Search Intensity and Wage Differences

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Differences in job search behaviour have long been recognized in theoretical literature as a potential source of wage differentials. The aim of the current paper is to estimate whether there exists a systematic difference in search activity between genders and whether this can explain a part of the gender wage gap. These hypotheses are tested using micro-level data for the years 1998–2000 from the Estonian Labour Force Survey. The empirical model yields a result that unemployed men search more actively for new jobs than women. Controlling for the difference in search intensity significantly reduces the residual gender wage differential.

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1. Introduction

The aim of this paper is to investigate whether gender differences in search activity influence the male-female wage gap. The existence of a gender wage gap has been observed ever since labour income statistics have been available. Although it has narrowed during the last decades in most industrial countries, a substantial disparity in relative wages still remains. Part of the gender wage gap is caused by differences in characteristics that affect labour market productivity (such as gender differences in education and labour market experience) and different occupational choices. However, a considerable male-female wage differential remains even after controlling for observable factors. The remaining gap is interpreted as the consequence of either labour market discrimination or the existence of unobservable factors that differ systematically between sexes and affect productivity.

In addition to the above-mentioned factors, differences in search behaviour have long been identified in theoretical literature as a potential source of wage differentials (see, e.g. van den Berg 1990a, 1990b). Although the notion that search behaviour differences affect the wage gap is well grounded by theoretical literature, only a few empirical papers look at the various aspects of search behaviour and their potential effect on wage differentials. Bowlus (1997) investigates the gender differences in exiting jobs to nonparticipation and unemployment duration and finds that they explain a substantial proportion of the male-female wage gap. A paper by Bowlus et al (2001) looks at the similar aspects of labour market behaviour and finds that a large proportion of the racial wage gap in the US can be explained by these factors as well. Raphael and Riker (1998) analyse geographic mobility of displaced workers and come to the conclusion that a difference in mobility also contributes to the racial wage gap in the US.

Although the above-mentioned aspects of search behaviour have been examined in this context, there exist no empirical papers that analyse the potential impact of search intensity on the gender wage gap. The aim of the current paper is to fill this gap. According to labour market search models, the more intensely a person looks for a job (either when employed or unemployed), the higher the possibility that he can find the most suitable match to his skills and the higher are his earnings at the new job, ceteris paribus. In the current paper this implication of theoretical search models is tested on the Estonian micro-level labour market data. The purpose of the paper is to investigate whether: (i) men look more intensely for a new job when unemployed; and (ii) controlling for this systematic difference in search behaviour reduces the unexplained fraction of the male-female wage gap.

Search intensity is endogenous with respect to labour income since it depends on the expected wage offer distribution. To account for the endogeneity of this explanatory variable, search intensity and wage regressions are estimated as a system of simultaneous equations. The estimation is based on two samples. Search intensity is estimated on a set of various demographic and individual-based characteristics using a sample of displaced workers that contains the data on workers' post-displacement job search behaviour. To control for the potential impact of an expected wage on search activity, the person's wage at the last occupation is included in the set of explanatory variables. On the basis of these regression estimates, an imputed search intensity variable is formed for a sample of current workers and added to the right-hand-side of a standard log-wage regression. The empirical model yields a result that is consistent with the hypothesis postulated above. Potential search activity is systematically higher for men than for women and strongly affects wages. Including this variable in the wage regression significantly reduces the residual gender wage differential. A more detailed description of the model set-up, the exclusion restrictions that are used, and the estimation of the asymptotic variance-covariance matrix of the structural wage equation coefficients are given in the fifth section of this paper.

The development of the gender wage gap in Estonia within the last decade has been influenced by the structural changes in the labour market that took place during the economic transition process. The section following the introduction analyses these recent developments in comparison to other Central and Eastern European (CEE) countries.

2. Development of the Gender Wage Gap during Transition

Although formally, all people had the same labour market opportunities and were treated equally during the Soviet era, the official rhetoric did not reflect the reality. Before the beginning of the transition period (i.e. at the end of the 1980s) there existed a substantial gender wage gap. Women earned, on average, only 66% of the male wages in Estonia in 1989 (Noorkõiv et al (1997)). Compared with other transition economies, Estonia was no exception regarding the gender pay difference; the average gender pay ratio in the CEE economies was 72% at the end of 1980s. (Table 2.1 presents an overview of the gender pay ratios in the CEE countries before the beginning of the transition.)

During Soviet times, the education-wage profile was flat due to the system of centrally set wages where manual jobs in the agricultural and industrial sectors were better paid on average than the service sector jobs. Since the central wage-setting system put a larger relevance to the skills needed for conducting manual jobs and a smaller importance to cognitive and interpersonal skills, female-dominated jobs were underpaid relative to male-dominated occupations. The segregation of women into low-paying occupations was enforced by the obligatory placement system, according to which all people were required to take the centrally assigned jobs after graduation. As a result, despite low income inequality in general, male-female pay differences were larger in the Soviet block than in the Western European countries.

There is a wealth of research studying the evolution of gender-specific wage differentials during the early years of transition. Table 2.1 presents a comparison of the gender pay ratios before the beginning of the transition period and in the middle of the 1990s. In almost all CEE countries gender pay gaps declined during this time period. This implies that economic reforms brought along a relative improvement in the women's labour market position. The economic transition was characterized by a rapid increase in wage differentiation and a simultaneous decline in the labour force participation rates from the artificially high levels of the Soviet era. Both of these factors contributed to the reduction of the gender pay gap.

An increase in pay inequality coincided with and was to some extent the consequence of an increasing demand for better-educated labourers. Relative returns to education and relative employment opportunities of more educated workers rose rapidly during transition. In comparison with males, women benefited more from this development, since in most former Soviet countries females were and are more educated on average.[1] In addition to benefiting from a greater demand for an educated labour force, women also worked disproportionately more in sectors that gained from the transition. Orazem and Vodopivec (2000) show that in Estonia and Slovenia, labour demand fell the most in predominantly male sectors, while predominantly female sectors either declined little or expanded. This was likely the case in many other transition economies as well, since the employment loss was the largest in heavy industry sectors and agriculture where the workforce was male-dominated. On the other hand, female-dominated sectors, such as trade and services, were underdeveloped under the socialist system and relative labour demand increased in these sectors during the transition.

Table 2.1. Gender pay ratios in the CEE countries before transition and in the mid-nineties

Country	Gender pay ratio		Gini coeff.
	Before transition	**Mid-nineties**	**Mid-nineties**
Czech Republic	0.66	0.81	25.4
Hungary	0.74	0.79	24.4
Poland	0.74	0.79	31.6
Slovakia	0.66	0.78	19.5
Bulgaria	0.74	0.69	26.4
Romania		0.76	28.2
Slovenia	0.87	0.87	28.4
FR Yugoslavia		0.88	
Estonia	0.66	0.75	37.4
Latvia		0.80	32.4
Lithuania		0.71	34.0
Russia	0.71	0.70	
Ukraine		0.78	
CEE average	0.72	0.78	28.8

Sources: Newell and Reilly (2000), Noorkõiv et al (1997), UNDP Human Development Report 2001.

[1] In Estonia 23% of working age women have a higher education degree, compared with 15% of working age men.

An additional factor causing a decline in the gender wage gap during the transition in Estonia and in some (but not all) other CEE countries was structural change in the labour force composition. Similarly to other post-socialist economies, economic transition in Estonia brought along a decline in the overall employment rate, but the drop in employment was more pronounced for women than for men. Since individuals with the lowest earnings potential (i.e. low-skilled workers) were the most likely to drop out of the labour force during the period of employment contraction, the gender difference in relative reductions in the employment rates changed the labour force composition. As a result, the skill pool of women who remained in the labour force improved relative to men. There is evidence of such a development in Estonia, where during the first years of transition (between 1989 and 1995) the employment shares for the least-educated groups fell relatively less (from 37 to 18 per cent) for men and relatively more (from 35 to 12 per cent) for women (Orazem and Vodopivec (2000)). The idea that the change in the labour force composition was a source of the reduction in the gender wage gap was first pointed out by Hunt (2002). She showed that in Eastern Germany this decline was in part caused by low-earning and low-skilled women selectively dropping out of the labour force.

To gauge the comparison of the gender pay differences in Eastern and Western Europe, Table 2.2 offers an overview of the gender pay ratios in the EU member countries in 1998. The average pay ratio was approximately 5 percentage points higher in the EU than in the CEE countries. As first noted by Blau and Kahn (1992), an important factor that influences gender differences in wages across countries is the overall income inequality. To offer a comparison in this respect, Tables 2.1 and 2.2 present Gini coefficients for the CEE and Western European countries. The average Gini coefficients are approximately the same in the CEE and in the Western Europe. Thus, overall income inequality cannot be the cause of a larger pay gap in the former Soviet block. A potential reason for a lower gender wage gap in the EU countries is the long-term existence of anti-discrimination labour market policies, which have been implemented only recently in former Socialist countries. In several CEE economies (including Estonia) the equal pay-related policies have not yet been legislated.

Table 2.2. Gender pay ratios (%) in the EU, 1998

Country	Gender pay ratio			Gini coefficient
	Total	Private sector	Public sector	
Austria	78.9	73.7	89.5	23.1
Belgium	92.7	87.3	97.9	25.0
Denmark	89.6	85.5	96	24.7
France	89.2	81.9	93.7	32.7
Germany	80.6	75.2	89	30.0
Greece	86.8	78.3	99.1	32.7
Ireland	80.2	75.8	89.3	35.9
Italy	91.4	90.6	108.1	27.3
Netherlands	78.9	76.4	74.5	32.6
Portugal	94.1	76.6		35.6
Spain	85.7	79.9	87.7	32.5
UK	75.7	70.6	79.7	36.1
EU average	83.8	76.3	89.3	29.7

Sources: Employment in Europe 2002, European Commission; UNDP Human Development Report 2001.

3. Why Might Men Search More Intensely for New Employment than Women?

If during unemployment periods men look for work more actively than women then according to the search models they should earn higher average wages. There are several reasons why men's search intensity may be higher. First, it is likely that women have a higher opportunity cost of search. The traditional division of labor within families usually means that women have a larger share of household work, while men work more intensely outside the house. Also, if there is a need to take care of family members – children, ill or disabled relatives – then this duty usually falls to a woman. This implies that on average it is more costly for women to look for new jobs when unemployed.

Another explanation to why women are likely to search less intensely than men is their lower relative return on employment, compared with unemployment income. Since women have lower expected wages, they are less motivated to look for a job. The existence of a gender wage gap means that unemployed wives whose husbands work have higher alternative income than vice versa. This is an additional reason why women are less motivated to search for a job in general.

In addition to the above-mentioned factors, there are several behavioural reasons why women's search intensity may be lower. A number of studies in the psychological literature have shown that while both men and women exhibit overconfidence in certain situations, men are on average more likely to overstate their characteristics relative to others. (See Barber and Odean (2001) for an overview.) Men's relative overconfidence may contribute to the gender wage gap as a separate factor independent from search activity. The evidence from several psychology studies implies that people who work in masculine occupations (such as investment bankers, lawyers, managers and negotiators) tend to be overconfident (Barber and Odean (2001)). Since the salaries tend to be higher in masculine occupations, men may get selected for such jobs due to overconfidence and that may partly explain their higher earnings. But men's relative overstatement of their abilities can also contribute to the differences in search behaviour, since search activity depends on how a person values his or her job finding prospects and what is the expected salary.

It is also shown that women perform worse when they have to compete with others, while the performance of males improves in competitive environment. Gneezy, Niederle, and Rustichini (2002) conducted a laboratory experiment where they showed that as the competitiveness of an environment increases, there is a significant improvement in performance for men, but not for women. (Their conclusions, however, were based on a small sample and therefore not statistically robust.) The inference from this behavioural difference to the current study is straightforward. A job search is a competitive process and if women's performance worsens in competitive environments, they might get more easily discouraged and search less in general compared with men.

Finally, evidence from behavioural economics and finance literature implies that women are in general more risk-averse than men (see, e.g. Sunden and Surette (1998), Lehmann and Warning (2001)). This may also contribute to differences in search intensity. If women are more risk-averse, they are more likely to accept a job offer for a lower wage (i.e. their reservation wages may be lower on average), and search intensity is positively related with the reservation wage. On the other hand, a more risk-averse person may be more inclined to an intensive search, i.e. he/she might aim to lessen the risk of remaining jobless by trying to get as many job offers as possible. Due to these opposite incentives, the overall effect of risk-averseness on search intensity is ambiguous.

4. Empirical Methodology

The aim of the empirical model employed in the current paper is to test two hypotheses. First, whether men search more intensely than women and, second, conditional on the positive outcome of the first test, whether controlling for search intensity reduces the gender wage gap. I estimate search activity for unemployed workers and use this prediction as an additional control variable in the wage equation, which is regressed on a sample of workers. To get around the potential selection bias that may stem from the differences in the unobserved characteristics of the samples of workers and unemployed, the search propensity is estimated for workers who are displaced from their previous jobs for exogenous reasons, such as enterprise bankruptcy or liquidation. By assessing the propensity of search for exogenously displaced workers, I follow the idea used in the empirical model of Raphael and Riker (1998). Their estimation strategy was to use information on the geographic mobility decisions of exogenously displaced workers for the estimation of the wage equation on the sample of people who currently work.

The assumption that restricting the sample of unemployed persons to workers who have lost their jobs through enterprise closures eliminates the causes of job loss that are non-random with respect to worker productivity is based on an article written by Gibbons and Katz (1991). They develop an asymmetric-information model of layoffs. Gibbons and Katz argue that if a worker is laid off for endogenous reasons the job market infers this as a signal that this worker is of low ability, which will affect negatively his/her job finding probability and potential wage. Such a negative inference is not warranted when a worker is displaced by enterprise liquidation. Thus, workers who are unemployed for exogenous reasons should face the same job-market opportunities as the workers who are switching jobs without being involuntarily unemployed in the intermediate period. Gibbons and Katz provide empirical evidence that supports the theoretical implications of their model.

Search intensity depends on the expected wage offer distribution and is therefore endogenous to a worker's wage. To account for the endogeneity of the search intensity variable, I define a set of instruments (exclusion restrictions) that are based on family and household characteristics and estimate the model in two stages. In the first stage regression, the search intensity data for a sample of exogenously displaced workers is used to impute potential search activity for a sample of wage earners. In the second stage, the potential search activity is included as a regressor to the specification of a standard log-wage regression.

The estimation strategy can be formulated as follows. For an observation in sample 1 (the sample of wage earners) the vector of variables (y_{i1}, X_{i1}) is observed, where y_{i1} denotes the log wage and X_{i1} is a set of personal, work-related, and regional characteristics for the i-th worker. For an observation in sample 2 (the sample of displaced workers) the vector of variables (y_{i2}, X_{i2}) is observed, where y_{i2} measures job search activity of the i-th person, and X_{i2} is a set of personal and regional characteristics, including exclusion restrictions and the wage in the last job. The latter variable is used as a proxy for the expected wage.

I use two different measures for the job search activity, y_{i2}. First, y_{i2} is defined as a dummy variable indicating whether an i-th person had been actively looking for a new job within the last four weeks. Alternatively, y_{i2} is defined as an index variable, which summarizes the number of different job search methods used within the last four weeks. The list of the search methods is given in Appendix 1. The two different measures of search activity are highly correlated: their correlation coefficient is 0.85.

When the search activity is measured as a dummy variable then the estimated model in the current paper is a special case of the simultaneous equations model described in the paper by Heckman (1978). Using Heckman's derivation of the model estimates, Amemiya (1978) developed a method of estimating the asymptotic variance-covariance matrix for the slope coefficients of simultaneous equations models where one of the dependent variables is dichotomous. In Amemiya's derivations, it is implicitly assumed that both equations of the simultaneous system are estimated on the same sample, whereas in the current model, each equation is estimated on a different sample. Based on the assumption that the two samples are random draws from the same population, Amemiya's method for the adjustment of standard errors is applicable in this framework as well.

Using the vector notation, the simultaneous equations model employed in the current paper is defined by:

$$y_1 = \gamma_1 y_2^* + X_1\beta_1 + u_1 \tag{1}$$

$$y_2^* = X_2\beta_2 + u_2 \tag{2}$$

and for each observation i:

$$y_{i2} = \begin{cases} 1 & \text{if} \quad y_{i2}^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where y_1 is a $n_1 \times 1$ vector of log wages, y_2^* is a $n_2 \times 1$ vector of unobservable search activity variables, and X_1 and X_2 are $n_1 \times t$ and $n_2 \times k$ matrices of model regressors. u_1 and u_2 denote the corresponding vectors of residuals that are assumed to be jointly normally distributed with variances and covariance given by σ_1^2, σ_2^2, and σ_{12}.

The estimation of the model is carried out in two stages. In the first stage, equation (2) is estimated by probit. In the second stage, equation (1) is estimated, using the fitted values $X_2\hat{\beta}_2$ from the first-stage regression as an instrument for y_2^*. Since the first-stage equation is estimated by probit, the variance of residuals σ_1^2 is normalized to one.

The second-stage regression is:

$$y_1 = \gamma_1 X_2\hat{\beta}_2 + X_1\beta_1 + w_1 \equiv X\hat{H}\alpha_1 + w_1 \tag{4}$$

where X is a $n_1 \times s$ matrix of distinct columns in (X_1, X_2). Matrix $\hat{H}$ is defined as $\hat{H} = (\hat{\Pi}_2, J_1)$ where $J_1 = (X'X)^{-1}X'X_1$, so that $XJ_1 = X_1$, and $\hat{\Pi}_2' = (\hat{\beta}_2', o')$ where o is a $(s-k) \times 1$ vector of zeros. Heckman's estimator is defined as an OLS estimator of α_1:

$$\hat{\alpha}_1 = (\hat{H}'X'X\hat{H})^{-1}\hat{H}'X'y_1 \tag{5}$$

Amemiya proved that a consistent estimate of an asymptotic variance-covariance matrix of the estimate given in (5) can be obtained by using the following formula:

$$V(\hat{\alpha}_1) = \hat{c}(\hat{H}'X'X\hat{H})^{-1} + \hat{\gamma}_1^2(\hat{H}'X'X\hat{H})^{-1}\hat{H}'X'XV(\hat{\Pi}_2)X'X\hat{H}((\hat{H}'X'X\hat{H})^{-1} \tag{6}$$

where V(.) denotes the asymptotic variance-covariance matrix of its argument. In the above formula $\hat{c}$ is defined as follows:

$$\hat{c} = \hat{\sigma}_1^2 - 2\hat{\gamma}\hat{\sigma}_{12} \quad (7)$$

A consistent estimate of the covariance term can be obtained by using the following formula:

$$\hat{\sigma}_{12} = T^{-1}\sum_{i=1}^{T}\hat{y}_{i2}\hat{u}_{i1}\hat{f}_i^{-1} \quad (8)$$

where $\hat{f}_i$ is the estimated probability density value of search for the i-th observation. The estimate of σ_{12} proposed by Amemiya contained the actual value of y_{i2} instead of its estimate. The actual estimate cannot be used in the current model, since the dichotomous search variable is not observable for the sample of workers. Given the assumption that the model residuals are jointly normally distributed, an estimate of y_{i2} is a function of an ML estimate of y_{i2}^* that is converging in probability to the corresponding population value at rate $\sqrt{T}$. Thus, formula (8) yields a consistent estimate of σ_{12}.

Since the last s-k elements of $\hat{\Pi}_2$ are zeros, $V(\hat{\Pi}_2)$ is defined as follows:

$$V(\hat{\Pi}_2) = \begin{bmatrix} V(\hat{\beta}_2) & o' \\ o & O \end{bmatrix}$$

where o and O are $(s-k)\times k$ and $(s-k)\times(s-k)$ matrices of zeros, correspondingly. The adjusted standard errors for the vector of coefficient estimates $\hat{\alpha}_1' = (\hat{\gamma}_1, \hat{\beta}_1')$ are the square roots of the corresponding diagonal elements of $V(\hat{\alpha}_1)$.

In addition to the above-described model, I use an alternative estimation strategy where search activity is defined as an index of different search methods instead of a dichotomous variable used in the above setting. The list of search methods is given in Appendix 1. The constructed index is a sum of different job search methods that an unemployed person has used within the last four weeks. The fourth method ("Followed job advertisements in the media") is excluded for the reason that it is a passive method compared to others.

When the index-based measure of search activity is used, the first-stage equation of the above model is estimated by OLS, i.e. an assumption is made that the probability of an index taking values 1,2,… is a linear function. Under regular normality assumptions an ordered probit estimation of the first-stage regression would yield more efficient estimates than the OLS-based estimation. The reason for using OLS instead of the ordered probit is the lack of related asymptotic theory. Amemiya's estimator for obtaining the adjusted standard errors is applicable if one of the dependent variables in a two-equation system is dichotomous. An analogous estimate of the asymptotic variance-covariance matrix of the coefficients is not available for the simultaneous equations models where one equation is estimable by OLS and the other equation can be estimated by ordered probit.

To be able to make inferences about the significance of the model estimates, I estimate both equations by OLS. If the dependent variables in a system of two simultaneous equations are observable, the model can be estimated by two stage least squares, using the corresponding error correction procedure. The use of the 2SLS estimate of the variance-covariance matrix is warranted in the context of the current model under the assumption that the two samples are random draws from the same population.

It is possible to test the implications for lower search intensity of women that are based on rational factors in the context of the empirical model that is used in this paper. To test the hypothesis that women with small children face a higher opportunity cost of search (therefore searching less than men), I include in the search equation an interactive variable of the female dummy times the number of small children in the family. The implication that women search less because search intensity is negatively related with the unemployment income is tested by including a variable that measures per capita labour income earned by other family members. To test whether unemployment income has a systematically different effect on women compared with men, I include an interactive variable of the female dummy times the per capita income of other family members.

The above-mentioned variables are also used in the model as exclusion restrictions in the first-stage regression equation. In addition, I use as exclusion restrictions a variable measuring the number of small children, a dummy variable indicating whether a person is a single wage earner in the family, and an interactive variable, which is a product of these two variables. It is assumed that none of the above-mentioned variables has a direct effect on wage, i.e. they influence the wage only through their impact on search intensity.

Theoretical search models imply that search activity is positively related to a person's expected wage. Due to the differences in the average wages of men and women, the expected wages may be higher for men than for women, and this may be one of the reasons why they search more actively for new jobs when unemployed. To control for this factor, I include in the first-stage regression the person's wage in his/her previous occupation. Another factor that potentially influences search activity, but is not included in the estimated regression equation, is unemployment duration. However, since the average unemployment duration in the sample of displaced workers is approximately the same for men and women, the exclusion of this variable should not generate a gender-related bias in the estimated search activity.

Although the person's wage at the most recent job (*lastwage*) is used as an additional control variable in the first-stage regressions, the predicted search activity variable is constructed without the inclusion of this variable, since it is not available for the current wage and salary workers. Assuming that the search activity is positively related with the expected wage, and labour income in the most recent employment is systematically higher for men than for women, the exclusion of this variable would yield an estimate of the fitted search activity that is downward biased for men in comparison to women. However, as shown in the next section, in the empirical model estimated in the current paper *lastwage* has an insignificant effect on search activity. Exclusion of *lastwage* from the fitted search activity variable should therefore not generate a gender-related bias in the second-stage estimation.

5. Data Description and Estimation Results

5.1. Data

The empirical estimation is based on the micro-level data of the personal and job-related characteristics of working-age individuals from the Estonian Labour Force Survey files that cover the years from 1998 to 2000. On the basis of the data two sub-samples are constructed, one containing all unemployed persons who lost their jobs due to exogenous reasons[2] and the other consisting of current wage and salary workers.

Table 1 in Appendix 2 summarizes the sample statistics of displaced persons related to their search behaviour. The search activity variable is defined as a dummy variable which equals one if a displaced person looked for a new job within the last four weeks. The figures in Table 1 provide the proportions of displaced workers within different labour market groups who report that they search actively for a new job, such as native Estonian speakers and non-native speakers, etc.[3] Also, Table 1 offers a differentiation of search activity by gender. Not controlling for other factors that may influence search activity, men look for a new job more actively than women and native Estonians search less vigorously than non-natives. Primary earners in the family are more active in the labour market. Finally, persons with secondary education search more intensely than people with either higher or lower education levels, this difference being more pronounced for men.

5.2. First-Stage Estimation Results

The estimated coefficients for the first-stage regressions are presented in Table 2. Estimation results support the hypothesis that was postulated above: controlling for other observable factors, men search more actively for new jobs than women. In addition to the gender dummy, factors that significantly influence search activity include the person's age (concave relationship) and the dummy variable of being married (negative relationship). Both versions of the first-stage regressions contain significant estimates for the exclusion

[2] The exogenous reasons for job loss are defined as enterprise bankruptcy, liquidation, or reorganization.
[3] About 1/3 of the Estonian population are either first- or second-generation immigrants (mainly Russians) whose native tongue is not Estonian.

restrictions, but they do not coincide. In the regression based on the dichotomous search variable, the set of significant instruments includes the number of small children for women and the number of small children for single wage earners in the family. In the regression based on the search activity index the only significant exclusionary restriction is the dummy variable indicating whether a person is a single wage earner in the family. A Wald test is used to assess the joint significance of all six explanatory variables that are used as exclusion restrictions. The probability values of the test statistic are presented in Table 2. The exclusion restrictions are jointly significant at the 5% significance level in both regression formulations.

Sample statistics imply that non-native Estonian speakers living in Estonia search more actively for new jobs when unemployed. This difference exists also within genders (see Table 1). After controlling for other factors that potentially influence search activity, the nationality dummy is not significant at the 5% level in the probit regression, whereas it turns out to be significant in the linear probability regression. Thus, although non-native Estonians earn lower wages on average, the regression results only partially support the idea that nationality-based wage differential is potentially influenced by differences in search behaviour. This result, although not conclusive, is nevertheless noteworthy, since it is hard to find any rational reasons why non-native Estonians search more actively than natives. This systematic difference in search intensity could only be based on behavioural differences.

The estimated coefficient for the interactive variable of the female dummy times the number of small children is negative and significant in the probit regression, whereas it is insignificant in the linear probability regression. The variable measuring the combined labour income of other family members and an interactive variable of the income of other family members times the female dummy are not significant in either regression. Consequently, the first-stage regression results offer only limited support to the rational-factors-based hypotheses about why women search less actively on average.

5.3. Second-Stage Estimation Results

The second-stage regression equation is estimated in four different versions. To separate the occupational segregation effect on the gender wage gap from person-related characteristics, I estimate two log-level wage regressions, the first excluding and the second including sector- and profession-related dummies. The third version of the wage regression includes fitted search activity measure that is based on the probit regression as an additional explanatory variable. In the fourth version, the potential search activity is replaced with the fitted value from the linear probability regression. Comparing the third and fourth versions with the second version enables to gauge the relative importance of differences in search activity on the gender wage gap.

The regression results are presented in Table 3. In the sample of Estonian workers used in the current study and covering the period 1998–2000, the difference in mean wages for men and women is 27.1%. As indicated by the regression results presented in the first column of Table 4, controlling for person-related characteristics that affect productivity reduces the unexplained wage gap to 21.2%. Including sector- and profession-related dummy variables reduces the remaining wage gap to 17.7%, as shown in the third column of Table 3. Both above-mentioned estimation results are significant at the 1% significance level. Comparing the two coefficients implies that occupational and sector-related effects do not explain much of the gender difference in wages. The small effect can be caused to some extent by insufficient differentiation. The dataset that is used in the current study includes only nine different classifications for occupations and fifteen sectors. Although the coefficient estimates for all occupational dummies and most of the sector-specific variables are significant, a more detailed differentiation would likely produce a better fit.

Estimating the third and fourth versions of the wage regression that include potential search activity as an additional regressor yield results which are consistent with the hypothesis that a part of the gender wage gap can be explained by systematic differences in search activity between genders. In both regressions, instrumented search intensity has a positive impact on wage, and the estimated slope coefficient is significant. Adding the potential search intensity as an additional regressor reduces the unexplained part of the gender wage gap from 17.7% to 14% in the third wage regression and to 11.2% in the fourth wage regression, i.e. by 21% to 37%.

In addition to the gender dummy and fitted search propensity variable, the slope estimates for most of the regressors in the four different versions of the log-wage equations presented in Table 3 are highly significant. In general, the regression results are analogous to the estimates of most standard wage equations. Controlling for observable factors that influence productivity, native Estonians earn on average higher wages than non-natives. This difference diminishes from 19.8% to 14.7% when the different occupational choices and sector effects are included as additional controls. Including the potential search activity variable increases the unexplained part of the nationality-based wage differential from 14.7% to 16.5% in the third wage regression and to 21.8% in the fourth wage regression.

Primary earners in the household and married people earn higher wages on average, whereas married females tend to earn less than their single counterparts. The number of children does not significantly affect the wage rate of men, but has a negative effect for women. Almost all skills- and job-related characteristics are significant in the four different versions of the wage regressions. More years of schooling as well as speaking other languages in addition to the native language have a positive effect on the wage. The more hours a person works, the higher is his/her salary, ceteris paribus. Also, tenure in the current workplace is positively related with the wage. Private sector workers earn lower salaries than public sector employees, while the labour income tends to be higher for workers in foreign-owned companies. Finally, enterprise size is positively related to the wage.

In addition to the linear-probability-based estimation of the first-stage regression, the model was also estimated by ordered probit in the first stage and OLS in the second stage. (The regression estimates are available from the author by request.) Although no inferences can be made about the standard errors, the point estimates of the coefficients were close to the estimates that were obtained using OLS in the first stage. This implies that the OLS-based estimation of the first stage equation is a sufficiently good proxy for the ordered probit estimation.

5.4. Estimating the Model with a Different Exclusion Restriction

Using the Estonian Labour Force Survey for constructing the displacement dummy simultaneously with the search activity measure can potentially cause a problem, since there is a considerable lag between the time a person is laid off and the time the survey is conducted. The average unemployment duration for displaced persons in the sample used is 3.45 years. It is possible that women who know that their wage prospects are below average will choose to drop out of the labour force and have children instead. Therefore, one of the variables used as an exclusion restriction in the current model – the number of small children for women (*schildfem*) – may be endogenous to search activity. Although this potentially endogenous variable is significant only in the first regression formulation (the probit model) and insignificant in the second formulation (the linear probability model), it may still impute a bias in the estimated coefficient for the gender dummy variable. To assess the significance of this problem, I replaced the number of small children for women in the model with an alternative measure – the number of small children during the time of displacement (*dchildfem*). Although this variable is not an accurate measure for the current opportunity cost of search, it may still have a negative impact on search activity, since if a person cannot search actively for a new job at the beginning of the unemployment period, she is less likely to enter the labour force in the later stage as well.

The regression estimates where the *smallchild* and *schildfem* variables are replaced with *dispchild* and *dchildfem* accordingly are presented in Tables 4 and 5 in Appendix 2. The estimates of the first-stage regressions are similar to the results presented above. There are only a few notable differences. The first difference is that the male dummy is only marginally significant at the 10% level in the index-based regression estimation. Secondly, in the probit estimation of the first-stage regression a different exclusion restriction is significant, compared with the base model (*singleearner* vs *schildsingle*). Finally, an additional exclusionary restriction (*oincfem*) is significant in addition to *singleearner* in the index variable-based regression.

In the second-stage regressions, the estimates are very similar to the base model as well. The only difference is that the estimated slope coefficients of the two different versions of the wage equation are closer than they were in the base model. The inclusion of the potential search activity variable reduces the residual gender wage gap from 17.7% to 10.5% or 11.8%, i.e. by 33% to 41%. In conclusion, using a replacement variable for *schildfem* that is not endogenous does not alter the main inferences that can be drawn from the empirical estimates of the model.

The search activity index contains various search methods that, by their nature, are different. Imposing the same weight to all these methods in the index composition may potentially mismeasure the true search activity. To address this problem I concluded a sensitivity analysis, where the model estimation was based on differently constructed search activity indices. The first version of the index variable that was employed in the additional regressions included all the different search methods with equal weight. In a second index formulation, the seventh method ("Looked for a job through the State Employment Office") was excluded since unemployed persons contact the State Employment Office for other motivations in addition to the hope of finding a job – it is often done to qualify for unemployment benefits. In the third version, I altered the index by giving more weight to the two last search methods that were related to the startup of a private business. Since different search activity indices were highly correlated with each other, the regression results based on alternative measures yielded an outcome that was analogous to the second version of the first-stage regression and the fourth version of the second-stage regression: the gender dummy was highly significant in the first-stage estimation, and including an index-based fitted value of search activity measure in the second-stage estimation significantly reduced the residual gender wage differential. The additional regression estimations are available from the author by request.

6. Conclusion

Labour market search models imply that the more intensely a labour market participant searches for a new job, the higher is his potential labour income. The positive relationship between search intensity and wages stems from the matching process: if a person spends more time searching for a job, he gets more job offers, ceteris paribus, which increases the probability that he will find a job which is a good match to his labour market skills. Thus, persons who search more intensely will be more productive at their future jobs and earn higher salaries.

According to the search models, if men look for work more actively than women during unemployment periods, they should earn higher wages on average. Several reasons are pointed out in the current paper that could create a difference in search activity between genders. This difference could stem from rational factors (such as different opportunity costs of search) or behavioural explanations.

The current paper postulates two hypotheses: (i) men look more intensely for a new job when unemployed; and (ii) controlling for this systematic difference in search behaviour reduces the male-female wage gap. These hypotheses are tested using the micro-level data for the years 1998–2000 from the Estonian Labour Force Survey. The empirical strategy of the current paper relates the search behaviour of exogenously displaced workers to various demographic and regional characteristics to impute a hypothetical search propensity variable for a sample of current wage and salary workers. Adding the constructed search variable to a standard log-wage regression yields a result that potential search intensity significantly reduces the residual gender wage differential.

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Appendix 1. Model Variables

1.1. Different Search Methods Used in the Construction of the Search Activity Index

1. Approached relatives or acquaintances
2. Answered to job offer advertisements
3. Sent out job search notifications
4. Followed job advertisements in the newspapers, etc.
5. Contacted a potential employer directly
6. Had an interview/interviews with potential employers
7. Looked for a job through the State Employment Office
8. Looked for a job through a private employment agency
9. Applied for a registration, operation permit, trade permit, loan, etc. with the purpose of starting a private business
10. Purchased land, real estate, equipment, etc. with the purpose of starting a private business

1.2. Regressors

lnwage	natural logarithm of the real wage net of taxes
lastwage	wage a person earned at the last job before unemployment (displaced persons only)
male	dummy variable, equals 1 if male
age	age (years)
agesquare	age squared
nationality	dummy variable, equals 1 if Estonian
language	dummy variable, equals 1 if a person speaks more than one language
primaryearner	dummy variable, equals 1 if a person is a primary earner in his/her household
education1	dummy variable, equals 1 if a person has primary education (8 years of schooling or less)
education2	dummy variable, equals 1 if a person has secondary education
education3	dummy variable, equals 1 if a person has higher education
children	number of children less than 16 years old
workhours	= number of hours worked per week
private	dummy variable, equals 1 if a person works in a privately owned company
foreign	dummy variable, equals 1 if a person works in a company owned by foreigners
dsize1	dummy variable, equals 1 if a person works in an enterprise with less than 20 workers
dsize2	dummy variable, equals 1 if a person works in an enterprise with more than 20 and less than 200 workers
married	dummy variable, equals 1 if a person is married
marrfem	= *married* * *female*

Exclusion Restrictions:

smallchild	number of children less than 6 years old
schildfem	= *smallchild * female*
oincome	combined per capita income of other household members
oincfem	= *oincome * female*
singleearner	dummy variable, equals 1 if a person is the only worker in the family
schildsingle	= *smallchild * singleearner*
dispchild	=number of small children (less than 6 years old) at the time of displacement
dchildfem	= *dispchild * female*

Profession Dummies:

dprof1	legislature, higher officials, managers
dprof2	high-level specialists
dprof3	medium-level specialists, technicians
dprof4	office clerks
dprof5	service and sales workers
dprof6	skilled specialists: agriculture and fishing
dprof7	skilled specialists
dprof8	operators of equipment and machinery
dprof9	low-skilled workers
dprof10	armed forces

Sector Dummies:

dsector1	agriculture
dsector2	fishing
dsector3	mining
dsector4	manufacturing
dsector5	energy and water supplies
dsector6	construction
dsector7	whole- and retail sales
dsector8	hotels and restaurants
dsector9	transport and logistics
dsector10	financial intermediation
dsector11	real estate
dsector12	public sector and defence
dsector13	education
dsector14	healthcare and social work
dsector15	other

Regional Dummies:

dregion1	Harjumaa, excluding Tallinn
dregion2	Hiiumaa
dregion3	Ida-Virumaa
dregion4	Jõgevamaa
dregion5	Järvamaa
dregion6	Läänemaa
dregion7	Lääne-Virumaa
dregion8	Põlvamaa
dregion9	Pärnumaa
dregion10	Raplamaa
dregion11	Saaremaa
dregion12	Tartumaa
dregion13	Valgamaa
dregion14	Viljandimaa
dregion15	Võrumaa
dregion16	Tallinn

Appendix 2. Sample Statistics and Empirical Estimates

Table 1. Percentage of displaced persons who searched actively for a new job

	Total	Male	Female
Whole Sample	47.04%	52.30%	41.91%
Estonians	42.39%	47.93%	37.00%
Non-Estonians	59.42%	63.97%	55.00%
Education1	39.88%	44.53%	33.95%
Education2	54.34%	60.34%	49.66%
Education3	48.20%	46.30%	49.41%
Primary earners	45.98%	48.04%	43.53%
Non-primary earners	48.64%	60.71%	40.00%

Notes: Percentages given in the table are calculated on the basis of a sample of displaced workers drawn from the Estonian Labour Force Survey files for the years 1998, 1999, and 2000. The sample includes working age people from three surveys, aged 15–65, that were displaced from their last jobs. The average unemployment duration is 3.47 years for women and 3.43 years for men.

Table 2. First-stage regressions. Dependent variable: search activity (sample of displaced persons)

	Search activity = Dummy (probit model)		Search activity = Index (linear probability model)	
	Coefficient	**P-value**	**Coefficient**	**P-value**
male	0.5201***	0.0020	0.2873**	0.0410
age	0.2161***	0.0000	0.0441	0.2210
agesquare	-3.1727***	0.0000	-1.0071***	0.0040
education1	0.0311	0.8740	-0.0534	0.7590
education2	-0.1908	0.3070	-0.1602	0.3840
nationality	-0.4264*	0.0900	-0.5507**	0.0200
primaryearner	-0.0560	0.8020	-0.1587	0.4090
children	-0.0980	0.2740	0.0461	0.6100
married	-0.3314**	0.0470	-0.3073**	0.0250
language	0.1403	0.5100	-0.1963	0.2860
smallchild	-0.2665	0.3460	-0.1603	0.5460
schildfem	-0.6615**	0.0110	-0.2438	0.3290
oincome	0.0003	0.4210	0.0005	0.1120
oincfem	-0.0002	0.6030	-0.0002	0.4000
singleearner	0.3183	0.1550	0.5163**	0.0220
schildsingle	0.7207**	0.0110	0.1882	0.4030
lastwage	0.1234	0.5130	0.2519	0.1570
dregion1	-0.8386**	0.0230	-0.6278*	0.0560
dregion2	-0.2605	0.6240	-0.7107*	0.0770
dregion3	0.1591	0.6440	0.5546*	0.0910
dregion4	-0.3699	0.3550	-0.1730	0.6170
dregion5	-0.3401	0.3600	-0.4776	0.1350
dregion6	-0.6459	0.1100	-0.1256	0.7600
dregion7	-0.5452	0.2270	-0.5097	0.1170
dregion8	-0.8263**	0.0180	-0.5229*	0.0800
dregion9	-0.4375	0.2580	-0.3124	0.3510
dregion10	0.0358	0.9370	0.3506	0.3930
dregion11	0.4049	0.3540	0.1638	0.6710
dregion12	-0.4729	0.1890	-0.2307	0.4420
dregion13	-0.1641	0.6370	-0.4035	0.1860
dregion14	-0.3850	0.2770	-0.5471**	0.0300
dregion15	-1.1572**	0.0140	-0.5600	0.2010
year1998	0.0155	0.9490	0.1533	0.4710
year1999	-0.3853**	0.0310	-0.1807	0.2500
constant	-3.3528**	0.0410	0.1534	0.9110
Number of obs.	643		624	
Pseudo R-squared	0.3564		0.3042	
Wald test (prob > Chi2)	0.0128		0.042	

Notes: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level.
The Wald test is used to test the probability that exclusion restrictions are jointly significant.

Table 3. Second-stage regressions. Dependent variable: log real wage (sample of workers)

	I Wage equation		II Wage equation		III Wage equation		IV Wage equation	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
fitsearch					0.0352**	0.0380	0.1330***	0.0000
male	0.2121***	0.0000	0.1770***	0.0000	0.1398***	0.0000	0.1115***	0.0000
age	0.0222***	0.0000	0.0189***	0.0000	0.0102**	0.0365	0.0122***	0.0000
agesquare	-0.3838***	0.0000	-0.3223***	0.0000	-0.1997**	0.0021	-0.1829***	0.0000
education1	-0.3136***	0.0000	-0.1224***	0.0000	-0.1237***	0.0000	-0.1126***	0.0000
education2	-0.1447***	0.0000	-0.0506***	0.0000	-0.0472***	0.0003	-0.0308**	0.0162
nationality	0.1979***	0.0000	0.1470***	0.0000	0.1650***	0.0000	0.2182***	0.0000
primaryearner	0.1775***	0.0000	0.1431***	0.0000	0.1548***	0.0000	0.1764***	0.0000
children	-0.0175**	0.0150	-0.0005	0.9440	0.0016	0.8459	0.0036	0.6507
married	0.1671***	0.0000	0.0930***	0.0000	0.1255***	0.0000	0.1633***	0.0000
language	0.1333***	0.0000	0.0723***	0.0000	0.0653***	0.0000	0.0966***	0.0000
childfemale	-0.0293***	0.0020	-0.0389***	0.0000	-0.0307	0.7571	-0.0324***	0.0029
marrfem	-0.0762***	0.0000	-0.0359*	0.0580	-0.0398***	0.0001	-0.0348	0.1500
workhours	0.0031**	0.0170	0.0031**	0.0150	0.0056	0.7979	0.0056***	0.0000
tenure	0.0071***	0.0000	0.0040***	0.0000	0.0040***	0.0000	0.0040***	0.0000
private	-0.0688***	0.0000	-0.0287**	0.0410	-0.0345***	0.0000	-0.0349**	0.0417
foreign	0.2609***	0.0000	0.2464***	0.0000	0.2513***	0.0000	0.2495***	0.0000
dsize1	-0.2031***	0.0000	-0.1983***	0.0000	-0.1912***	0.0000	-0.1909***	0.0000
dsize2	-0.0986***	0.0000	-0.0809***	0.0000	-0.0799***	0.0000	-0.0795***	0.0000
dregion1			-0.0272	0.1450	-0.0182	0.5075	0.0376	0.1453
dregion2			-0.0625*	0.0750	-0.0745*	0.0649	0.0139	0.7470
dregion3			-0.2565***	0.0000	-0.2616***	0.0000	-0.3233***	0.0000
dregion4			-0.3538***	0.0000	-0.3590***	0.0000	-0.3396***	0.0000
dregion5			-0.1999***	0.0000	-0.1866***	0.0000	-0.1281***	0.0000
dregion6			-0.1940***	0.0000	-0.2010***	0.0000	-0.2013***	0.0000
dregion7			-0.1860***	0.0000	-0.1842***	0.0000	-0.1290***	0.0000
dregion8			-0.3295***	0.0000	-0.3160***	0.0000	-0.2669***	0.0000
dregion9			-0.2088***	0.0000	-0.2065***	0.0000	-0.1731***	0.0000
dregion10			-0.1520***	0.0000	-0.1764***	0.0000	-0.2150***	0.0000
dregion11			-0.2597***	0.0000	-0.2721***	0.0000	-0.2703***	0.0000
dregion12			-0.2043***	0.0000	-0.1835***	0.0000	-0.1628***	0.0000
dregion13			-0.2592***	0.0000	-0.2756***	0.0000	-0.2185***	0.0000
dregion14			-0.2472***	0.0000	-0.2425***	0.0000	-0.1759***	0.0000
dregion15			-0.3123***	0.0000	-0.2650***	0.0000	-0.2218***	0.0000
dsector1			-0.1214***	0.0000	-0.1568***	0.0000	-0.1540***	0.0000
dsector2			0.1996**	0.0180	0.2369***	0.0000	0.2329***	0.0014
dsector3			0.4043***	0.0000	0.4104***	0.0000	0.4112***	0.0000
dsector4			0.1466***	0.0000	0.1345***	0.0022	0.1350***	0.0000

	I Wage equation		II Wage equation		III Wage equation		IV Wage equation	
	Coefficient	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
dsector5			0.2943***	0.0000	0.2715***	0.0000	0.2734***	0.0000
dsector6			0.2740***	0.0000	0.2680***	0.0000	0.2668***	0.0000
dsector7			0.1519***	0.0000	0.1301***	0.0000	0.1293***	0.0000
dsector8			0.0671**	0.0340	0.0313	0.2272	0.0332	0.4155
dsector9			0.2649***	0.0000	0.2574***	0.0000	0.2559***	0.0000
dsector10			0.4374***	0.0000	0.4242***	0.0000	0.4176***	0.0000
dsector11			0.0964***	0.0010	0.0966**	0.0365	0.0966***	0.0034
dsector12			0.2346***	0.0000	0.2133***	0.0000	0.2103***	0.0000
dsector13			-0.0132	0.5830	-0.0230	0.4104	-0.0227	0.4399
dsector14			0.0015	0.9530	-0.0135	0.6016	-0.0133	0.6773
dprof1			0.7116***	0.0000	0.7146***	0.0000	0.7085***	0.0000
dprof2			0.6214***	0.0000	0.6247***	0.0000	0.6195***	0.0000
dprof3			0.3925***	0.0000	0.4062***	0.0000	0.4046***	0.0000
dprof4			0.2140***	0.0000	0.2202***	0.0000	0.2196***	0.0000
dprof5			0.1339***	0.0000	0.1417***	0.0000	0.1414***	0.0000
dprof6			0.3726***	0.0000	0.3967***	0.0000	0.3954***	0.0000
dprof7			0.2357***	0.0000	0.2403***	0.0000	0.2394***	0.0000
dprof8			0.1931***	0.0000	0.1878***	0.0000	0.1883***	0.0000
year1998			-0.0350***	0.0030	-0.0574***	0.0002	-0.0786***	0.0000
year1999			0.0372***	0.0010	0.0307**	0.0456	0.0413***	0.0052
constant	7.1394***	0.0000	6.7642***	0.0000	6.8220***	0.0000	6.6310***	0.0000
Number of obs.	14077		14077		11330		11330	
R-squared	0.2829		0.418		0.4370		0.4393	

Notes: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level.
The explanation of model variables is presented in Appendix 1.

The variable *fitsearch* is based on a search activity dummy (probit model) in the third wage equation and the search activity index (linear probability model) in the fourth wage equation.

Table 4. Variable *smallchild* is replaced with *dispchild*. First-stage regressions. Dependent variable: search activity (sample of displaced persons).

	Search activity = Dummy (probit model)		Search activity = Index (linear probability model)	
	Coefficient	**P-Value**	**Coefficient**	**P-Value**
male	0.4931***	0.0040	0.2484*	0.0810
age	0.1986***	0.0010	0.0297	0.4790
agesquare	-3.0593***	0.0000	-0.8995**	0.0240
education1	0.0450	0.8290	-0.0246	0.8910
education2	-0.2481	0.2050	-0.1569	0.4100
nationality	-0.3726	0.1690	-0.5496**	0.0260
primaryearner	-0.2533	0.3010	-0.2731	0.1820
children	-0.0752	0.4270	0.0724	0.4360
married	-0.4044**	0.0270	-0.3291**	0.0240
language	0.0717	0.7520	-0.2649	0.1620
dispchild	-0.0983	0.7240	-0.3398	0.2140
dchildfem	-0.6870**	0.0360	-0.1530	0.6170
oincome	0.0006	0.1190	0.0007**	0.0400
oincfem	-0.0003	0.3660	-0.0003	0.3450
singleearner	0.6268***	0.0080	0.7451***	0.0010
schildsingle	0.1903	0.3930	0.0389	0.8480
lastwage	0.2501	0.2140	0.3497*	0.0570
dregion1	-1.0102**	0.0160	-0.6182*	0.0670
dregion2	-0.6105	0.2640	-0.9144**	0.0290
dregion3	0.3246	0.3660	0.6439**	0.0540
dregion4	-0.4329	0.3100	-0.2859	0.4130
dregion5	-0.4448	0.2530	-0.4949	0.1300
dregion6	-0.7820*	0.0610	-0.1485	0.7280
dregion7	-0.6862	0.1410	-0.6221*	0.0620
dregion8	-0.9850***	0.0070	-0.5904*	0.0530
dregion9	-0.6197	0.1250	-0.3926	0.2600
dregion10	0.3102	0.5140	0.5732	0.1660
dregion11	0.3988	0.3610	0.2045	0.5940
dregion12	-0.4902	0.1880	-0.2336	0.4490
dregion13	-0.1979	0.5890	-0.4449	0.1560
dregion14	-0.5044	0.1720	-0.6219**	0.0180
dregion15	-1.2389**	0.0120	-0.5895	0.1780
year1998	0.1926	0.4430	0.2972	0.1680
year1999	-0.4050**	0.0300	-0.1588	0.3160
constant	-3.7696**	0.0300	-0.2122	0.8840
Number of obs.	605		588	
Pseudo R-squared	0.3691		0.3288	
Wald test (prob > Chi2)	0.0208		0.0091	

Notes: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level.
The Wald test is used to test the probability that exclusion restrictions are jointly significant.

Table 5. Variable *smallchild* is replaced with *dispchild*. Second-stage regressions. Dependent variable: log real wage (sample of workers).

	III Wage equation		IV Wage equation	
	Coefficient	**P-value**	**Coefficient**	**P-value**
fitsearch	0.0838***	0.0035	0.1058***	0.0000
male	0.1054***	0.0002	0.1182***	0.0000
age	0.0005	0.9536	0.0136***	0.0000
agesquare	-0.0482	0.6504	-0.2077***	0.0000
education1	-0.1219***	0.0000	-0.1141***	0.0000
education2	-0.0318	0.1327	-0.0350***	0.0076
nationality	0.1766***	0.0000	0.2011***	0.0000
primaryearner	0.1698***	0.0000	0.1820***	0.0000
children	0.0118	0.2793	0.0081	0.3334
married	0.1558***	0.0000	0.1631***	0.0000
language	0.0713***	0.0026	0.1046***	0.0000
childfemale	-0.0351	0.8430	-0.0431***	0.0001
marrfem	-0.0398***	0.0006	-0.0434*	0.0976
workhours	0.0052	0.8488	0.0052***	0.0000
tenure	0.0038***	0.0000	0.0038***	0.0000
private	-0.0366***	0.0000	-0.0365**	0.0410
foreign	0.2571***	0.0000	0.2562***	0.0000
dsize1	-0.1947***	0.0000	-0.1937***	0.0000
dsize2	-0.0822***	0.0000	-0.0816***	0.0000
dregion1	0.0466	0.3646	0.0280	0.2714
dregion2	-0.0252	0.6728	0.0222	0.6208
dregion3	-0.2670***	0.0000	-0.3043***	0.0000
dregion4	-0.3228***	0.0000	-0.3236***	0.0000
dregion5	-0.1491***	0.0004	-0.1298***	0.0000
dregion6	-0.1394***	0.0044	-0.1857***	0.0000
dregion7	-0.1309***	0.0072	-0.1188***	0.0000
dregion8	-0.2509***	0.0000	-0.2660***	0.0000
dregion9	-0.1576***	0.0005	-0.1636***	0.0000
dregion10	-0.1843***	0.0001	-0.2148***	0.0000
dregion11	-0.2710***	0.0000	-0.2548***	0.0000
dregion12	-0.1417***	0.0005	-0.1545***	0.0000
dregion13	-0.2511***	0.0000	-0.2158***	0.0000
dregion14	-0.2022***	0.0000	-0.1745***	0.0000
dregion15	-0.1815***	0.0037	-0.2178***	0.0000
dsector1	-0.1648***	0.0000	-0.1636***	0.0000
dsector2	0.2217***	0.0000	0.2199***	0.0048
dsector3	0.4109***	0.0000	0.4103***	0.0000
dsector4	0.1283***	0.0043	0.1289***	0.0000

	III Wage equation		IV Wage equation	
	Coefficient	**P-value**	**Coefficient**	**P-value**
dsector5	0.2725***	0.0000	0.2741***	0.0000
dsector6	0.2667***	0.0000	0.2667***	0.0000
dsector7	0.1230***	0.0000	0.1235***	0.0001
dsector8	0.0312	0.2396	0.0324	0.4531
dsector9	0.2535***	0.0000	0.2535***	0.0000
dsector10	0.4339***	0.0000	0.4308***	0.0000
dsector11	0.0853*	0.0765	0.0863**	0.0127
dsector12	0.2145***	0.0000	0.2138***	0.0000
dsector13	-0.0231	0.4192	-0.0222	0.4680
dsector14	-0.0122	0.6421	-0.0109	0.7439
dprof1	0.7227***	0.0000	0.7183***	0.0000
dprof2	0.6314***	0.0000	0.6274***	0.0000
dprof3	0.4172***	0.0000	0.4155***	0.0000
dprof4	0.2344***	0.0000	0.2330***	0.0000
dprof5	0.1491***	0.0000	0.1484***	0.0000
dprof6	0.4230***	0.0000	0.4224***	0.0000
dprof7	0.2461***	0.0000	0.2448***	0.0000
dprof8	0.2006***	0.0000	0.1989***	0.0000
year1998	-0.0697***	0.0050	-0.0838***	0.0000
year1999	0.0505**	0.0271	0.0344**	0.0218
constant	7.0055***	0.0000	6.6913***	0.0000
Number of obs.	10774		10774	
R-squared	0.4395		0.4408	

Notes: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level.
The explanation of model variables is presented in Appendix 1.
The variable *fitsearch* is based on a search activity dummy (probit model) in the third wage equation and the search activity index (linear probability model) in the fourth wage equation.