

The Wage Costs of Motherhood: Which Mothers are Better Off and Why

Ludmila Nivorozhkina
Rostov State Economic University
Anton Nivorozhkin*
Institute for Employment Research (IAB)
Sergey Arzhenovskiy
Rostov State Economic University

November 1, 2006

Abstract

In this paper we analyze how motherhood affects women's wages. Using a dataset from Russia we adopt a matching technique to account for possible selection effects. Our findings indicate that mothers tend to suffer a moderate wage penalty. We also confine our analysis to sector-specific effects and find that the negative effect may primarily be attributed to mothers working in the public sector. The differences across sectors may be explained by considerable job flexibility and a system of promotion based on work experience which has been adopted in the public sector.

JEL Classification: J13 J18 P35 C14

Keywords: Family gap; Fertility; Transition Economics; Matching

We thank Eugene Nivorozhkin for providing comments and the Independent Institute for Social Policy Evaluation (Ford Foundation) for financial support. The usual disclaimer applies.

*Corresponding address: Regensburger Str. 104, 90327 Nuremberg, Germany; e-mail: anton.nivorozhkin@iab.de

1. Introduction

This paper presents new evidence on how labour markets respond to motherhood by exploring the effects of motherhood on wages. The wage differentials between mothers and non-mothers have often been referred to as the “family gap” and have received a lot of attention from economists, sociologists and policy makers. Recent trends show that while the overall wage gap between males and females is declining over time, the wage gap between mothers and non-mothers is widening (Waldfogel, 1998). Empirical estimates suggest that the wage penalty for motherhood may be as large as 10-15% and could be even larger than the gender wage gap (Korenman and Neumark, 1991).

It is important to study the wage penalty for motherhood for a number of reasons related to gender inequality. Women tend to pay a disproportionately high price for childbearing and child-rearing activities. Recent research has shown that the effect of having children on wages is strongly negative for mothers but positive for fathers (e.g. Lundberg and Rose, 2000). The latter factor may have a pronounced effect on other aspects of gender inequality, for example, bargaining power in the household or disparity in lifetime earnings. Moreover, raising children is important from the social point of view and should be encouraged, thus appropriate policies should be introduced in order to eliminate the motherhood penalty (Folbre, 1994).

There are several theories which aim to explain the persistence of the “family gap”. Human capital theory suggests that more productive workers should be paid higher wages and an individual’s productivity depends positively on the level of human capital, such as formal education, vocational training and work experience. It is often suggested that the wage penalty for having children exists due to the fact that mothers have lower levels of human capital. Anderson et al. (2003) report that in the U.S.A. mothers had almost one year less of formal schooling compared to non-mothers. In addition to having low levels of education, mothers are likely to accumulate less vocational training and work experience due to career

interruptions (e.g. Budig and England, 2001). More importantly, as a consequence of motherhood a lot of women do not return to a full-time job, choosing to work part-time instead (e.g. Anderson et al, 2003; Strober and Chan, 1999). Empirical research found a 4-9% wage penalty for mothers after controlling for the level of human capital and experience (Waldfogel, 1998).

Another rationale for the existence of the motherhood wage penalty comes from the work-effort theory. According to this theory, women cannot deliver full effort at work due to the disproportionately large burden of family responsibilities. Becker (1981, 1985) points out that these family responsibilities limit career developments and thus suppress the wage growth of mothers. In this view, even holding the stock of human capital equal between mothers and non-mothers, mothers would earn less due to the primary responsibilities for childcare and other house work. Becker suggests that women self-select themselves into occupations that are family-friendly and require less effort, which often pay less. Empirical evidence of work-effort and the wage penalty for mothers is mixed. Budig and England (2001) did not find any sizeable effect on the wage penalty resulting from mothers' occupations and the effort associated with these choices. In contrast, Anderson et al. (2003) report that the wage penalty tends to decrease as the age of the children rises, which could potentially indicate that as children grow older and become more independent, mothers can devote more energy to work. A large amount of empirical research is devoted to occupational segregation, when mothers are assumed to select occupations that are potentially family-friendly. For example, Nielsen et al. (2004) find that women self-select themselves into the public sector in order to avoid excessive wage penalties for having children.

A final possibility is that the low wages of mothers could be driven by discrimination in the labour market. Statistical discrimination occurs if employers use motherhood as a screening device in hiring or promotions, assuming that mothers are less productive and should therefore be paid less. Alternatively, an employer might find it "distasteful" to hire a

mother for reasons other than productivity. Although any type of discrimination is prohibited by law, there is no clear-cut method in empirical research to detect the possible scope of discrimination.

The aim of this study is to further investigate the current effects of having children on the wage penalty and to bring attention to this issue in the context of Russia. To our knowledge the effects of motherhood on labour income has not yet been investigated in Russia and relatively little research has been conducted for transition economies in general. We fill the gap in the knowledge by presenting a comprehensive analysis of the motherhood wage penalty using the NOBUS data set recently collected in Russia (see Ovcharova and Tesliuc (2005) for a description of the dataset).¹ We implement propensity score matching and attempt to take into account the fact that some variables, such as education and experience may be predetermined with respect to motherhood. Moreover, following Simonsen and Skipper (2006) we estimate a model of sector choice and the decision to become a mother simultaneously, thus presenting estimates of the motherhood wage penalty in the public and the private sectors.²

The next section presents a brief review of the research on the gender wage gap in transition economies and describes the data. Section 3 outlines the methodology and describes the matching algorithm used in the paper. Section 4 presents and discusses the results of the estimation. Finally, Section 5 concludes and discusses the limitations of the presented analysis.

2. Background

Historically, the labour force participation of women in the countries of Central and Eastern Europe and the former Soviet Union has been high by international standards. Prior to

¹ The survey is representative for 47 out of 89 subjects (regions) of the Russian Federation and covers 72% of the total population of the country (more information on NOBUS is available at: <http://nobus.worldbank.org.ru>).

² Beblo et al. (2006) also use matching estimator to investigate the motherhood wage penalty

the beginning of transition women's labour force participation ranged from 65% to 85% and was only marginally lower than that of the male labour force. From the start of economic transition women's labour force participation began to decline primarily due to the rise in unemployment. The gender wage gap, however, has remained relatively stable over the past years, amounting to 25% – 30% (Gerry et al., 2004). A number of papers have aimed at explaining the relatively stable gender wage gap in transition economies (e.g. Glinskaya and Morz (2000), Hunt (2002), Newell and Reilly (1996 and 2000)). One of the explanations which were put forward regarding the existence of the gender wage gap is occupational segregation. Jurajda (2003) investigates gender-specific occupational segregation in the Czech and Slovak Republics, Ogloblin (1999) performs a similar analysis for the case of Russia. Both studies conclude that the existing gender segregation is an important factor which contributes to the overall gender wage gap. Wage differentials between the private and public sectors in Russia were addressed by Jovanovic and Lokshin (2004) using the Moscow labour force survey. The authors estimate the gap between the public and the private sector to be around 14% for men and 18% for women. Moreover, they indicate that, compared to men, women face a larger wage penalty in the public sector than in the private sector.³ Although undoubtedly important, none of the reviewed studies has focused so far on another aspect of earnings inequality – a gap due to motherhood. We fill the gap in the existing literature on the wage penalty in transition economies and contribute to the emerging discussion of gender segregation between the public and the private sector.

This study is based on the Sample Survey of Household Welfare and Participation in Social Programs, also known as the NOBUS for its Russian acronym. The survey was carried out by the Russian Statistical Agency with the assistance of the World Bank. The survey was conducted in the second quarter of 2003 and covers 44,529 households.

³ It is important to bear in mind that the authors' estimates are based on information related to the capital and can not necessarily be used to make a generalization for Russia as a whole.

For the purpose of our study we restrict our sample to women aged 18-49 who reported positive wages and hours worked, who are not self-employed and not undertaken education. Table 1 shows the descriptive statistics of the chosen variables in the sample for mothers and non-mothers. We define a mother as a woman who reports having a child who lives with her in the same household, 58.8% of the women in our sample have children.⁴ The outcome of interest in the analysis is the log monthly wage after tax.⁵ It is seen that the average wage of non-mothers differs from that of mothers. It is also clear from Table 1 that non-mothers differ significantly from mothers in terms of observable characteristics: mothers are older; they have more work experience and they are also more likely to be better educated. Furthermore, mothers are likely to live in rural areas and, not surprisingly, to be married.

3. Evaluation approach

The objective of our evaluation analysis is to measure the impact of treatment D on the outcome Y . In our case the treatment is having children and the outcome is the logarithm of the monthly wage. Let Y_1 and Y_0 be the outcomes in two states, $D = 0$, no children and $D = 1$, some children respectively. Then the person-specific wage impact of having children is defined as $\Delta_i = Y_{0i} - Y_{1i}$. The problem is that it is not possible to observe outcomes in two states for the same person simultaneously. The problem of unobserved outcomes could easily be solved if we were able to conduct a control experiment, randomly assigning participation in the programme. Random assignment would ensure full comparability of participants and non-participants. Then the effect of the programme could be calculated as a simple average difference between outcomes. Unfortunately, the experimental approach is impossible to implement in our case for obvious reasons. Since randomisation is not possible, one can use

⁴ It is possible that some children in the household are stepchildren.

⁵ Some may argue that the concept of the monthly wage is not appropriate. According to this argument, the hourly wage would yield a more accurate assessment of the wage structure. However, we chose the monthly wage since wages in Russia are usually paid on a monthly basis. Moreover, by restricting ourselves to a monthly wage we minimize measurement error self-reported hours worked.

non-experimental data to construct a counterfactual situation. However, the decision to become a mother is unlikely to be random, but might rather be governed by some observed characteristics. Since mothers and non-mothers are likely to be different, it is necessary to construct an appropriate estimator. The estimator used here was based on a statistical matching procedure which tries to mimic a controlled experiment. An important contribution to the literature on matching methods was Rosenbaum and Rubin's (1983, 1984) seminal papers. They proposed statistical matching on the basis of the predicted probability of being treated i.e., propensity score, $p(X_i)$, where X_i is a vector of observed individual characteristics.

The propensity score can be estimated using logistic regression and has the property that, if all relevant covariates were included in its estimation, matching could be performed on the basis of the propensity score alone. An important assumption made in order to justify propensity score matching is that all relevant differences in outcomes are captured by the observed variables, and that no unobserved characteristics influence the decision to participate. This is the so-called conditional-independence assumption (CIA), which means that conditional on $p(X_i)$, participation and outcome are assumed to be independent.

We choose to estimate Average Treatment Effect on the Treated (ATT) since we are interested in the effect of motherhood on those women who already have children. Using CIA and the fact that $0 < p(X_i) < 1$ we can define ATT as:

$$\begin{aligned} \Delta_{ATT} &= E\{Y_i(1) - Y_i(0) \mid D_i = 1\} \\ &= E\{E[Y_i(1) - Y_i(0) \mid D_i = 1, p(X_i)]\} \\ &\stackrel{CIA}{=} E_{p(X)}\{E[Y_i(1) \mid D_i = 1, p(X_i)] - E[Y_i(0) \mid D_i = 0, p(X_i)] \mid D_i = 1\} \end{aligned}$$

A potential problem of our set-up is the existence of explanatory variables which are potentially affected by the treatment. Rosenbaum (1984) examines the consequences of including potentially predetermined variables in the estimation and concludes that such adjustment results in unbiased estimates only if the variables are not affected by the treatment.

Furthermore, Robins and Greenland (1992) point out that in the presence of predetermined covariates the identification of the effect becomes problematic.

One of the variables that are presumably affected by motherhood is sector choice. The choice between work in the public or the private sector may be affected by the presence of children and may simultaneously affect wages. In a recent study Simonsen and Skipper (2006) suggest estimating the propensity score using a bivariate probit model of sector choice and the fertility decision in order to assess the impact of motherhood and sector choice simultaneously. In the following sections we adopt the approach of Simonsen and Skipper (2006) assuming sector choice to be predetermined with respect to fertility.

4. Propensity score matching

We first estimate the standard probability model to determine the propensity score for becoming a mother.⁶ For the estimation of the propensity score we select variables which are certainly not affected by the treatment. The set of explanatory variables includes age, regional identifiers and area dummies. We also include education dummies assuming that in most of the cases they are not affected by motherhood. The results are presented in Table 2. As expected, the probability of becoming a mother increases with age and declines with the size of the area in which the individual is living. We also find that women with a postgraduate degree face the lowest probability of becoming a mother. The model predicts relatively well: 76% of all the observations are predicted correctly and the R^2 equals 0.172. Figure 1 shows the distribution of the propensity score for both mothers and non-mothers. It is seen from the graph that propensity scores of mothers are more concentrated around high values compared to the propensity scores of non-mothers. Note that most of the observations lie in the area of common support, i.e. it is possible to find a match for mothers even for the highest propensity score values.

⁶ We choose to estimate a standard probit model.

As we mentioned above, in our sample mothers differ from non-mothers in observed characteristics. Thus, a direct comparison of wages for these groups is incorrect since any disparities may be caused by other observed characteristics, such as age and/or educational mismatch.

We first perform matching based solely on the propensity score; this should give us the net effect of being a mother. The net effect includes the direct effect of being a mother as well as indirect effects resulting from the reduced labour market experience and/or the higher probability of working in the public sector. Thus, the net effect measures the total costs of being a mother, resulting from all contaminant variables. The results of the estimation of the net effect are presented in the middle column of Table 4. We estimate the effect using a single nearest neighbour matching method. The net effect of being a mother is negative. Mothers in general earn 4% less than non-mothers. To test the balance of covariates, or to check that the means of the variables used in the estimation of the propensity score do not differ between the treatment and control groups, we implement a balancing test as suggested by Rosenbaum and Rubin (1985). The results are presented in Table 3. Using a matched sample we conclude that most of the observed differences in the values of the covariates were eliminated after matching, for example we eliminated large covariate imbalances related to the age distribution of mothers and non-mothers.

We next proceed to the estimation of the direct effect of motherhood: the direct effect measures the effect of motherhood free of the effect of other variables. To measure this we use a regression-adjusted method as suggested by Abadie and Imbens (2002) and Abadie et al (2001). The regression-adjusted method adjusts the difference within the matches for the difference in the values of their covariates and is performed using the ordinary least squares procedure on the matched observations.⁷ We make the adjustment based on the work

⁷ To estimate the direct effect, following Simonsen and Skipper (2006), we need to assume additive separability of the outcome equation and that the effect of unobservable in the outcome equation is mean independent of

experience and individual occupation. The results of the estimations are presented in the right-hand column of Table 4. As before we find that being a mother has a negative effect on wages. This adjusted effect is smaller, however, compared to the non-adjusted effect. After controlling for experience and occupation mothers on average earn 3% less than non-mothers.

An important variable which is left out of the analysis is the sector in which the woman is employed. To account for the sector choice we adopt the methodology proposed by Simonsen and Skipper (2006) and estimate a bivariate probit of sector choice and motherhood. The results are presented in Table 5. Based on the results of the estimation we predict a joint probability of being a mother and working in the private or public sector. When modelling the sector selection we condition on the motherhood indicator, type of education, region and place of residence. Comparing Table 5 and Table 2 it is obvious that the coefficients in the motherhood equation remained unaffected, while, as expected, the results from the sector choice equation (Table 5) confirm our hypothesis that mothers are less likely to work in the private sector. We next proceed to estimate the joint impact of motherhood and sector choice. As before we estimate both the net and the direct effects of motherhood.

Rows 2-3 of Table 4 present the results from the estimation taking into account the endogeneity of sector choice. A striking feature of the analysis is that estimates of the motherhood wage penalty clearly differ depending on the sector choice. We observe a relatively small positive and significant net effect for mothers in the private sector, while the net effect of being a mother in the public sector does not differ statistically from zero. Moreover after performing regression adjustment we observe that the penalty for having children and working in the public sector increases to 8% and is statistically significant. At the same time the direct effect of motherhood and employment in the private sector is smaller in absolute terms but remains positive, though statistically insignificant.

variables that are potentially affected by the treatment conditional on the variables that are included in the estimation of the propensity score.

It is important to mention that the net effect cannot be used to conclude that being a mother is more “expensive” in the public sector. To a large degree the differences may reflect that women in the private sector make different choices with respect to working hours, effort, occupation compared to women in the public sector. An alternative explanation comes from the fact that in the public sector promotion is often based on the seniority principle, thus mothers who spend some time on maternity leave may be disadvantaged in terms of their career prospects and salary increase. Moreover, greater job flexibility in the public sector may make it possible for mothers to relocate to more “family-friendly” positions which allow flexible or reduced working hours along with fewer career and pay prospects.

Our finding of a moderate yet insignificant direct wage gain in the private sector may be somewhat surprising. One explanation is that a mother who chooses to remain in the private sector increases her work effort believing that she would otherwise be discriminated. However, discrimination in the private sector does not exist or is relatively rare and thus the woman is able to offset it and to contribute to her wage growth. Another explanation comes from the fact that private employers may actually discriminate young non-mothers, believing that they may soon have a child and use their maternity leave. Finally, the wage premium for motherhood in the private sector may be interpreted as a compensation for low flexibility and higher disutility of work for mothers.

How does our result relate to previous findings on a motherhood wage penalty? As we mentioned before we are not aware of a study which investigates the motherhood penalty in Russia or any transition economy. However, in comparison to the wage penalty of 7% - 13% found in studies for western Europe and the USA, our finding of an overall 4% penalty seems relatively low (see Ellwood, 2004). The relatively moderate wage penalty may be explained by the relatively well-developed system of child care inherited from the former Soviet Union. Moreover, a surprising result that emerges from our study is that mothers who work in the public sector are penalized to a greater extent compared to mothers working in the private

sector. Similar results were obtained for Denmark by Simonsen and Skipper (2006), who used similar methodology to study the impact of motherhood and sector choice.

6. Conclusion

Eliminating the motherhood wage penalty is undoubtedly important because of the equality issues. Moreover, it is in the best interest of society to utilise fully the abilities that women provide and to reward them accordingly.

In this paper we provide first evidence of the motherhood wage penalty in Russia and investigate an important aspect of heterogeneity related to a sector choice made by mothers. Our findings indicate the presence of a moderate wage penalty of 4% - less than previously found for other countries. Despite a prevailing belief that public sector work is family-friendly, it is evident that most of the wage penalty is borne by women working in the public sector. We estimate the wage penalty of mothers working in the public sector to be 8%; at the same time we find a positive but small and insignificant premium for being a mother working in the private sector. However, this does not necessarily contradict the notion of a “family-friendly” job, but rather highlights the relative flexibility in terms of work load that mothers can choose to take in the public sector.

Russian social policy is at a crossroads. After a period of economic stagnation, an economic upheaval and a shift in policy attracted attention to fertility problems. Several measures have recently been put forward to encourage childbearing. These measures include monetary transfers and state subsidies. However, little attention has been paid to the issues of poor labour protection for mothers and the existence of a wage gap. Our study is the first attempt to draw attention to these issues and may provide a new venue for research.

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Table 1

Descriptive statistics for selected variables

Variables	Full sample	Non-mothers 41.24%	Mothers 58.76%
Wage	3051.37	3175.23	2964.43
<i>Age</i>	36.17	35.52	36.64
18 ≤ Age < 25	10.96	23.27	2.33
25 ≤ Age < 30	15.30	15.10	15.43
30 ≤ Age < 35	14.54	5.55	20.85
35 ≤ Age < 40	16.18	5.92	23.38
40 ≤ Age < 50	43.02	50.16	38.01
<i>Education</i>			
No education or incomplete primary	0.41	0.59	0.29
Primary	4.49	5.07	4.09
Less than secondary	18.17	18.90	17.65
Secondary	7.57	7.08	7.91
Initial vocational secondary	3.95	4.06	3.88
Advanced vocational secondary	37.18	34.87	38.81
Incomplete university	5.01	6.01	4.31
University	23.03	23.17	22.96
Postgraduate	0.18	0.28	0.10
Enterprise ownership			
State	45.19	46.43	44.32
Municipal	19.73	17.91	21.00
Non-profit	2.08	2.32	1.91
Private	25.52	25.91	25.25
Mixed (State and Private)	4.91	5.07	4.80
Mixed (Foreign and Private)	0.54	0.60	0.49
Foreign		0.02	0.02
Work Experience			
Exp. < 1	3.81	5.87	2.36
3 < Exp. ≤ 1	8.87	13.75	5.44
5 < Exp. ≤ 3	7.13	7.96	6.55
10 < Exp. ≤ 5	13.87	10.43	16.29
Exp. ≥ 10	66.31	61.98	69.35
<i>Size of place of residence</i>			
> 1 million	18.28	23.37	14.72
1 million – 250,000	20.26	21.04	19.72
250,000 – 20,000	28.17	28.37	28.03
Small town	12.58	12.50	12.63
Village	20.71	14.73	24.90
Family status			
Married	58.63	46.55	67.11

Table 2

Coefficient estimates and asy. std. err. from motherhood probit
 Dep. variable: 1 Mothers. 0 Non-mothers
 Full Sample

Variables	Coefficients	Std. deviation
<i>Age</i>		
18 ≤ Age < 25	-1.219***	0.062
25 ≤ Age < 30	0.204***	0.044
30 ≤ Age < 35	0.976***	0.069
35 ≤ Age < 40	0.976***	0.059
40 ≤ Age < 50	-	-
<i>Education</i>		
No ed. or incomplete primary	0.453	0.384
Primary	0.609	0.326
Less than secondary	0.658*	0.319
Secondary	0.725*	0.322
Initial vocational secondary	0.721*	0.326
Advanced vocational secondary	0.659*	0.318
Incomplete university	0.658*	0.325
University	0.640*	0.318
Postgraduate	-	-
<i>Regions</i>		
Region 1	-0.029	0.168
Region 2	0.062	0.162
Region 3	0.231	0.159
Region 4	0.064	0.159
Region 5	0.082	0.160
Region 6	0.131	0.203
Region 7	0.326*	0.163
Region 8	0.184	0.169
Region 9	-0.011	0.175
Region 10	0.393*	0.168
Region 11	0.077	0.164
<i>Size of place of residence</i>		
>1 million	-0.573***	0.063
1million – 250,000	-0.368***	0.051
250,000 – 20,000	-0.302***	0.051
Small town	-0.259**	0.081
Village	-	-
Constant	-0.405	0.356
Log-likelihood		-85243459

Table 3
Covariates imbalance after matching
Mean and standardized difference in percentage points

Variable		Mean		% bias
		Treated	Control	
<i>Age</i>				
18 ≤ Age < 25	Unmatched	0.02587	0.20535	-58.5
	Matched	0.02588	0.02616	-0.1
25 ≤ Age < 30	Unmatched	0.1573	0.15587	0.4
	Matched	0.15733	0.1528	1.2
30 ≤ Age < 35	Unmatched	0.21282	0.05757	46.6
	Matched	0.21286	0.20096	3.6
40 ≤ Age < 50	Unmatched	0.23359	0.05988	50.6
	Matched	0.23345	0.24762	-4.1
<i>Education</i>				
No ed. or incomplete primary	Unmatched	0.0034	0.00347	-0.1
	Matched	0.0034	0.00085	4.4
Primary	Unmatched	0.04362	0.04202	0.8
	Matched	0.04363	0.03589	3.8
Less than secondary	Unmatched	0.1793	0.18337	-1.1
	Matched	0.17934	0.16791	3
Secondary	Unmatched	0.0728	0.0708	0.8
	Matched	0.07262	0.07716	-1.8
Initial vocational secondary	Unmatched	0.03191	0.03418	-1.3
	Matched	0.03192	0.02965	1.3
Advanced vocational secondary	Unmatched	0.39307	0.36816	5.1
	Matched	0.39314	0.41553	-4.6
Incomplete university	Unmatched	0.03918	0.05269	-6.5
	Matched	0.03919	0.03154	3.7
University	Unmatched	0.23577	0.24274	-1.6
	Matched	0.23581	0.2411	-1.2
<i>Region</i>				
Region1	Unmatched	0.04069	0.05757	-7.8
	Matched	0.0407	0.03608	2.1
Region2	Unmatched	0.16599	0.20059	-9
	Matched	0.16602	0.17339	-1.9
Region3	Unmatched	0.14267	0.12208	6.1
	Matched	0.1427	0.14543	-0.8
Region4	Unmatched	0.16429	0.16564	-0.4
	Matched	0.16432	0.16073	1
Region5	Unmatched	0.09716	0.10357	-2.1
	Matched	0.09718	0.0951	0.7
Region6	Unmatched	0.01671	0.01812	-1.1
	Matched	0.01672	0.01738	-0.5

Region7	Unmatched	0.1371	0.10897	8.6
	Matched	0.13712	0.13996	-0.9
Region8	Unmatched	0.06288	0.05474	3.5
	Matched	0.0629	0.06337	-0.2
Region9	Unmatched	0.03475	0.03213	1.5
	Matched	0.03475	0.03674	-1.1
Region10	Unmatched	0.03569	0.02557	5.9
	Matched	0.03551	0.03674	3.5
<i>Size</i>				
>1 million	Unmatched	0.08063	0.13634	-18
	Matched	0.08065	0.08141	-0.2
1million – 250,000	Unmatched	0.21027	0.25765	-11.2
	Matched	0.21031	0.21928	-2.1
Small town	Unmatched	0.27826	0.28515	-1.5
	Matched	0.27831	0.27632	0.4
Village	Unmatched	0.14597	0.12709	5.5
	Matched	0.146	0.14109	1.4

Table 4
 Comparison of estimated ATT
Dependent variable log monthly wage

	Net effect	Direct effect
Overall	-0.040 (0.0144)	- 0.029 (0.0141)
Mother and private	0.0334 (0.0154)	0.020 (0.0148)
Mother and public	0.0229 (0.0179)	-0.085 (0.0174)

Table 5
Coefficient estimates and asy. std. err.
Motherhood and sector bivariate probit

	Private sector			Motherhood		
	Coefficients	Std. deviation	t-stat	Coefficients	Std. deviation	t-stat
<i>Age</i>						
18 ≤ Age < 25				-1.23	0.06	-19.62
25 ≤ Age < 30				0.19	0.05	4.09
30 ≤ Age < 35				0.97	0.07	14.12
35 ≤ Age < 40				0.97	0.06	16.37
Child	-0.17	0.08	-2.18			
<i>Education</i>						
No ed. or incomplete primary	0.34	0.57	0.60	0.45	0.39	1.16
Primary	0.61	0.49	1.25	0.61	0.33	1.85
Less than secondary	0.60	0.49	1.22	0.66	0.32	2.05
Secondary	0.46	0.49	0.94	0.72	0.32	2.23
Initial vocational secondary	0.58	0.49	1.17	0.72	0.33	2.19
Advanced vocational secondary	0.34	0.49	0.69	0.66	0.32	2.05
Incomplete university	0.38	0.49	0.76	0.66	0.33	2.02
University	0.09	0.49	0.18	0.64	0.32	1.99
Postgraduate	-	-	-	-	-	-
<i>Region</i>						
reg1	-0.69	0.08	-8.65	-0.10	0.08	-1.28
reg2	-0.12	0.06	-2.17	-0.01	0.07	-0.11
reg3	-0.06	0.06	-0.92	0.16	0.07	2.44
reg4	0.03	0.06	0.41	-0.01	0.07	-0.08
reg5	0.04	0.06	0.67	0.01	0.07	0.19
reg6	-0.04	0.14	-0.25	0.06	0.14	0.44
reg7	-0.12	0.07	-1.64	0.26	0.08	3.45
reg8	0.11	0.08	1.32	0.12	0.09	1.31
reg9	-0.50	0.10	-5.16	-0.08	0.10	-0.78
reg10	-0.67	0.10	-6.92	0.32	0.09	3.57
Size of place of residence						
>1 million	0.19	0.06	3.10	-0.57	0.06	-9.07
1million – 250,000	0.35	0.05	7.07	-0.37	0.05	-7.24
250,000 – 20,000	0.20	0.05	3.98	-0.30	0.05	-5.93
Small town	-0.05	0.07	-0.79	-0.26	0.08	-3.19
Constant	-0.82	0.49	-1.67	-0.33	0.33	-1.01
Log-likelihood			-85243459			

Figure 1

Distribution of the propensity score

