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Estimating Labor Market Discrimination with Selectivity-Corrected Wage Equations: Methodological Considerations and An Illustration from Israel

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Abstract

This paper examines the implications of the standard Heckman correction for selectivity bias in wage and earnings functions that are subsequently used in wage decompositions. While justified in many instances, selectivity correction introduces some fundamental ambiguities in the context of wage decompositions. The ambiguities arise from group differences in the selection term which consists of a parameter multiplied by the Inverse Mills Ratio (IMR). The parameter is identified as the product of the standard deviation of the errors in the wage equation and the correlation between the wage equation error and the selection equation error. How should group differences in these parameters be interpreted in terms of structural differences and endowment effects? The same issue arises with respect to group differences in the IMR which reflect nonlinear group differences in the determinants of selection and in the probit coefficients. We present a set of decompositions that represent alternative assignments of group differences in the selection components to structural effects and endowment effects. An empirical application to labor market discrimination among professional workers in Israel illustrates how varied the decompositions can be as well as the corresponding inferences about the relative strengths of labor market inequity and endowment differences.

I. Introduction

Estimation of labor market discrimination by gender, race, and ethnicity has become routine since the popularization of the wage decomposition methodology by Blinder (1973) and Oaxaca (1973). Typically, one uses the separately estimated (log) wage equations for two groups of workers to decompose the difference in their (geometric) mean wages into a discrimination (unexplained) portion and a human capital (endowments or explained) portion. The simplest decomposition procedure is to adopt one of the estimated wage structures as the nondiscriminatory norm. Often researchers select the wage structure for the group of workers believed to be dominant in the labor market (at least relative to the comparison group). Differences in the mean characteristics of the two groups are weighted by the estimated coefficients for the nondiscriminatory wage standard and summed to obtain the human capital portion of the overall wage differential. The discrimination portion of the overall wage differential is the residual left over after netting out the human capital portion. Equivalently, the discrimination portion can be directly obtained as the summed difference in estimated coefficients between the two groups of workers weighted by the mean characteristics of the subordinate group. An implication of this procedure is that all of the discriminatory wage differential is ascribed to underpayment of the subordinate group rather than to overpayment of the dominant group.

A more general approach to wage decompositions is found in Neumark (1988), Oaxaca and Ransom (1988), and Oaxaca and Ransom (1994). In the more general approach the nondiscriminatory wage structure is estimated from a pooled sample of the two demographic groups. This approach allows the discrimination component to be further disaggregated into overpayment (favoritism) and underpayment (pure discrimination).

Panel data methods have been used to control for individual wage effects. Polachek and Kim (1994) uses fixed effects to estimate the gender earnings gap with intercept and slope specific effects. Since gender is a time invariant variable in the panel data models, a two-stage procedure is employed to estimate the gender gap. Rosholm and Smith (1996) estimates separate wage equations for male and female workers in Denmark using panel data techniques in order to identify the sources of changes in the wage gap.

Other refinements to measuring labor market discrimination incorporate the gender and ethnic compositions of each occupation as determinants of occupational wages: Hirsch and Macpherson (1994), Hirsch and Schumacher (1992), and Macpherson and Hirsch (1995). Panel data techniques are used to control for occupational characteristics and unmeasured worker characteristics encompassing skill and tastes. In another set of studies the contribution of occupational segregation to the wage differential was estimated separately so that the difference between the wages of the groups under consideration was now decomposed into three components: the endowment component, wage discrimination, and segregation. Examples of such papers are Brown et al. (1980), Miller (1987), Reilly (1991), and Neuman and Silber (1996). Most of these studies, however, were not based on theoretical models. However, Baldwin et al. (1993) seeks to build a coherent theory that incorporates both wage differences and occupational segregation.

Another twist in wage decomposition methodology is occasioned by selectivity bias. Selectivity bias might be found at two stages of the employment process: at the stage of joining the employed labor force and when a specific occupation or an occupational status (e.g. union/nonunion) is chosen. Occupational selectivity bias affects wage differentials as occupations differ in average wage rates (even after controlling for workers' characteristics) and barriers to entrance of the subordinate group create another source of discrimination. In the presence of sample selection, of both types, OLS estimation of the wage equations can yield biased and inconsistent estimators, Gronau (1974) and Heckman (1976, 1979). While correction for the first type is standard, correction for the second type is not usually done, and if it is performed it is not taken to the stage of decomposing wage differentials including the decomposition of the Inverse Mills Ratio. Dolton et al. (1989) estimate a simultaneous model of occupational choice, wage determination, and occupational status in which selectivity corrections are included in the wage and occupational status equations. Selectivity corrections are made for labor force participation of women and occupational selectivity corrections are made for both men and women. Wage decompositions are not performed and gender discrimination is not estimated, though male and female occupational choices are predicted using own characteristics with the estimated model for the opposite sex. Reimers (1983) and Boymond et.al. (1994) correct for sample selection bias when estimating the effects of labor market discrimination. As we show below, sample selection complicates the interpretation of wage decompositions. Section II is a discussion of some methodological issues that arise when attempting to conduct wage decompositions with selectivity corrected wage equations. Section III uses Israeli census data to illustrate how estimates of labor market discrimination vary with different approaches to using selectivity corrected wage equations. Finally, section IV is a summary and conclusion.

II. Methodology

For purposes of illustration we will consider gender (or ethnic) wage differentials *within a given occupation* — in our case Professionals. A simple two equation model of wage determination and occupational participation/employment among employed workers illustrates the application. Let the occupational assignment/employment and wage functions for occupation 1 be given by

$$L_{1i}^{*} = H_i'\gamma_1 + \varepsilon_{1i}, \tag{1}$$

$$Y_{1i} = X_i'\beta_1 + u_{1i} \ , \tag{2}$$

where L_{1i}^{*} is a latent variable associated with being employed in occupation 1, H_i', is a vector of determinants of occupational affiliation, Y_{1i} is the market wage (in logs) for occupation 1, X_i' is a vector of determinants of market wages, γ_1 and β_1 are the associated parameter vectors, and ε_{1i} and u_{1i} are $i.i.d$ error terms that follow a bivariate normal distribution $(0, 0, \sigma_{\varepsilon 1}, \sigma_{u_1}, \rho_1)$.

The probability of being assigned or employed in occupation 1 is given by

$$\begin{aligned} \Pr\text{ob}(L_{1i}^{*} &> 0) = \Pr\text{ob}\left(\varepsilon_{1i} > -H_i'\gamma_1\right) \\ &= \Phi(H_i'\,\gamma_1), \end{aligned} \tag{3}$$

where $\Phi(\cdot)$ is the standard normal C.D.F. (the variance of ε_1 is normalized to 1). Wages are observed in occupation 1 for those for whom $L_{1i}^{*} > 0$, so that the expected wage of a worker observed to be in occupation 1 is given by

$$\begin{aligned} E\left(Y_{1i} \mid L_{1i}^{*} > 0\right) &= X_i'\beta_1 + E\left(u_{1i} \mid \varepsilon_{1i} > -H_i'\gamma_1\right) \\ &= X_i'\beta_1 + \theta_1\,\lambda_{1i}, \end{aligned} \tag{4}$$

where $\theta_1 = \rho_1\sigma_{u_1}$, $\lambda_{1i} = \phi(H_i'\;\gamma_1)/\Phi(H_i'\;\gamma_1)$, and $\phi\left(\cdot\right)$ is the standard normal density function. The estimating equation for those employed in occupation 1 may be expressed as

$$Y_{1i} \mid L_{1i}^{*} > 0 \; = X_i'\beta_1 + \theta_1\,\lambda_{1i} + error. \tag{5}$$

Suppose one is interested in estimating wage discrimination between males and females in the presence of sample selectivity. For simplicity we will adopt the estimated male wage structure as the nondiscriminatory norm. The parameters of (5) would be estimated by the Heckman procedure separately for males and females.

It is clear from (5) that correction for selectivity bias requires a wage decomposition of the following sort:

$$\begin{aligned} \overline{Y}_{1m} - \overline{Y}_{1f} &= \left(\bar{X}_m'\widehat{\beta}_{1m} + \widehat{\theta}_{1m}\widehat{\lambda}_{1m}\right) - \left(\bar{X}_f'\widehat{\beta}_{1f} + \widehat{\theta}_{1f}\widehat{\lambda}_{1f}\right) \\ &= \bar{X}_f'\left(\widehat{\beta}_{1m} - \widehat{\beta}_{1f}\right) + \left(\bar{X}_m - \bar{X}_f\right)'\widehat{\beta}_{1m} + \left(\widehat{\theta}_{1m}\widehat{\lambda}_{1m} - \widehat{\theta}_{1f}\widehat{\lambda}_{1f}\right) \end{aligned} \tag{6}$$

where $\bar{Y}_1$ is the predicted mean (log) wage, $\bar{X}'$ is the mean vector of wage determining variables (human capital variables), $\widehat{\beta}_1$ is vector of the estimated returns to the wage determinants, $\hat{\theta}_1$ is an estimate of $\rho_1\sigma_{u_1}$, and $\hat{\lambda}_1$ is an estimate of the mean Inverse Mills Ratio (IMR). The first two terms in (6) are the familiar discrimination and human capital components. However, it is not immediately obvious how the last term in (6) should be regarded in the overall decomposition scheme. Should this term be subject to further decomposition into discrimination and human capital components, and if so, how should this be done? There is no simple answer to this question. Estimation of wage inequity in the presence of sample selectivity bias depends on assumptions as well as objectives as we show below.

If we are interested in a decomposition of the observed wage differential for occupation 1, there is still a question of how to measure the unadjusted differential. The complication is that λ_1 is a nonlinear function of the index function $H_i'\,\gamma_1$. The central tendency of λ_1 could be estimated as

$$\widehat{\lambda}_1 = \frac{\sum_{i=1}^{N_1} \widehat{\lambda}_{1i}}{N_1} \tag{7}$$

where $\widehat{\lambda}_{1i} = \phi(H_i'\,\widehat{\gamma}_1)/\Phi(H_i'\,\widehat{\gamma}_1)$ and N_1 is the number of individuals employed in occupation 1. The decomposition corresponding to (7) has particular appeal in the case in which the Heckman two-step estimation procedure is used. Evaluation of the selectivity corrected wage equation at the sample mean values that include $\hat{\lambda}_1$ from (7) guarantees that the predicted value of Y will be the sample mean value.[1]

[1] An alternative measure of the central tendency of the IMR is given by $\tilde{\lambda}_1 = \dfrac{\phi(\bar{H}'\,\hat{\gamma}_1)}{\Phi(\bar{H}'\,\hat{\gamma}_1)}$ where $\bar{H}'$ is the vector of mean values of the determinants of occupational assignment for those who are in occupation 1. The corresponding decomposition is given by

$$\begin{aligned}
\tilde{Y}_{1m} - \tilde{Y}_{1f} &= \left(\bar{X}_m'\,\widehat{\beta}_{1m} + \widehat{\theta}_{1m}\tilde{\lambda}_{1m}\right) - \left(\bar{X}_f'\,\widehat{\beta}_{1f} + \widehat{\theta}_{1f}\tilde{\lambda}_{1f}\right) \\
&= \bar{X}_f'\left(\widehat{\beta}_{1m} - \widehat{\beta}_{1f}\right) + \left(\bar{X}_m - \bar{X}_f\right)'\widehat{\beta}_{1m} + \left(\widehat{\theta}_{1m}\tilde{\lambda}_{1m} - \widehat{\theta}_{1f}\tilde{\lambda}_{1f}\right).
\end{aligned}$$

One way to finesse the problem of what to do with the term $\left(\widehat{\theta}_{1m}\widehat{\lambda}_{1m} - \widehat{\theta}_{1f}\widehat{\lambda}_{1f}\right)$ is to simply net out the estimated differences in conditional means from the overall wage differential so that one is left with the familiar decomposition terms:

$$\left(\overline{Y}_{1m} - \overline{Y}_{1f}\right) - \left(\widehat{\theta}_{1m}\widehat{\lambda}_{1m} - \widehat{\theta}_{1f}\widehat{\lambda}_{1f}\right) = \bar{X}_f' \left(\widehat{\beta}_{1m} - \widehat{\beta}_{1f}\right) + \left(\bar{X}_m - \bar{X}_f\right)' \widehat{\beta}_{1m}. \quad (8)$$

Examples of this type of approach may be found in Duncan and Leigh (1980), Reimers (1983) and Boymond et.al. (1994).[2] While (8) is a decomposition of the selectivity corrected wage differential, it does not necessarily provide a decomposition of the *observed* wage differential $\overline{Y}_{1m} - \overline{Y}_{1f}$.

Our task is to estimate wage inequity from an appropriately defined wage decomposition that includes the effects of selectivity such as (6). One can pursue an exact decomposition of the gender difference in the conditional mean error terms. Estimates of the contributions of human capital (endowments) and discrimination to the wage differential can be obtained from (6) in a number of alternative ways that derive from a decomposition of the gender difference in selectivity effects. In keeping with our adoption of the male (dominant group) wage structure as the standard, we introduce the following decomposition of the gender difference in the conditional mean error terms for the wage equations for those employed in occupation 1:

$$\begin{aligned}\bar{E}\left(u_{1m} \mid \varepsilon_{1m} > -H_m'\hat{\gamma}_{1m}\right) - \bar{E}\left(u_{1f} \mid \varepsilon_{1f} > -H_f'\,\hat{\gamma}_{1f}\right) &= \widehat{\theta}_{1m}\widehat{\lambda}_{1m} - \widehat{\theta}_{1f}\widehat{\lambda}_{1f} \\ &= \widehat{\theta}_{1m}\left(\widehat{\lambda}^0_{1f} - \widehat{\lambda}_{1f}\right) + \widehat{\theta}_{1m}\left(\widehat{\lambda}_{1m} - \widehat{\lambda}^0_{1f}\right) + \left(\widehat{\theta}_{1m} - \widehat{\theta}_{1f}\right)\widehat{\lambda}_{1f}, \end{aligned} \quad (9)$$

[2] Duncan and Leigh estimated separate selectivity-corrected wage equations for union and nonunion workers and presented estimates of the union/nonunion wage differential with and without the weighted difference in the mean values of the $\lambda's$ for union workers and nonunion workers. Conceptually, their context differs from ours in that a single selection equation is estimated for endogenous union status while our application is conditional on gender status and involves estimation of separate selection equations for males and females.

where $\widehat{\lambda}^0_{1f} = \sum_{i=1}^{N_{1f}} \widehat{\lambda}^0_{1if}/N_{1f}$, and $\widehat{\lambda}^0_{if} = \phi(H'_{if}\,\widehat{\gamma}_{1m})/\Phi(H'_{if}\,\widehat{\gamma}_{1m})$. The term $\widehat{\lambda}^0_{1f}$ is the mean value of the IMR if females faced the same selection equation that the men face. The term $\widehat{\theta}_{1m}\,(\widehat{\lambda}^0_{1f} - \widehat{\lambda}_{1f})$ measures the effects of gender differences in the parameters of the probit selectivity equation on the male/female wage differential. The effects of gender differences in the variables that determine professional employment are measured by the term $\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1m} - \widehat{\lambda}^0_{1f})$. Finally, the effects of gender differences in the wage response to the probability of professional employment are captured by the term $(\widehat{\theta}_{1m} - \widehat{\theta}_{1f})\,\widehat{\lambda}_{1f}$. Equivalently, this last term reflects the wage gap effects of gender differences in the correlation between the selectivity equation error term and the wage equation error term as well as gender differences in wage variability.

How should the components of (9) be allocated to discrimination and endowments? One possibility is to include the effects of gender differences in θ_1 in the estimated endowment (human capital) effects, and to include in the discrimination component gender differences in the estimated γ parameters from the probit selection equation for employment in occupation 1. In this case the overall wage decomposition is given by

$$\begin{aligned} \overline{Y}_{1m} - \overline{Y}_{1f} &= \underbrace{\overline{X}'_{1f}\,(\widehat{\beta}_{1m} - \widehat{\beta}_{1f}) + \widehat{\theta}_{1m}\,(\widehat{\lambda}^0_{1f} - \widehat{\lambda}_{1f})}_{\text{discrimination}} \\ &\quad + \underbrace{(\overline{X}_{1m} - \overline{X}_{1f})'\,\widehat{\beta}_{1m} + \widehat{\theta}_{1m}\,(\widehat{\lambda}_{1m} - \widehat{\lambda}^0_{1f}) + (\widehat{\theta}_{1m} - \widehat{\theta}_{1f})\,\widehat{\lambda}_{1f}}_{\text{endowments}}\ . \end{aligned} \tag{10}$$

We shall refer to the decomposition defined by (10) as Selectivity #1.

The most encompassing view of discrimination would be to regard gender differences in the estimated γ parameters from the probit selection equation for employment in occupation 1 and gender differences in the wage effects of selectivity (θ) as manifestations of discrimination. Gender differences in the values of the occupation determining variables (H') would be treated as nondiscriminatory endowment effects. These assumptions lead to the following decomposition:

$$\begin{aligned}\overline{Y}_{1m}-\overline{Y}_{1f} &= \underbrace{\overline{X}_{1f}'\,(\widehat{\beta}_{1m}-\widehat{\beta}_{1f})+\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1f}^{0}-\widehat{\lambda}_{1f})+(\widehat{\theta}_{1m}-\widehat{\theta}_{1f})\,\widehat{\lambda}_{1f}}_{\text{discrimination}} \\ &\quad+\underbrace{(\overline{X}_{1m}-\overline{X}_{1f})'\,\widehat{\beta}_{1m}+\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1m}-\widehat{\lambda}_{1f}^{0})}_{\text{endowments}}\,. \\ &= \underbrace{\overline{X}_{1f}'\,(\widehat{\beta}_{1m}-\widehat{\beta}_{1f})+\widehat{\theta}_{1m}\,\widehat{\lambda}_{1f}^{0}-\widehat{\theta}_{1f}\,\widehat{\lambda}_{1f}}_{\text{discrimination}} \\ &\quad+\underbrace{(\overline{X}_{1m}-\overline{X}_{1f})'\,\widehat{\beta}_{1m}+\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1m}-\widehat{\lambda}_{1f}^{0})}_{\text{endowments}}\end{aligned} \tag{11}$$

We refer to the decomposition defined by (11) as Selectivity #2.

Given that the θ parameters are the products of ρ_1 and σ_{u_1} , it may be difficult to make the case that gender differences in the correlation between the selectivity equation error term and the wage equation error term results from labor market discrimination. It may be equally difficult to make the case that gender differences in the standard deviation of the wage equation error term are necessarily signs of labor market discrimination. An alternative would simply be to regard gender differences in the wage effects of selectivity as a separate selectivity contribution:

$$\begin{aligned}\overline{Y}_{1m}-\overline{Y}_{1f} &= \underbrace{\overline{X}_{1f}'\,(\widehat{\beta}_{1m}-\widehat{\beta}_{1f})+\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1f}^{0}-\widehat{\lambda}_{1f})}_{\text{discrimination}} \\ &\quad+\underbrace{(\overline{X}_{1m}-\overline{X}_{1f})'\,\widehat{\beta}_{1m}+\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1m}-\widehat{\lambda}_{1f}^{0})}_{\text{endowments}} \\ &\quad+\underbrace{(\widehat{\theta}_{1m}-\widehat{\theta}_{1f})\,\widehat{\lambda}_{1f}}_{\text{selectivity}}\,.\end{aligned} \tag{12}$$

We refer to the decomposition defined by (12) as Selectivity #3.

A possible objection to the decompositions expressed in (10), (11), and (12) has to do with the interpretation of gender differences in γ as manifestations of labor market discrimination. The parameter vector γ presumably reflects supply side as well as demand side valuations of personal characteristics pertaining to occupational outcomes. Also, gender differences in γ actually reflect differences in σ_{ε_1} , since σ_{ε_1} is not identified and is normalized to 1 for convenience. Should gender differences in σ_{ε_1} be regarded as discriminatory?

The simplest approach would be to treat gender differences in the selectivity terms as a separate component of the wage decomposition:

$$\overline{Y}_{1m} - \overline{Y}_{1f} = \underbrace{\bar{X}'_{1f}\left(\widehat{\beta}_{1m} - \widehat{\beta}_{1f}\right)}_{\text{discrimination}} + \underbrace{\left(\bar{X}_{1m} - \bar{X}_{1f}\right)'\widehat{\beta}_{1m}}_{\text{endowments}} + \underbrace{\left(\widehat{\theta}_{1m}\widehat{\lambda}_{1m} - \widehat{\theta}_{1f}\widehat{\lambda}_{1f}\right)}_{\text{selectivity}} \quad (13)$$

We shall refer to the decomposition defined by (13) as Selectivity #4. Reimers (1983) uses a similar decomposition. Apart from the selectivity correction, the Reimers decomposition is a special case of the methodology presented in Oaxaca and Ransom (1994) in which the non discriminatory wage structure is a weighted average of the separately estimated wage structures. If treating the selectivity contribution as a final summary statistic seems incomplete and unsatisfactory, then one is pretty much confined to choosing from among Selectivity #1 – Selectivity #3 or something like these.

III. Illustration

For an illustration of the proposed decomposition methodologies we will use a sample of Israeli professionals (occupation 1) - split by gender and by ethnicity. A comparison of gender versus ethnic wage differentials and their components is interesting and Israel provides a tailor-made setting for ethnic studies since the Israeli Jewish population (4.5 million in 1995) consists of people with a large diversity in their countries of origin. The dominant distinction is between Westerners and Easterners. A worker is referred to as a Westerner if he was born in Europe, America, South Africa or Australia, or if he is Israeli-born and his father was born in one of these places. An Easterner is a worker who was born in Asia or Africa (excluding

South Africa and Israel), or if he is Israeli-born and his father was born in Asia/Africa. Second generation Israelis are part of the Western group. The shares of Westerners and Easterners in the Jewish population (in 1995) are about 65% and 35%.

We will analyze wages of professional workers who include the following: Academic professionals; Associate professionals and technicians; and Managers. Reference to professional workers only results in more homogeneous groups, however there is still a diversity of occupations within the professional occupation (25 two-digit occupations).

The Sample

For our illustration we investigate wage differentials between the various subgroups of Israeli Jewish professional workers, using the 20% sample of the 1995 Census of Population and Housing, conducted by the Israeli Central Bureau of Statistics (Israel, Central Bureau of Statistics, 1998). A distinction will be made between the genders and between the two ethnicities: Westerners versus Easterners. The analysis will be restricted to full-time, full-year salaried workers who have resided in Israel more than ten years.[3]

Table 1 summarizes some socio-economic characteristics of female and male workers in the two ethnic groups. The samples used for the empirical analysis of wage differentials of professionals are large. The female sample is composed of 10,074 Jewish women - one-fourth of them are of an Eastern ethnic origin and three-fourths are Westerners. The male sample is composed of 20,388 men - only 30% of them are Easterners. The lower representation of Easterners is partly a result of lower educational attainments. In our sample of full-time, full-year salaried workers - the share of women who are professionals is smaller than the share of men.[4] Moreover, the distribution within the 3 categories of professionals is different for women and

[3] We excluded from our sample immigrants who have resided less than 10 years in the country in order to confine our analysis to workers who are relatively absorbed in the Israeli labor market.

[4] An examination of the total labor force shows that relatively more female workers than male

men: A similar percentage of women and men (39% and 38%, respectively) work in academic occupations. However, only 16% of women compared with 35% of men are managers. The majority of women (45%) work as "Associate professionals and Technicians", mainly as teachers and nurses. Only 28% of professional men belong to this category. More details can be gained from an examination of the economic sector (Table 1). About 50% of women are in the sectors of 'Education' and 'Health and Welfare', while close to 50% of men are in 'Manufacturing' and in 'Real Estate, Rent and Business Activities'.

A comparison of male-female hourly wages shows that women, in both ethnic groups, get only about 75% of the male hourly wage. Wage differences between men and women are larger than wage differences between the ethnicities (an Easterner/Westerner wage ratio of about 82%). Educational attainments are more similar between the sexes: The average total number of years of schooling of men and women is almost identical (16 for Westerners and 14 for Easterners), and the share of workers who have at least some academic education is even larger for women. Eastern workers are less educated than their Western co-workers - a difference of about one and a half years on average. Wage differentials are therefore not explained by differences in education.

Male workers have somewhat more (potential) experience than female workers (by 1-2 years) and work longer hours per week (about 6 hours more). There are minor differences in these variables by ethnicity. About 60% of Jewish men (and women) are Israeli-born and the average period of residence in Israel (for workers not born in Israel) is around 30 years. More men than women are married (88% of men compared to 75% of women) and the average number of children is about two.[5]

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workers are professionals (34.5% of Jewish working women, compared to 30.7% of Jewish working men). Many women work part-time (Israel, Central Bureau of Statisitcs, 1996).

[5] While Eastern Israeli women have on average more children than Western women(2.4 and 2.0 respectively in our sample of full-time, full-year salaried women), among professional women the

Entrance Probabilities to the Professional Occupations

We now examine the respective probabilities of employment in the professional occupations. Probit models are estimated in which the dependent variable takes on the value of 1 if the worker is employed in the professional occupations and 0 if the worker is employed in other occupations.[6] The estimates of the probit regressions are used to construct the Inverse Mills Ratio for the purpose of correcting professional hourly wage equations for selection bias and are reported in the appendix. Predictably, schooling has a major positive effect on the probability of being employed as a professional worker for all groups. Age has parabolic effects that vary across groups. Over a normal working life age generally exhibits a positive effect on the probability of professional employment for all groups; however for women the age effect is increasing whereas for men it is declining. Married Westerners have a higher probability of professional employment. For Eastern workers the effect is insignificant. Number of children was never statistically significant and was subsequently dropped without altering any of the basic conclusions. Male workers not born in Israel have a lower tendency to work as professionals while female workers not born in Israel have a greater propensity to be employed as professionals. City of residence is generally statistically significant for women but not generally so for men. The effect of the size of locality of residence is generally significant for women and Western men, but not so for Eastern men.

Wage Equations by Gender and Ethnicity

Mincer-type wage equations are now estimated and then used to calculate the share of the human capital (explained) component versus the discrimination (unexplained) component and the selectivity component, in explaining wage differentials between the

number is almost identical.

[6] Non-employed individuals are excluded from the sample.

various groups. Two sets of wage equations are estimated: one set are the standard Mincer-type equations later used for the standard Oaxaca (1973) decomposition, and the second set are those corrected for selectivity bias, using the two-stage Heckman procedure. In all wage regressions, the logarithm of individual hourly wages was regressed against the following explanatory variables: dummy variables representing the highest educational certificate obtained, years of potential work experience (age - years of schooling - 6), experience squared, a dummy variable for foreign born, the length of residence in Israel, dummy variables for city and size of locality and the economic sector in which the worker is employed (a series of dummy variables for one-digit economic sectors).

The results of the regressions with selectivity correction (reported in the appendix) conform to the results found in numerous other studies: earnings are increasing with the higher the degree or certificate obtained, the relationship between earnings and experience has the inverted U-shape, and length of residence in Israel is positively related to earnings.[7] The magnitudes of the effects of the various explanatory variables on earnings are less straightforward. There are gender differences in the returns to the human capital variables. Returns to experience are larger for men than for women, as well as to years of residence in Israel. On the other hand the returns to education and to the size of locality are higher for women, and the wage penalty associated with being foreign born is smaller for women. There are also differences between the ethnic groups. Educational attainment has a stronger effect on the wages of Easterners. The wage penalty for not being Israeli born is higher for Westerners.

[7] It should be noted that the length of residence in the country is one of the elements of human capital, since it presumably measures the degree of understanding of the operation of the local labor market and also, which is most important, the command of the spoken language, i.e., the ability to communicate verbally. (On language and earnings, see Chiswick and Miller (1995)).

The returns to size of locality are higher for Westerners.

The results are quite similar when the wage equations are estimated without correction for sample selection (not reported). The main effects of estimation of the wage equations without sample selection correction are that the returns to educational attainment, being Israeli born, and years of residency are exaggerated while the effects of size of locality are understated.

Table 2 presents the estimates of the averages of the IMR variable (λ) and the respective coefficients of this variable in the wage equations (θ). For ease of notation we drop the subscript 1 for professionals. The coefficient of λ is negative and statistically significant in all cases. Since λ is inversely related to the probability of employment in the professional occupation, a negative coefficient indicates that (cet. par.) workers with higher probabilities of being employed in the professional occupation will earn higher wages conditional upon employment in the professional occupation. In particular an increase in a variable H_k with a positive coefficient γ_k will increase the probability of employment in the professional occupation (decrease λ) and hence have a positive partial effect on the conditional mean wage of a worker in the professional occupation (apart from any direct wage effect that H_k may have).

The estimates of λ are higher for women and for Easterners which is consistent with the lower probabilities for members of these groups being employed as professionals. Adopting the estimated probit coefficients of males (Westerners) further increases the value of λ for females (Easterners). This implies that the probit weights for females (Easterners) favor higher probabilities of professional employment compared with the probit weights for males (Westerners). Furthermore, the personal characteristics of females (Easterners) favor lower probabilities of professional employment compared with the personal characteristics of males (Westerners).

Decomposition of Wage Differentials

We now come to the core of our illustration - the breakdown of gender and ethnic wage differentials into the human capital (explained), the discrimination (unexplained), and the selectivity components. Table 3 presents the decomposition for the various comparisons. Each decomposition is done five times - first using the standard Oaxaca (1973) decomposition technique and then integrating into it Heckman's selectivity bias correction procedure, in four alternative ways. We label the selectivity corrected decompositions Selectivity #1 – Selectivity #4 corresponding to expressions (10), (11), (12), and (13). By construction, the discrimination estimates for Selectivity #1 and Selectivity #3 are identical as are the estimated human capital contributions for Selectivity #2 and Selectivity #3. For economy of notation when analyzing ethnic wage differentials, we will let 'm' and 'f' denote Westerner and Easterner, respectively.

The overall results are the following. Gender wage differentials (at the mean points) are larger than ethnic wage differentials. Among both Westerners and Easterners Jewish men earn 26% more (per hour) than Jewish women, while among both men and women Westerners earn 19% more than Easterners. When professional employment probabilities are not taken into account (no selectivity correction), differences in characteristics explain between 36% and 74% of the wage differentials. The explained share is smallest (36%) in a gender comparison among Westerners and largest (74%) in an ethnic comparison of women.

It is evident from Table 3 that the decomposition results are acutely sensitive to assumptions about how or whether to incorporate selection effects. For example, ethnic comparisons among women indicate that without correction for selectivity estimated discrimination against Eastern women accounts for about 26.4% of the ethnic (log) wage gap. Yet correcting for selection bias suggests that favoritism toward Eastern women vis a$'$ vis Western women could be as high as -43.4% of the wage gap. Similar results obtain for ethnic comparisons among men. In the case of gender comparisons, all of the decompositions employed yield positive estimates of discrimination against women. However, the estimates vary widely across alternative decompositions. For example the unexplained gender wage gap among Easterners varies from 63.4% of the total gap if selection is not taken into account to 22.7% of the gap under Selectivity #3.

Selection contributes to a narrowing of the observed gender wage gap among Westerners. This is attributable to the fact that the wage effect of λ is more negative for Western men ($(\widehat{\theta}_{1m}-\widehat{\theta}_{1f})\,\widehat{\lambda}_{1f} < 0$), and the estimated Western male selection equation lowers the probability of professional employment for the average Western female professional worker ($\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1f}^{0} - \widehat{\lambda}_{1f}) < 0$). What this means is that the conditional mean value of the wage equation error term for professional workers is lower on average for Western men than for Western Women. In other words relatively higher earnings potential women are employed in the professional occupations. This is in contrast to the ethnic comparisons and the gender comparison among Easterners. For example, the conditional mean value of the wage equation error term for professional workers is higher on average for Westerners (Eastern men) than Easterners (Eastern women). In other words selection increases the observed ethnic (Eastern gender) wage gap because relatively lower earnings potential Easterners (Eastern women) are employed in the professional occupations. For the ethnic comparison among men, selection has a partial negative impact on the wage gap in Selectivity #3 ($(\widehat{\theta}_{1m} - \widehat{\theta}_{1f})\,\widehat{\lambda}_{1f} < 0$), but overall this is more than offset by the other components of the selection decomposition as evidenced in selection decomposition #4 ($\widehat{\theta}_{1m}\,\widehat{\lambda}_{1m} - \widehat{\theta}_{1f}\,\widehat{\lambda}_{1f} > 0$).

I.V. Summary and Conclusions

Our results amply demonstrate that selectivity corrected decompositions are quite capable of yielding very different conclusions than those based on the standard Oaxaca decompositions without selectivity correction. Not only can the magnitudes of the discrimination estimates be greatly affected but even the direction of discrimination. In all cases the Inverse Mills Ratio was statistically significant, indicating the presence of selection bias in professional employment. For both the gender and ethnic comparisons, Selectivity #4 came the closest to replicating the estimates of the human capital and discrimination components obtained from the standard Oaxaca decomposition without selectivity correction. This is certainly the most non committal decomposition as none of the decomposition selection effects are allocated to human capital or discrimination estimates. If the overall gap in the selection contribution is subtracted from both sides of the wage decomposition formula, one arrives at a decomposition (8) that in appearances looks exactly like the standard decomposition. Except what is being decomposed is not the observed wage gap but rather the estimated wage gap that would exist had the selection effects not been present for the current sample of professional workers.

None of what has been presented here authoritatively identifies the "correct" decomposition except that selection effects should be taken into account. Beyond that, the determination of what really constitutes inequity rests upon opinions about which parameter differences constitute discrimination. While this issue could in principal apply to any of the β parameters, it is particularly relevant to the selection parameters θ and γ. The choice of which selectivity corrected decomposition to use is largely judgmental because it inevitably reflects value judgments about what constitutes labor market inequity. Under what theoretical framework would group differences in the correlation parameters, the wage dispersion parameters, or the probit selection weights constitute labor market discrimination?

If one decides that some aspects of group differences in the selectivity terms should be apportioned to either discrimination or human capital, it would seem that group differences in the values of the explanatory variables in the selectivity equation, $\widehat{\theta}_{1m}\,(\widehat{\lambda}_{1m} - \widehat{\lambda}^{0}_{1f})$, ought to be counted as an endowment effect. This would leave Selectivity #2 or #3 as candidate decompositions. There is of course the argument that occupational choice is purely supply side driven which would be manifested by different values of the selectivity equation parameters (see Polachek (1975)). A simple modification of Selectivity #3 that yields a fifth selectivity decomposition is to transfer the term $\widehat{\theta}_{1m}(\widehat{\lambda}^{0}_{1f} - \widehat{\lambda}_{1f})$ from the discrimination component to the selectivity residual. It is easily shown that this decomposition produces a selectivity residual equal to $\widehat{\theta}_{1m}\widehat{\lambda}^{0}_{1f} - \widehat{\theta}_{1f}\,\widehat{\lambda}_{1f}$. The selectivity residual in this case is the average group difference in the conditional mean wage equation error terms simultaneously attributable to group differences in the wage effects of the IMR $(\hat{\theta})$ and in the probit weights $(\hat{\lambda})$. In the case of the gender wage decomposition for Westerners, this procedure would decompose the log wage gap of 0.2567 into $H = 0.1595$, $D = 0.1730$, and Selectivity $= -0.0758$. In fact this decomposition would indicate that selection narrows the observed wage gaps for all of the group comparisons we have made

Possible further extensions of our work could include estimating a selectivity corrected wage equation for nonprofessionals and performing wage decompositions for nonprofessionals as a group. The wage determination model would be similar to the mover-stayer migration model analyzed in Nakosteen and Zimmer (1980). It might even be possible to extend this to a manageable number of occupational categories in which the probit selectivity equation is replaced by a multinomial probit model or multinomial logit model along the lines of Dolton et al. (1989).

Our paper is mainly technical, dealing with measurement techniques. However, it might also be policy oriented and lead to suggested policies to fight wage inequality. In order to do so it is important to establish empirically the major source of wage dissimilarity. If wage discrimination is the main factor behind wage inequality - affirmative action could be an efficient policy (as suggested by Bergmann, 1974, 1986, 1996). On the other hand, if differences in qualifications are a major factor, policy should be targeted at minimizing them, mainly by providing the subordinate groups with better access to quality education. And if discriminatory selectivity exists, barriers to the more prestigious high-pay occupations should be loosened.

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TABLE 1: Sample Characteristics by Ethnic Origin
Israeli Women and Men, 25-65 Year-Olds, Salaried Professionals - Israeli Census, 1995

CHARACTERISTICS	WESTERN WOMEN Mean	WESTERN WOMEN Standard Deviation	EASTERN WOMEN Mean	EASTERN WOMEN Standard Deviation	WESTERN MEN Mean	WESTERN MEN Standard Deviation	EASTERN MEN Mean	EASTERN MEN Standard Deviation
Share in employed labor force	40.68	-	17.43	-	48.89	-	21.24	-
Gross hourly wage (NIS)	38.34	21.24	31.88	20.51	51.17	34.98	42.06	27.66
Number of years of schooling	15.87	2.63	14.34	2.70	15.66	3.28	14.17	2.89
Certificates (%)								
- Elementary school or no certificate	0.98	-	5.06	-	2.45	-	7.72	-
- High school	4.38	-	12.76	-	7.77	-	17.02	-
- Matriculation	7.76	-	12.15	-	8.96	-	11.09	-
- Post secondary (not academic)	25.45	-	36.32	-	21.24	-	29.54	-
- Bachelor's degree	34.38	-	26.27	-	32.39	-	24.74	-
- Masters's degree	20.53	-	6.20	-	17.54	-	7.17	-
- Ph.D degree	6.52	-	1.25	-	9.65	-	11.09	-
Experience (years)	20.35	10.04	18.22	9.99	21.51	9.99	20.51	10.15
Hours of work per week	43.49	7.12	43.06	6.91	49.94	8.83	49.51	9.18
Marital status - married (%)	75.36	-	74.77	-	88.85	-	88.15	-
Number of children	1.97	1.32	2.05	1.54	-	-	-	-
Israeli born (%)	59.82	-	63.61	-	65.01	-	56.96	-
Years since migration	28.21	11.17	36.39	9.22	30.89	12.01	36.35	9.26
Locality of 100,000+ inhabitants	55.39	-	50.39	-	51.72	-	49.51	-
Economic Sector (%)								
- Agriculture	0.18	-	0.39	-	0.45	-	0.40	-
- Manufacturing	10.61	-	10.55	-	29.04	-	27.00	-
- Electricity and Water	1.22	-	0.96	-	2.36	-	2.21	-
- Construction	0.84		0.68	-	3.38		4.18	
- Wholesale and Retail Trade	3.67	-	4.78	-	9.42	-	11.24	-
- Transport and Communication	2.34		2.57		4.40		5.42	
- Financial Services	3.41	-	3.99	-	4.95	-	5.17	-
- Business Activities	16.22		13.79		17.74		14.47	
- Public Administration	8.61	-	7.27	-	6.91	-	10.21	-

- Education	18.85		19.60		10.25		8.71	
- Health and Welfare	30.15	-	31.68	-	7.79	-	6.15	-
- Other Personal Services	3.89	-	3.74	-	3.30	-	4.84	-
Sample size	7,268	-	2,806	-	14,336	-	6,052	-

Notes: A worker is referred to as a Westerner if he was born in Europe, America, South Africa or Australia, or if he is Israeli-born and his father was born in one of these places. An Easterner is a worker who was born in Asia or Africa (excluding South Africa and Israel), or if he is Israeli born and his father was born in Asia/Africa. Second generation Israelis are part of the Western group.

TABLE 2: Estimates of Average Lambdas and Lambda's Coefficients

Wage differential	$\hat{\lambda}_m$	$\hat{\lambda}_f$	$\hat{\lambda}_f^0$	$\hat{\theta}_m$	$\hat{\theta}_f$	Z_1	Z_2	Z_3	Z_4	Z_5
				Westerners: Men-Women						
0.2567	0.6206	0.7121	0.9128	-0.2119	-0.1651	0.0976	0.0619	-0.0333	0.1730	-0.0425
				Easterners: Men-Women						
0.2623	1.0313	1.1362	1.5080	-0.1875	-0.1962	0.1036	0.0894	0.0098	0.1292	-0.0697
				Men: Westerners-Easterners						
0.1871	0.6206	1.0313	1.3524	-0.2119	-0.1875	0.0776	0.1551	-0.0252	0.0476	-0.0680
				Women: Westerners- Easterners						
0.1927	0.7121	1.1363	1.5400	-0.1651	-0.1962	0.1044	0.1367	0.0353	-0.0170	-0.0666

NOTES: $\hat{\lambda}_m$, $\hat{\lambda}_f$ are averages of the inverse of Mill's ratios, for men and women (or Westerners and Easterners), respectively. $\hat{\theta}_m, \hat{\theta}_f$ are estimates of the coefficients of $\hat{\lambda}_m$, $\hat{\lambda}_f$ in the corrected wage equations.

Legend:

$$Z_1 = (\overline{X}_m - \overline{X}_f)' \hat{\beta}_m$$

$$Z_2 = \hat{\theta}_m (\hat{\lambda}_m - \hat{\lambda}_f^0)$$

$$Z_3 = \hat{\lambda}_f (\hat{\theta}_m - \hat{\theta}_f)$$

$$Z_4 = \overline{X}_f' (\hat{\beta}_m - \hat{\beta}_f)$$

$$Z_5 = \hat{\theta}_m (\hat{\lambda}_f^0 - \hat{\lambda}_f)$$

TABLE 3: Decompositions of Wage Differentials
Israeli, Jewish, 25-65 year olds, salaried professionals
Israeli Census, 1995

		Contribution of		
Decomposition method	Wage differential	H	D	Selectivity
		Westerners: Men-Women		
Standard Oaxaca	0.2567	0.0916 (35.68%)	0.1651 (64.32%)	0.0000 (0.00%)
Selectivity # 1		0.1262 (49.16%)	0.1305 (50.84%)	0.0000 (0.00%)
Selectivity # 2		0.1595 (62.13%)	0.0972 (37.87%)	0.0000 (0.00%)
Selectivity # 3		0.1595 (62.13%)	0.1305 (50.84%)	-0.0333 (-12.97%)
Selectivity # 4		0.0976 (38.02%)	0.1730 (67.39%)	-0.0139 (-5.41%)
		Easterners: Men-Women		
Standard Oaxaca	0.2623	0.0959 (36.56%)	0.1664 (63.44%)	0.0000 (0.00%)
Selectivity # 1		0.2028 (77.32%)	0.0595 (22.68%)	0.0000 (0.00%)
Selectivity # 2		0.1930 (73.58%)	0.0693 (26.42%)	0.0000 (0.00%)
Selectivity # 3		0.1930 (73.58%)	0.0595 (22.68%)	0.0098 (3.74%)
Selectivity # 4		0.1036 (39.50%)	0.1292 (49.26%)	0.0295 (11.24%)
		Men: Westerners-Easterners		
Standard Oaxaca	0.1871	0.1200 (64.14%)	0.0671 (35.86%)	0.0000 (0.00%)
Selectivity # 1		0.2075 (110.90%)	-0.0204 (-10.90%)	0.0000 (0.00%)
Selectivity # 2		0.2327 (124.37%)	-0.0456 (-24.37%)	0.0000 (0.00%)
Selectivity # 3		0.2327 (124.37%)	-0.0204 (-10.90%)	-0.0252 (-13.47%)
Selectivity # 4		0.0776 (41.48%)	0.0476 (25.44%)	0.0619 (33.08%)

	Women: Westerners-Easterners			
Standard Oaxaca	0.1927	0.1419 (73.64%)	0.0508 (26.36%)	0.0000 (0.00%)
Selectivity # 1		0.2763 (143.38%)	-0.0836 (-43.38%)	0.0000 (0.00%)
Selectivity # 2		0.2410 (125.06%)	-0.0483 (-25.06%)	0.0000 (0.00%)
Selectivity # 3		0.2410 (125.06%)	-0.0836 (-43.38%)	0.0353 (18.32%)
Selectivity # 4		0.1044 (54.15%)	-0.0170 (-8.82%)	0.1054 (54.67%)

Legend:

Selectivity # 1: $H = Z_1 + Z_2 + Z_3$; $D = Z_4 + Z_5$

Selectivity # 2: $H = Z_1 + Z_2$; $D = Z_3 + Z_4 + Z_5$

Selectivity # 3: $H = Z_1 + Z_2$; $D = Z_4 + Z_5$; Selectivity = Z_3

Selectivity # 4: $H = Z_1$; $D = Z_4$; Selectivity = $Z_2 + Z_3 + Z_5$

where:

$$Z_1 = (\overline{X}_m - \overline{X}_f)^{/} \hat{\beta}_m$$

$$Z_2 = \hat{\theta}_m (\hat{\lambda}_m - \hat{\lambda}_f^0)$$

$$Z_3 = \hat{\lambda}_f (\hat{\theta}_m - \hat{\theta}_f)$$

$$Z_4 = \overline{X}_f^{/} (\hat{\beta}_m - \hat{\beta}_f)$$

$$Z_5 = \hat{\theta}_m (\hat{\lambda}_f^0 - \hat{\lambda}_f)$$

Table A1:
Maximum Likelihood Estimates of Probit Model
of Employment in the Professional Occupations
Israeli Women and Men, 25-65 Year-Olds, Salaried Professionals
Israeli Census, 1995

INDEPENDENT VARIABLES	Women		Men	
	Western	**Eastern**	**Western**	**Eastern**
Years of schooling	0.289 (65.86)	0.302 (50.36)	0.252 (81.95)	0.287 (71.58)
Age	-0.012 (1.38)	-0.026 (2.16)	0.032 (4.71)	0.040 (4.92)
Age squared	0.0002 (2.06)	0.0005 (3.26)	-0.0003 (3.56)	-0.0003 (3.29)
Not Israeli born	0.118 (5.04)	0.086 (2.58)	-0.732 (4.02)	-0.008 (0.34)
Place of residence				
- Jerusalem	-0.112 (2.08)	-0.188 (2.82)	-0.040 (0.93)	0.047 (0.92)
- Tel Aviv	-0.139 (2.72)	-0.075 (1.10)	0.018 (0.44)	0.015 (0.28)
- Haifa	-0.064 (1.16)	-0.204 (2.46)	0.041 (0.99)	0.170 (2.78)
- Locality of 100-200 thousand	-0.200 (4.381)	-0.248 (4.48)	-0.116 (3.40)	-0.042 (1.03)
- Locality of 10-100 thousand	-0.165 (3.70)	-0.169 (3.13)	-0.089 (2.70)	-0.069 (1.73)
- Locality of 2-10 thousand	-0.132 (2.11)	-0.128 (1.75)	-0.081 (1.79)	0.043 (0.81)
Marital status: married	0.067 (2.63)	-0.014(0.45)	0.060 (2.28)	-0.008 (0.26)
Intercept	-4.171 (21.36)	-4.353 (17.10)	-4.337 (29.82)	-5.394 (30.49)
Sample size	17,865	16,094	29,320	28,486

Notes:

For the definition of Western and Eastern see notes of Table 1
Dependent variable = 1 if in professional occupations, and 0 if in other occupations.
Numbers in parentheses are absolute t-statistics.
Reference group for marital status: single; either bachelor, divorced or widowed.
Reference group for place of residence: agricultural localities.
Samples include professionals and employed in other occupations. New immigrants (less than 10 years in Israel) are excluded.

Table A2:
Log Hourly Wage Regressions
Israeli Women and Men, 25-65 Year-Olds, Salaried Professionals
Israeli Census, 1995

INDEPENDENT VARIABLES	Women		Men	
	Western	Eastern	Western	Eastern
Highest certificate obtained				
- High school	0.069 (1.07)	0.037 (0.74)	0.050 (1.51)	0.069 (2.29)
- Matriculation	0.143 (2.26)	0.170 (3.18)	0.119 (3.52)	0.171 (4.94)
- Post secondary (not academic)	0.190 (2.99)	0.218 (3.99)	0.106 (3.09)	0.202 (5.82)
- Bachelor's degree	0.344 (5.15)	0.433 (6.84)	0.287 (7.61)	0.354 (8.49)
- Master's degree	0.374 (5.32)	0.364 (4.76)	0.350 (8.48)	0.443 (8.70)
- Ph.D	0.466 (6.20)	0.646 (5.93)	0.375 (8.34)	0.536 (8.56)
Experience	0.045 (19.33)	0.048 (13.54)	0.052 (28.09)	0.044 (16.50)
Experience squared	-0.0007 (12.65)	-0.0007 (9.31)	-0.0007 (18.83)	-0.0005 (9.28)
Not Israeli born	-0.139 (5.14)	-0.119 (1.88)	-0.256 (11.40)	-0.173 (4.14)
Years of residence	0.002 (2.61)	0.002 (1.29)	0.006 (9.27)	0.004 (3.44)
Place of residence				
- Jerusalem	0.091 (3.29)	0.043 (0.99)	0.051 (2.26)	-0.005 (0.17)
- Tel Aviv	0.135 (5.01)	0.029 (0.67)	0.092 (4.26)	0.007 (0.21)
- Haifa	0.113 (4.06)	0.028 (0.52)	0.041 (1.89)	0.040 (1.07)
- Locality of 100-200 thousand	0.128 (5.25)	0.059 (1.61)	0.051 (2.73)	0.023 (0.89)
- Locality of 10-100 thousand	0.129 (5.55)	0.024 (0.70)	0.088 (4.94)	0.035 (1.33)
- Locality of 2-10 thousand	0.160 (4.93)	0.083 (1.71)	0.111 (4.60)	0.046 (1.33)
Economic Branch				
- Manufacturing	0.295 (2.15)	0.169 (1.19)	0.231 (4.50)	0.260 (2.57)
- Electricity and water	0.479 (3.29)	0.309 (1.86)	0.304 (4.25)	0.344 (3.15)
- Construction	0.232 (1.55)	0.271 (1.54)	0.128 (1.84)	0.216 (2.06)
- Wholesale and retail trade	0.229 (1.64)	0.096 (0.66)	0.201 (3.00)	0.226 (2.22)
- Transportation and communication	0.355 (2.51)	0.306 (2.04)	0.371 (5.40)	0.406 (3.90)
- Financial services	0.627 (4.49)	0.463 (3.16)	0.501 (7.32)	0.594 (5.68)
- Real estate and business activities	0.285 (2.08)	0.204 (1.44)	0.153 (2.30)	0.228 (2.24)
- Public services	0.336 (2.45)	0.097 (0.68)	0.138 (2.04)	0.236 (2.31)
- Education	0.089 (0.65)	-0.160 (1.13)	-0.028 (0.40)	0.056 (0.54)
- Health and welfare	0.260 (1.90)	0.084 (0.60)	0.474 (0.70)	0.137 (1.32)
- Private services	0.144 (1.03)	0.011 (0.08)	0.407 (0.59)	0.100 (0.96)
Lambda	-0.165 (6.66)	-0.196 (6.84)	-0.212 (9.30)	-0.188 (8.22)
Constant	2.429 (15.51)	2.631 (16.02)	2.740 (33.40)	2.661 (22.56)
R^2	0.1973	0.2638	0.2240	0.2638
Sample size	7,268	2,806	14,336	6,052
Percent of professional	40.68	17.43	48.89	21.24

Notes:

For the definition of Western and Eastern see notes of Table 1
Numbers in parentheses are absolute t-statistics.
Reference group for: 'Highest certificate obtained' is 'Elementary school certificate.'
Reference group for: 'Place of residence' is 'Localities with less than 2 thousand inhabitants and agricultural localities'.
Reference group for 'Economic branch' is 'Agriculture'.
New immigrants (less than 10 years in Israel) are excluded from the samples.