	(0.530)	(0.450)	(0.440)	(0.190)	(0.550)	(2.06)*	(3.08)**	(1.790)	(0.780)	(0.790)
High School	(0.584)	(0.319)	(0.249)	(0.277)	(0.293)	0.266	0.199	0.047	(0.036)	(0.051)
	(2.13)*	(1.600)	(1.300)	(1.270)	(1.190)	(2.01)*	(2.07)*	(0.560)	(0.380)	(0.440)
Young Kids in HH	0.027	0.023	0.030	0.038	0.037	0.000	0.000	0.000	0.000	0.000
	(2.62)**	(2.39)*	(2.78)**	(3.03)**	(2.71)**	.	.	.	.	.
Adult Males in HH	0.059	0.049	0.107	0.105	0.126	0.120	0.083	0.069	0.041	0.028
	(1.070)	(0.990)	(2.02)*	(1.750)	(1.890)	(2.73)**	(2.14)*	(1.750)	(0.910)	(0.520)
Adult Females in HH	(0.260)	(0.191)	(0.215)	(0.290)	(0.306)	(0.205)	(0.172)	(0.183)	(0.186)	(0.296)
	(2.07)*	(1.610)	(1.680)	(1.99)*	(1.800)	(3.21)**	(3.02)**	(3.13)**	(2.80)**	(3.71)**
Older Males in HH	0.029	0.033	0.042	0.039	0.044	0.021	0.040	0.049	0.047	0.042
	(1.640)	(1.99)*	(2.37)*	(2.02)*	(1.810)	(1.520)	(3.19)**	(3.87)**	(3.25)**	(2.46)*
Older Females in HH	0.003	(0.034)	(0.061)	(0.070)	(0.036)	(0.049)	(0.048)	(0.090)	(0.072)	(0.052)
	(0.070)	(0.990)	(1.660)	(1.700)	(0.720)	(1.940)	(2.04)*	(3.67)**	(2.60)**	(1.570)
Constant	1.071	0.537	0.654	0.877	0.871	(0.142)	(0.002)	0.435	0.444	0.499
	(2.28)*	(1.380)	(1.610)	(1.910)	(1.580)	(0.500)	(0.010)	(1.820)	(1.620)	(1.550)
N	8,109					14,606				

Standard Errors in parentheses
***p<0.01,**p<0.05,*p<0.1

Table 7: Detailed decomposition of the log-wage differential by percentile.

Discussion

This paper considers three econometric approaches to identifying and examining a motherhood and caregiver wage penalty in post-Soviet Russia. Fixed Effects and Heckman estimation results show that wages decrease with motherhood and caregiver status; while the RIF regression, coupled with the Oaxaca Blinder decomposition, quantified the wage gaps between mothers and non-mothers, as well as caregivers and non-caregivers, by earning quantiles. The first two methods were chosen in order to address known issues with panel and truncated data. The latter method was used to measure the wage gap at key points along the earning spectrum. Seen together, the results paint a detailed picture of the nature of wage penalties faced by Russian women.

The results unambiguously show that there are wage gaps favoring women without children of their own and, even, children in their households. However, some of the discrepancies between the FE and Heckman estimation results, as well as the very large wage gaps between caregivers and non-caregivers, need to be addressed in further iterations of this paper.

The Russian government revealed strong motivation to increase the nation's fertility rate through policy changes in recent years. Rather than focusing on policy that nudges women towards motherhood, such as one time baby bonuses or implementing further restrictions on abortion, the research into the wage penalties faced by women who want or need to work in the formal sector while raising children indicates that there are other routes to pursue in order make child rearing more appealing – routes that lower the long term opportunity cost for women to have children. Furthermore, findings to do with the motherhood wage penalty in Russia are generalizable to a large degree, given that similar labor market penalties to motherhood are observed globally.

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Appendix

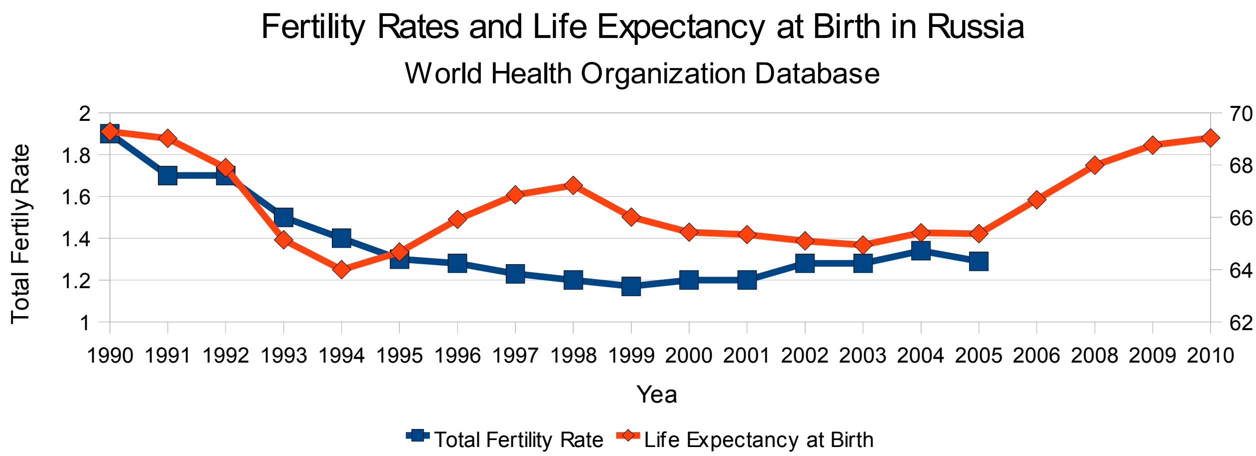

Figure 1: Annual total fertility rates and life expectancy at birth rates in Russia from 1990 to 2010

	Male 1994-2012	Male 2003-2012	Female 1994-2012	Female 2003-2012	Mother 2003-2012	Non-Mother 2003-2012	Caregiver 1994-2012	Caregiver 2003-2012	Non-Caregiver 1994-2012	Non-Caregiver 2003-2012
Log Hourly Wage	4.207	4.159	3.939	3.915	3.900	3.981	3.984	3.964	3.923	3.897
Number of Kids*	1.752	1.752	1.740	1.740	1.740	.	1.701	1.701	1.758	1.758
Russian	0.498	0.563	0.507	0.578	0.590	0.541	0.533	0.607	0.498	0.568
Married	0.585	0.549	0.458	0.427	0.515	0.141	0.596	0.563	0.413	0.381
Age	40.624	40.614	45.211	45.389	50.124	29.504	36.978	37.178	48.124	48.391
Urban	0.659	0.663	0.678	0.685	0.676	0.715	0.677	0.693	0.678	0.682
Pregnancy Leave	0.713	0.696	0.855	0.844	0.855	0.795	0.871	0.866	0.849	0.835
Experience	21.525	21.996	22.714	23.511	25.633	15.291	16.811	18.155	24.707	25.345
Higher Education	0.315	0.333	0.443	0.473	0.509	0.353	0.468	0.493	0.434	0.466
Technical Education	0.356	0.316	0.209	0.189	0.210	0.118	0.228	0.198	0.203	0.185
High School Education	0.796	0.897	0.817	0.918	0.933	0.866	0.869	0.941	0.799	0.909
Young Kids	0.265	0.269	0.253	0.257	0.307	0.091	1.176	1.169	.	.
Older Kids	0.523	0.461	0.485	0.432	0.426	0.455	0.463	0.439	0.491	0.430
Adult Males	1.179	1.217	0.825	0.839	0.846	0.818	1.128	1.143	0.742	0.753
Adult Females	0.953	0.968	1.026	1.046	0.952	1.363	1.418	1.448	0.918	0.933
Older Males	0.215	0.209	0.147	0.141	0.154	0.099	0.086	0.077	0.163	0.159
Older Females	0.347	0.354	0.487	0.493	0.528	0.378	0.299	0.299	0.539	0.548

Table 8: Selected variable means, extended table

Variable	(1) Log-W	(2) Log-W	(3) Log-W
Mother	-0.118*		
	(.0718)		
Number of kids		-0.0945*	
		(.0493)	
Caregiver			-0.0664
			(.081)
Russian	-0.0298*	-0.0333*	-0.0299*
	(.0178)	(.0192)	(.0178)
Married	-0.0031	-0.0410	-0.0081
	(.03)	(.0332)	(.0299)
Age	0.0063	0.0118*	0.0036
	(.0046)	(.0064)	(.0044)
Urban	0.622***	0.868***	0.639***
	(.0905)	(.121)	(.0901)
Pregnancy Leave	-0.0424*	-0.0283	-0.0431*
	(.025)	(.0276)	(.025)
Experience	0.214***	0.202***	0.214***
	(.008)	(.0103)	(.008)
Age*Experience	-0.0001	0.0000	0.0000
	(.0001)	(.0002)	(.0001)
Higher Education	0.0864**	0.0989**	0.0863**
	(.0379)	(.0472)	(.0379)
Technical Education	0.0060	0.0321	0.0054
	(.0242)	(.0263)	(.0242)
High School	0.0105	0.1230	0.0029
	(.0677)	(.0755)	(.0677)
Young Kids in HH	-0.0092	-0.0075	0.0357
	(.0276)	(.0292)	(.0741)
Adult Males in HH	0.0259	0.0287	0.0260
	(.019)	(.0205)	(.019)
Adult Females in HH	0.0330	0.0356	0.0366*
	(.0212)	(.0238)	(.0212)
Older Males in HH	0.0159	0.0301	0.0159
	(.0515)	(.0587)	(.0515)
Older Females in HH	-0.0406	-0.0463	-0.0381
	(.0308)	(.0354)	(.0307)
Constant	-1.359***	-2.017***	-1.368***
	(.2)	(.27)	(.2)
Observations	9714	7902	9714
R-squared	0.34	0.34	0.34
Number of idind	4409	3456	4409

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Three specifications of the Fixed Effects estimation for the Log-hourly Wage with sample limited to only females and rounds 13-21.

Variable	(1) Log-W	(1) Select	(2) Log-W	(2) Select	(3) Log-W	(3) Select
mother13	-0.00383*	-0.0670				
	(.0361)	(.0429)				
nkids			-0.0248	-0.0696***		
			(.0197)	(.0217)		
caregiver					-0.0218	-0.139*
					(.099)	(.0747)
russian	0.429***	0.0342	0.431***	0.0416	0.423***	0.0343
	(.0214)	(.0256)	(.0215)	(.0282)	(.0289)	(.0256)
married	-0.0001	-0.0574*	-0.0281	-0.0090	0.0098	-0.0636**
	(.0263)	(.0294)	(.0233)	(.0321)	(.0376)	(.0289)
age_yr	-0.00761**	0.0161***	-0.0120**	0.0254***	-0.00975*	0.0139***
	(.0039)	(.0029)	(.0049)	(.0035)	(.0051)	(.0026)
urban	0.261***	0.149***	0.281***	0.142***	0.239***	0.151***
	(.0377)	(.0274)	(.0329)	(.0299)	(.0566)	(.0274)
preglv	0.0234	-0.0616*	0.0283	-0.0691*	0.0310	-0.0608*
	(.0294)	(.0352)	(.0298)	(.0398)	(.0401)	(.0352)
exp	0.00479*	0.0010	0.0019	0.00868**	0.0046	-0.0004
	(.0028)	(.0033)	(.0037)	(.0042)	(.0035)	(.0033)
age_exp	0.0000	-0.0001	0.0000	-0.000302***	0.0000	-0.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
grdlev	0.0726***	-0.0239*	0.0705***	-0.0298**	0.0762***	-0.0221*
	(.0111)	(.0126)	(.0111)	(.0137)	(.0149)	(.0125)
higher_ed	0.333***	0.0447*	0.373***	0.0114	0.327***	0.0450*
	(.0232)	(.0269)	(.0217)	(.0297)	(.0316)	(.0268)
tech_ed	0.0023	0.0492	0.0298	0.0282	-0.0045	0.0478
	(.0266)	(.0314)	(.0249)	(.034)	(.0359)	(.0314)
ncat1	0.260**	-0.455***	0.217**	-0.421***	0.359**	-0.367***
	(.111)	(.0261)	(.0872)	(.0289)	(.183)	(.0617)
ncat3	0.0306*	-0.0431**	0.0569***	-0.0734***	0.0360	-0.0436**
	(.0173)	(.0201)	(.0193)	(.0224)	(.0237)	(.0201)
ncat4	-0.0586**	0.0905***	-0.0269	0.0836***	-0.0722*	0.0943***
	(.0247)	(.0218)	(.0224)	(.0252)	(.0372)	(.0215)
ncat5	-0.0136	-0.0312	0.0037	-0.0751	-0.0111	-0.0310
	(.0375)	(.0504)	(.0396)	(.0567)	(.0494)	(.0503)
ncat6		0.0241		0.0351		0.0281
		(.0307)		(.035)		(.0304)
lambda		-1.159**		-1.051**		-1.534*
		(.525)		(.436)		(.824)
Constant	2.938***	0.660***	3.027***	0.444**	3.095***	0.675***
	(.256)	(.165)	(.26)	(.189)	(.386)	(.165)
Observations	14974	14974	12358	12358	14977	14977

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Three specifications of the Heckman Selection estimation for the Log-hourly Wage with sample limited to only females and rounds 13-21.