The Gender Wage Gap in Israel, 1982-1997

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Abstract

The analysis of the change in the differences between male and female earnings is the topic of this paper. On the basis of income surveys conducted in Israel, we take a look at the factors which may explain the changes that occurred over time in the gender gap, applying a methodology first proposed by Juhn et al. (1993). This is the first time such an approach is used in an analysis of differences between male and female earnings in Israel. In addition, the bootstrap method is used to check the significance of the change in the gap and its sources. Also included in the analysis is a correction for the selectivity bias suggested by Heckman (1979), which leads to the conclusion that the gap between the wage offers men and women face is equal to twice the gap actually observed in the market, and this selectivity effect does not seem to change over time. Our results indicate also that although the gender wage gap in Israel is significant, it seems to have been stable during the period of investigation. The small closure of the gap is likely to be the result of female improving their skills relative to men, and not of a reduction in discrimination or a more favoring wage structure.

I. Introduction

The existence of wage differentials, especially race and gender differentials has been the subject of an extensive research. In the original literature on discrimination (see Oaxaca, 1973 and Blinder, 1973), the wage differential is analyzed within the context of what might be called “gender- specific factors”, meaning gender differences in human capital and discrimination. There exists, however, another important factor, the wage structure.

Many industrial countries have experienced a major change in their wage structure during the last decades, with a trend towards greater inequality both between and within skill groups and an increase in the dispersion of the overall wage distribution. Several determinants have been given to such an increased inequality: changes in the skill composition of the labor force or variations in the relative demand for skills (Katz and Murphy 1992, Juhn and Kim 1999, Juhn 1999), technological change and particularly the rapidly increasing use of computers (Krueger 1993) or a decrease in the power of wage setting institutions (such as unions and central bargaining). Other studies have stressed the growing impact of international trade, which induces companies to remove their production lines from industrial countries where the wages are relatively high to developing countries.

The real determinant of the growing inequality is probably a combination of all factors mentioned previously. However, no matter what the main determinants of the wage structure are, what interests us is its impact on the gender pay differential.

The wage structure refers really to the distribution of the prices for both measured and unmeasured skills. In one of the first papers on this subject, Juhn, Murphy and Pierce (1993) attribute the increase in wage inequality in the U.S. to a rise in the returns to skills (measured and unmeasured) and an increase in the reward for being employed in favorable sectors. As is well known, women have on average lower skills and tend to concentrate in low paying jobs. When the returns to skill (or the reward for working in favored occupations) increase, women will be pushed down the wage distribution, and wage differences are expected to grow.

Our analysis of the change in the gender wage gap in Israel between 1982 and 1997 tries to account for the factors influencing the change, using the method proposed by Juhn et al (1993). The method was applied in several papers by Blau and Kahn (1996a, 1996b, 1997 and 1999) and others (Reilly, 1999) for analyzing international differences in the gender pay gap as well as for exploring the sources of the change in race or gender differentials. However, the significance of the "gender-specific" and "wage structure" effects on the overall change in the wage difference was not tested in those papers. In this paper, the bootstrap method is used to check the significance of the change in the gap and its sources. Also included in this analysis, unlike in previous papers, is the correction for the selectivity bias suggested by Heckman (1979). This correction turned to be significant, implying that in our data, the gap between the wage offers men and women face is twice the gap actually observed in the market, and this selectivity effect does not seem to change over time.

Our results indicate that there is a significant gender wage gap in Israel. This gap seems to have decreased over the years, but it turns out that the variation in the gap observed during our period of investigation is negligible. This small closure of the gap seems to be the result of female improving their skills relative to men rather than of a reduction in discrimination or a more favoring wage structure.

II. Decomposing the gender wage differential

a. Taking the wage structure into account.

Both the traditional wage decomposition (Oaxaca, 1973 and Blinder, 1973) and the decomposition used in this paper (Juhn et al., 1993) are based on the Mincerian earnings function which may be written as

$$\ln y_{it} = x_{it}\beta_t + u_{it} \tag{1}$$

where the subindices i and t refer respectively to the individual and the year, while u_{it} is the residual, the unexplained part of the wage equation attributed to unmeasured skills and the returns to those skills.

The framework suggested by Juhn, Murphy and Pierce (1993) is that the change in inequality comes from three factors; changes in the distribution of the individual characteristics, x, changes in the returns to those characteristics, β, and changes in the distribution of the residual.

This residual is assumed to depend on two elements, the residual distribution function and the rank of individual i in the distribution. More precisely

$$u_{it} = F_t^{-1}(\psi_{it} | x_{it}) \tag{2}$$

where $F(\cdot | x_{it})$ is the cumulative distribution function of the residual at year t, F_t^{-1} is the inverse function and ψ_{it} is individual i's percentile in the residual distribution in year t.

We will now analyze the implications of such an approach for the gender wage gap. The decomposition method was first suggested by Juhn, Murphy and Pierce (1991) who analyzed wage differentials between races, and has been lately applied to the analysis of the gender pay gap (e.g. Blau and Kahn 1996a, 1996b, 1997, 1999, Blackaby, Murphy and O'Leary 1996, Reilly 1999).

Going back to (2) let us write the residual u_{it} as

$$u_{it} = \sigma_t \theta_{it} \tag{3}$$

where σ_t is the standard deviation of the residual distribution function and θ_{it} is the standardized residual. $\theta_{it} = (u_{it} - \bar{u}) / \sigma_t$, where by the OLS assumptions, $\mathrm{E}(u) = 0$ and $VAR(u) = \sigma$. σ_t describes the dispersion of the distribution, while θ_{it} shows the individual's rank in the distribution.

Let us assume that we estimate the vector β of the rates of return on the basis of the male sample only. We may then write that

$$\overline{\ln y_t^m} = \overline{x_t}^m \beta_t \tag{4}$$

where $\beta_t = \beta_t^m$. The average wage differential between men and women in year t is then

$$D_t = \overline{\ln y_t^m} - \overline{\ln y_t^f} \tag{5}$$

where $$\overline{\ln y_t^f} = \overline{x_t^f} \beta_t^m + \sigma_t^m \overline{\theta_t^f} \tag{6}$$

As noted before, $\overline{\ln y_t^f}$ is the average pay of females in year t, $\overline{x_t^f}$ is a vector of the average human capital characteristics, σ_t^m is the standard deviation of the male residual distribution and $\overline{\theta_t^f}$ is the average location of a woman in the male residual distribution.

The differential D_t may then be written as

$$D_t = \overline{\ln y_t^m} - \overline{\ln y_t^f} = (\overline{x_t^m} - \overline{x_t^f})\beta_t + \sigma_t(\overline{\theta_t^m} - \overline{\theta_t^f}) = \Delta x_t \beta_t + \sigma_t \Delta\theta_t \tag{7}$$

where $\beta_t = \beta_t^m$ and $\sigma_t = \sigma_t^m$ as mentioned previously, whereas Δ is the difference between the average man and the average woman. Note that $\Delta\theta_t$ is in fact equal to $(-\theta_t^f)$ as $\sigma_t \overline{\theta_t^m} = 0$ by the OLS assumption.

The pay gap between men and women is decomposed into an element due to gender differences in human capital characteristics and another one taking into account differences in the ranking of the genders in the male residual distribution. One may then express the change in the gender wage gap between time t and t' as

$$D_{t'} - D_t = \Delta x_{t'} \beta_{t'} - \Delta x_t \beta_t + \sigma_{t'} \Delta\theta_{t'} - \sigma_t \Delta\theta_t \tag{8}$$

or, after some simple algebraic manipulations, as

$$D_{t'} - D_t = (\Delta x_{t'} - \Delta x_t)\beta_t + \Delta x_{t'}(\beta_{t'} - \beta_t) + (\Delta\theta_{t'} - \Delta\theta_t)\sigma_t + \Delta\theta_{t'}(\sigma_{t'} - \sigma_t) \tag{9}$$

$(\Delta x_{t'} - \Delta x_t)\beta_t$ and $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$ are the gender- specific factors which affect the change in the pay gap. The first term reflects the contribution of the changes that occurred during the period t and t' in the distribution of skills of men relative to those of women (one may for example observe a convergence in the work experience or education level of males and females). The second term shows the women's movement in the male residual distribution. This movement can be explained by a change in the dispersion of the distribution which affects the distribution tails where the women usually rank (as will be discussed immediately), by changes in unmeasured human capital characteristics or by a change in discrimination which causes women to change their location in the male residual distribution.

The next two expressions, $\Delta x_{t'}(\beta_{t'} - \beta_t)$ and $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$ measure the impact of the wage structure on the gap. The first term shows the changes in the male returns to measured skills and their contribution to the wage gap. Women, for example, have on average less years of work experience compared to men, so that a rise in the return to experience would increase the wage gap. The second term refers to the impact of the returns to unmeasured skills, and reflects the effect of the change in the dispersion of the residual distribution from year t to t', when the rank of the average woman (her percentile) does not change.

The interpretation of the residual as unmeasured quantities and prices has been recently criticized by Suen (1997). His major claim is that the percentile ranking is not independent of changes in the residual dispersion and that "with rising wage inequality, the mean percentile rank of low- wage groups will rise simply because more dispersed distributions have thicker tails." (Suen, 1997). He also casts some doubts on the interpretation of the fourth term[1] and suggests that the change in the standard deviation of the residual distribution may not be only the consequence of changes in unmeasured prices[2].

We should also pay attention to the fact that this analysis does not concentrate on the identification of discrimination. The effect of discrimination is hidden, as mentioned before, in the third term- the advance of the female ranking in the male residual distribution, but the fourth component also depends on the women's location in the distribution.

b. Comparing Oaxaca's decomposition method with the method of Juhn et al.

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[1] Blau and Kahn (1997) also mention this interpretation problem.

[2] A rise in the variance could be caused, for example, by an increase in measurement or pricing errors or due to the fact that the market has come to value a more diverse set of worker attributes as the economy becomes more complex.

When looking at the decomposition of the gender wage gap in year t one may observe, that the "discrimination" term in the traditional Oaxaca decomposition is equal to the component indicating women's rank in the male residual distribution by the Juhn et al. method. By the latter method this component is interpreted as discrimination but also as differences in unmeasured skills between the sexes causing women to rank lower than men in the male residual distribution. More importantly, the method adds the aspect of wage structure by distinguishing the residual dispersion from the relative ranking of men and women in the residual distribution. Oaxaca's decomposition, on the other hand, could have an advantage if one could disaggregate the discrimination term in order to see the contribution of each rate of return. This usually cannot be done because of the use of dummy variables in the earnings equation, for the values received by such a disaggregation depend on the decision concerning which category in the set of dummies should be left out (Jones, 1983 and Oaxaca and Ransom, 1999)[3].

When comparing the gender pay gap between two years, t and t', the advantage of using the wage- structure related decomposition is more pronounced. As noted previously (see equation (16)), the change in the wage gender gap can be decomposed into four components expressing the change in the gender endowment differential, the contribution of the changes in the rates of return on human capital characteristics, the change in the female relative rank in the male residual distribution and the change in the male residual dispersion. When applying Oaxaca's method to decompose the change in the gender gap over time, the interpretation of the components received by the decomposition is more problematic. Wellington (1993) presents two such possible decompositions, one which leaves two interaction terms with no clear interpretation, while the other does not thoroughly separate the effect of human capital differences from that of discrimination, because, for example, both the male and the female rates of return are used as weights in order to measure the impact of the change in characteristics differences[4].

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[3] The problem is explained in more details in Israeli (2001).

[4] The first decomposition mentioned above is

$$D_{t'} - D_t = \beta_{t'}^m[(x_{t'}^m - x_t^m) - (x_{t'}^f - x_t^f)] + x_t^f[(\beta_{t'}^m - \beta_t^m) - (\beta_{t'}^f - \beta_t^f)] + [(x_t^m - x_t^f)(\beta_{t'}^m - \beta_t^m)] + [(x_{t'}^f - x_t^f)(\beta_{t'}^m - \beta_{t'}^f)]$$

while the second is

$$D_{t'} - D_t = [\beta_{t'}^m(x_{t'}^m - x_t^m) - \beta_{t'}^f(x_{t'}^f - x_t^f)] + [x_t^m(\beta_{t'}^m - \beta_t^m) - x_t^f(\beta_{t'}^f - \beta_t^f)].$$

For all these reasons we adopted Juhn et al. (1993) breakdown to analyze the change in the gender gap over time.

III. The Gender Wage Gap in Israel

During the last two decades, the Israeli labor market has gone through two major dramatic changes: first, a period of rising inflation reaching almost a stage of hyper-inflation since in 1984 the rate of inflation was 474%. The 1985 stabilization program put abruptly an end to this spiraling inflation but is likely to have caused a rise in the unemployment rate. The second important event is the immigration wave from the former Soviet Union which began unexpectedly at the end of 1989. About 700,000 new immigrants arrived in a short period and forced the labor market to adjust itself quickly to the new conditions. Additional factors, some of them unique to Israel and some others which also played a role abroad are related to the inflow of foreign workers, the peace process, technological change and international trade growth.

It appears that male wage inequality (measured by the standard deviation of the log of wages), the main cause of income inequality, fluctuated in accordance to these changes. It increased when the inflation rate rose, and fell when the stabilization program succeeded. Wage inequality reached its peak when the new immigrants entered the labor market (Dahan, 2000).

During the sampled period, the gender pay difference was fairly stable, showing a 22% to 25% advantage for male workers. The labor force participation rate of women has, however, increased substantially. Laws aimed at fighting discrimination were enacted, such as the 1981 and 1988 Equal Opportunities in Employment Laws which are supposed to guarantee equal opportunities in promotion and hiring in employment.

The data for the present research are taken from the Israel Income Surveys (IIS) conducted by the Israeli Central Bureau of Statistics (CBS). This Income Survey is a supplement to the quarterly Labour Force Surveys (LFS), when a sub- sample of 25% of the participants of the LFS are asked additional questions about their incomes. The surveys are written surveys, conducted annually; until 1984 the families were asked to report their earnings for the year ending a month before the reviewer's arrival and are presented on a yearly basis, and since 1985 the surveys are conducted four times a year and presented on a monthly basis. The surveys' sample provides information about 80% of the salaried population in Israel. By combining results from these two surveys one is able to obtain data on the income, the employment status and the socio- demographic characteristics of the individual[5].

Note that in the present study the data of each survey which were given in current prices were all transformed and expressed in 1997 prices.

IV. The results of the empirical investigation

One. The wage and labor force participation equations.

Earning functions have been estimated for the years 1982, 1990 and 1997, on the basis of the IIS data. The independent variables include socio- demographic variables such as potential experience and education, as well as occupational variables. The dependent variable, the natural log of the hourly wage, is derived from either the monthly or the yearly income (depending on the year), taking into account the number of weeks and hours worked.

The sample used in this work is restricted to Jewish salaried workers or non-working individuals only (due to limitations of the IIS mentioned before), aged 25 to 60. We exclude self- employed individuals because their salary from self employment and other job characteristics are not reported. The purpose of the age restriction is to avoid sample selection problems due to low rates of participation in the labor force of the age groups not included in the sample. The Israeli individual enters the labor force later than his American counterpart for example, because of the compulsory military service that also postpones his high education acquirement. After the age of 60 the retirement rate increases and this might also give rise to selectivity bias.

Selectivity bias is a problem that arises when the sample used is not randomly selected. It affects the regression coefficients because some of the exogenous variables may also have an influence on the probability that an observation will be included in the sample. In our case it means that the wages we observe are the wages of individuals who chose to work- a decision based on several factors some of which might affect the wage itself. Education, for example, is a factor influencing the decision to work and it has also an impact on the wage. Thus, in a simple regression, the coefficient of education would not only show the effect of education on the wage,

[5] Problems concerning the definitions of the variables and their measurement methods are referred to in my Ph.D. dissertation (Israeli, 2001).

but also its effect on the participation decision. In addition, variables that do not really affect the wage, such as the number of children, might nonetheless appear to have a significant effect on wages because they play a role in the decision to work (see Gronau, 1974).

In a basic paper on the subject, Heckman (1979) showed that the selectivity bias issue is actually a problem of specification error where the variable omitted is λ, also known as the inverse of Mill's ratio, which is negatively correlated with the decision to work. Heckman (1979) suggested an econometric technique, known as a Heckman's two-step procedure, that produces efficient estimates of the parameters, standard errors and covariance matrix. His idea is to first estimate the parameters of the participation in the labor force equation by a probit model, use these results to compute λ, and then enter λ as an additional variable in the OLS wage regression.

The procedure has come under criticism because of its lack of robustness (Manski, 1989) since the model can be unstable if not properly specified. The results presented here support the specification used and confirm that there exists a selectivity bias for both men and women.

The wage regression specification includes potential experience and its square[6], a dummy variable which receives the value 1 if the individual was born in Israel and 0 otherwise[7]. Dummy variables for school attainment (the full details are presented in Appendix 1) are also included, plus two interaction terms: a dummy variable which is equal to 1 if the last school attended is a Talmudic school[8], multiplied by 13-15 years of schooling, and the same dummy variable multiplied by 16+ years of schooling[9] to catch the effect of the quality of education. We also added one- digit (the CBS classification, see Appendix 1) occupational dummies[10].

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[6] Potential experience is computed as experience= age- years of schooling – 6. In 1982 and 1997 the variable "years of schooling" is measured in exact number of years but appears also as a grouped variable, while in 1990 it appears as a grouped (qualitative) variable. This is why we had to use grouped years of schooling for all surveys. In computing the experience variables we used the average of each "years-of-schooling" group.

[7] The differences between individuals from different countries of origin (all else equal) were mostly insignificant and thus no other dummy variables were used.

[8] The Talmudic school program concentrates mostly on the studying of the Talmud, and therefore we expect individuals who studied in the Talmudic school to receive lower wages than individuals with the same years of schooling who studied in other high- education institutions.

[9] We tried other interactions, such as last school is post- secondary school*13-15 or 16+ years of schooling (as opposed to academic institution) but the coefficients were not statistically significant.

[10] A specification including industry dummies had been originally estimated as well, but the coefficients of the industry variables were not significant. In addition, Dahan (2000) claims that

The sample of the labor force participation equation includes individuals that do not work and individuals who work as salaried workers, omitting observations on self- employed or salaried workers who also work as self- employed, due to the lack of information on wages and other job characteristics. As a consequence, the labor force participation equation introduced to solve the selectivity problem refers really to the decision to be a salaried worker rather than to the decision to work.

Some of the explanatory variables of the participation equation are similar to those of the wage equation: schooling years (grouped) and the country of origin dummy, and some are unique: age and its square, marital status (1 if married, 0 otherwise[11]) and the number of persons younger than 14 in the household.

Table 1 gives the results of the labor force participation regression.

As we can see from the table, the coefficients of the variables have usually the same signs throughout the years[12]. Except for the case of the coefficients of the marital status in the female regression, generally when the sign of a coefficient changes over time, it is not significant. One should remember that the coefficients of a probit regression, unlike in a linear model, are not the marginal effect of the variables[13] but show us the direction of the impact of the variables on the probability to work.

The country of origin dummy, indicating whether the individual was born in Israel or not, has usually a positive, although mostly insignificant, effect on the chances to be employed[14]. However, its impact was significant in 1990, at a time of massive immigration of Jews from the former Soviet Union. Such an effect indicates that the language problem, a different occupational structure in the land of origin and other factors make it difficult for new immigrants to be integrated immediately in the

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industry variables should not be included in order not to confuse changes in the demand for labor with variations on the supply side. On the other hand, inter- industry wage differences could reflect the presence of efficiency wages.

[11] See Appendix 1 for the definitions of marital status. The "separated" category appears in 1990 and 1997 surveys only. Separated individuals in 1982 were probably considered as married. This doesn't seem to have affected the results, however.

[12] Except for the coefficients of the marital status in the female regression, when the sign of a coefficient changes over time, it is generally not significant.

[13] The marginal effect of a variable depends not only on its coefficient, but also on the values of all the other variables and their coefficients.

[14] The period of immigration is not precisely defined in some of the IIS used; only in 1990 do we know the exact year of immigration.

labor force. The impact of education[15] seems to be different for males and females. From the female regressions it is clear that the more educated you are, the higher the probability of working. As expected, a more educated woman is likely to be offered a higher wage in the labor market, making it probable that her offered wage will exceed her reservation wage and inducing her to work outside the house[16]. The results for the male regressions are less clear. Education increases the probability of being employed up to a certain degree; the probability drops for men who have 16+ years of schooling, and in 1982 the decrease starts at 13-15 years of schooling. The age variable and its square show the familiar parabolic form, as the rate of participation in the labor force increases up to a certain age (between 36 and 44 years of age) and then starts declining. Married males, as expected, are more likely to be employed (as salaried workers) than unmarried males as they need to support a family, but we observe an interesting phenomenon when looking at the female regressions estimates. In 1982, a married woman was less likely to work than her unmarried counterpart. This was also true in 1990, though the difference is much smaller. In 1997, the tendency seems to have changed altogether, and married women are now more likely to work than single women. For both men and women, the more children under the age of 13 you have, the less likely it is that you will work. This effect is stronger for women, and this may be due to their traditional role in the family or to their lower expected wages in the market. One may note that in 1997, in spite of the positive coefficient of the marriage variable, married women with young children are still less likely to work than unmarried women with no children, ceteris paribus.

Table 2 gives the results of the earning functions. It is hard to see a time pattern in the regression results. This is understandable considering the changes the Israeli labor market has gone through during the period analyzed. The experience variables show the common form of a parabola (although in the 1997 male regression the coefficient of the non- linear component is not significant), and the fluctuations observed in the male regressions are in line with the tendency observed by Dahan (2000). When computing the rate of return on an additional year of experience (evaluated at the average years of experience), we can see that it increases for both

[15] The omitted group is 0-4 years of schooling. See Appendix 1 for the definitions of the other education dummies.

[16] Notice that the impact of education decreases over the years, this being true for each educational group.

men and women, from 0.9% in 1982 to 1.6% in 1997 for men, and from 0.5% to 1.2% respectively for women.

For both men and women, in all years, we can see that the rate of return on education increases with the educational attainment[17], but all our results show also a decline in the return to high education (school6 and school7, 13-15 and 16+ years of schooling respectively) from 1990 to 1997, a decline of about 20 percent for 13 to 15 years of schooling (21% for women) and 34% for men with 16+ years of education (17% for women). Those results suggest that the rising demand for skilled workers has been met with an even greater change in their supply. As may be observed in Appendix 2, the shares of individuals with a high education has risen by 32% among males and by 20% among women between 1990 and 1997. The decline may be also due to the fact that an important share of the labor force in 1997 included new immigrants. When one measures the latter's human capital in years, one should not be surprised to find a lower rate of return on education and experience than is observed among those born in Israel or among immigrants who have been in Israel for a long time (see Deutsch and Silber, 2001). The "type of last school is a Talmudic school" variable (dscht5y6 and dscht5y7) indicates[18] that the quality of education has an important impact on the return to education[19]. The average return to 16+ years of schooling for men is 57% (compared to men with none to four years of schooling), while men whose last school was a Talmudic school have an average return of only 27%, all else equal[20].

The occupational dummies show that scientific and professional salaried workers (the omitted occupational category) and managers (occup3) are at the top of the wage distribution, all else equal. The most unprofitable occupations vary through the years between service workers (occup6) and farm workers (occup7) (unskilled workers, occup10, do only slightly better) in the male regressions, and between

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[17] It should be mentioned that, since the education variables appear in both the wage and the participation equation, the coefficients in the wage equations do not show the full effect of a change in an education variable on the wage *in the observed sample*. For further details see Greene (1993).

[18] However, dsch5y6's coefficient in 1990 is statistically insignificant at the level of 10% and the 1997 coefficient is insignificant at the level of 5%.

[19] A regression including additional interaction variables of 13-15 and 16+ years of schooling with post secondary schools (in comparison with academic institutions) did not yield significant results.

[20] Very few women (between 1 to 3 women) were indicated as finishing a Talmudic school or a religious seminar. As the coefficients that would have been obtained would have had no meaning, and the proportions of those women in the female sample are close to zero, we have dropped those interaction variables from the female regressions.

skilled workers in industry, transportation and construction (occup9) and unskilled workers of the same industries in the female regressions. The average difference between the most (scientific and academic professionals and managers) and the least paying occupations is equal to 56% for men and 73% for women. The coefficients fluctuate considerably through the years, a result that is in accordance with those of Dahan (2000). We also notice the important difference between the values of the coefficients of the occupational variables for men and women.

The last variable presented in the Table 2 is "Mills lambda". As mentioned before, lambda is inversely correlated with the probability to work, and as we see from the averages given in Appendix 2, the average lambda for women is much higher than that for men and shows a declining pattern. The sign of the coefficient indicates whether the individuals for which the hourly wage is observed have a higher or a lower pay than that which would prevail if the distribution would refer to the whole labor force. When the sign is positive, as is the case in the female equations, it attests that the wages observed in the labor market are the upper part of the underlying offered wage distribution, or in other words, that working women earn higher wages than non- working women would earn, had the latter decided to join the workforce. This fact does suggest that more skilled women are positively selected into the labor force. This is not true, however, for the male regressions. It seems that working men are facing lower wages than their non- working counterparts would. This could be because they are negatively selected due to their unmeasured characteristics, yet we should keep in mind that our sample includes salaried workers only, and that self employed men are probably concentrating at the upper percentiles of the offered wage distribution.

b. The gender wage gap decompositions

The wage differential decomposition applied in this paper is based on the technique first presented in a paper by Juhn, Murphy and Pierce (1993). After taking care of the problem of selectivity bias, we made a distinction between the observed wage (the actual average wage of the sample, that of those who work), and the offered wage (the average wage in the whole labor force, i.e. the wages minus the selection component) which refers to the wage every individual faces when deciding to enter the labor force. The gender gap is much higher when measured by the offered wage (more than twice the observed differential) because of the selectivity regressor. As mentioned previously, observed wages refer to the upper percentiles of the female wage distribution but to the lower part of that of the males, so that the average wage gap is smaller than the gap between the averages of the entire hypothetical male and female distributions.

The bootstrap method was used to compute confidence intervals for the components of the decomposition. The bootstrap is a statistical method that provides a way of obtaining measures of statistical accuracy when no formula is available. The idea is to use the data to create a distribution for the requested estimate (in our case the decomposition components) by randomly resampling the data, with replacement, and estimating the term each time[21]. The 2.5 percentile and the 97.5 percentile of this distribution would be our 95 percent confidence interval. According to the literature (Efron and Tibshirany, 1986, Efron, 1993) we need to draw 1000 resamples from our data in order to achieve a good estimate of the confidence intervals.

<u>Juhn et al. decomposition</u>

As explained earlier (see equation (9)), Juhn et al. (1993) decompose the change in the wage gender gap into four parts. The first two terms are easily computed. The third and fourth term, under the assumption of normality, could be evaluated by estimating the value of σ, the standard error of the male residual of each year, and the mean female residual. However, following Juhn et al. (1991) and Blau and Kahn (1996a, 1996b, 1997, 1999) the last two terms have been computed using the entire male and female residual distributions. After estimating each female's residual (from the male wage regression) in year t', every women receives a percentile number based on her residual ranking in the male residual distribution of that same year. Then we estimate the female's residual, given her percentile ranking and the male wage residual distribution in year t. For example, a woman who ranks at the 20th percentile of the male residual distribution in t' would be given the value of the residual corresponding to the 20th percentile in the male wage residual distribution of year t. The average of these imputed residuals, multiplied by (-1) (in an OLS model applied for the male regressions, the mean residual is always zero) is $\Delta\theta_t\sigma_t$. $\Delta\theta_{t'}\sigma_t$ and $\Delta\theta_{t'}\sigma_{t'}$ are the average female residuals from the male wage regressions of year t and t' respectively. By using the actual distribution of male residuals the assumption of symmetry is not imposed on the residual distribution.

[21] The word "bootstrap" originates from the Baron Munchausen stories where he picks himself up by his bootstraps, as here we use the data for both estimating an expression and checking its significance.

As indicated in the paragraph discussing the wage structure, the method suggested by Juhn et al. (1991) is used to make a difference between the role of "gender specific" factors and that of the "wage structure" effect. The third term is interpreted as changes in unmeasured skills and together with the first term give the "gender specific" factor (that might include discrimination as well as a change in the relative endowment of men and women), while the fourth term is interpreted as changes in unmeasured prices and together with the measured prices component represents the "wage structure" factor. As mentioned previously, the interpretation of the residual as unmeasured quantities and prices has been recently criticized by Suen (1997) so that caution is required when analyzing the results.

The residual decomposition in this paper is divided into two parts; the observed wage (of the working individuals) residual and the offered wage residual. The male residual is the same in both definitions since the only difference is whether the selection term is placed on the right or the left hand side of the wage equation. Nevertheless, there is a difference when it comes to the female residual. When computing the female observed wage residual, the residual is what remains when subtracting the expected wage from the actual wage. The expected wage is calculated on the basis of the female average characteristics using the male returns to skill, including the female average of the inverse of Mill's ratio (lambda) calculated from the male participation equation and its coefficient from the male regression. The offered female residual is computed by first subtracting the selection term (lambda and its coefficient from the female regression) from the observed wages in order to obtain the offered wage and then by subtracting the expected offered wage which was just calculated (but this time evidently without the selection term). wehave decided to present those two possibilities because although it seems more correct to analyze the whole wage distribution, the observed wages are those we actually see in the labor market.

It is worth stressing that in this method an implicit assumption is made when the male regression serves as a reference: the same prices are supposed to affect women and men. We find some evidence supporting this assumption when measuring male and female wage inequality by the standard deviation of the natural log of hourly wage and of the residuals, which shows a small decline[22] in inequality between 1982 and 1990 and clearly a rise during the 1990's. This might imply that the same forces affected both men and women. On the other hand, the estimated wage regressions did not display too many similarities between the two genders.[23]

A final issue to note before presenting the empirical results is the index number problem. A change in any of the weights employed could alter the value and even the sign of the four components. The weights used in the results presented below match the weights in equation (16) in paragraph I.2.b[24].

The Juhn et al. decomposition was first applied to the changes in the gender gap during 1990-1982 and during 1997-1990. The results were mostly insignificant: the closure of the (observed and offered) gender wage difference is insignificant and so are almost all terms composing the changes, as may be seen in Table 4 and 5[25]. Therefore, we present here only the analysis of the changes that occurred through the whole period, between 1982 and 1997 (Table 3), which are a little more meaningful than the two sub- periods results.

As we can see from the table, both the observed and the offered wage gap narrowed during the period, by 3 to 4 percent, but both changes are insignificant and we can't reject the hypothesis that there was no change in the gap. However, when looking at the determinants of the change, we may see that this is a result of opposing influences.

On the one hand, the wage gap narrowed by 0.041 log points because of an improvement in women skills relative to the male human capital. This is especially due to the improvement in the occupational distribution[26] and experience of women

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[22] The male wage standard deviation increased by a very small portion between 1982 and 1990 (from 0.539 to 0.543), but it seems negligible.

[23] The other options are to use the female coefficients or the coefficients from a pooled male- female equation.

[24] A second possibility is

$$D_{t'} - D_t = (\Delta x_{t'} - \Delta x_t)\beta_{t'} + \Delta x_t(\beta_{t'} - \beta_t) + (\Delta\theta_{t'} - \Delta\theta_t)\sigma_{t'} + \Delta\theta_t(\sigma_{t'} - \sigma_t)$$

Decomposition using these weights are presented in Appendix 4.

[25] We received somewhat better but basically similar results when using different weights (see footnote 24 above) and they are presented in Appendix 4. Because the results are very close to those presented in tables 5 and 6, we did not apply this version of the decomposition to the 1997- 1982 gender gap as we believe that it would yield results similar to those already presented in the paper.

[26] Thus assuming that gender differences in the occupational structure are not the result of discrimination faced when entering the labor market, but caused by different choices made by men and women.

relative to men[27] (46% and 84% of this closure respectively), while the changes in the origin and education components were small and insignificant. The total improvement is actually more than the closure of both the offered and observed gap. On the other hand, the wage structure term, meaning the change in the male rates of return during this period, worked to widen the gap although it is insignificant. Here we also see different effects when looking at the detailed decomposition, but the only significant (and largest) expression is the change in the rate of return on education which worked to widen the gap by 0.01 log points; as we observed in the earnings function, the rate of return on education decreased and it hurt women relatively more than men because of their higher educational attainment.

The effect of the selectivity term (if we want to inspect the change in the observed gap) is the result of a combination of the change in the weight given to each characteristic influencing the probability to work (from the male function) and the change in the participation rates of men and women that are closing due to the female improvement in the characteristics encouraging participation. Those changes are weighted by the male coefficients of the lambda variables of years t and t' which didn't change much through the years.

Looking at the decomposition of the residual, we can see that both in the observed wage definition and the offered wage definition women have improved their relative position in the male residual distribution, although we can't reject the null hypothesis. This may be interpreted as an improvement in unmeasured characteristics of women relative to that of men and/or as a reduction in discrimination. However, we should keep in mind the alternative explanation that with rising wage dispersion, the mean percentile rank of a low wage group (women) might rise simply because more dispersed distributions have thicker tails (Suen, 1997).

The "residual inequality" term is positive (and significant when using the offered wage definition), showing the growing dispersion of the residual, which we also consider as a wage structure effect. This term worked to increase the gender gap by 1% -2.8% because women are pushed down the wage distribution when inequality rises as they are located lower in the male residual distribution. As we mentioned above, this term was interpreted as changes in unmeasured prices. However, Blau and

[27] The average years of experience of women have generally remained the same while those of men have decreased. Yet, as expected, men have consistently more experience than women, a difference which might be even downward biased because we are not able to use actual experience.

Kahn (1997) and Suen (1997) note a potential drawback in this interpretation. Other factors that could affect the standard deviation of the residual are, for example, a misspecification of the equation, measurement errors or a change in the distribution of unmeasured male productivity characteristics. Blau and Kahn (1997) find some supporting evidence for the rising unmeasured prices explanation as the "residual inequality" factor has the same negative sign as the "observed prices" component (they report increases in the observed prices in the U.S. during their sample period which worked to widen the gender gap). This could also be the interpretation here, although in the earnings functions we observed a decrease in some rates of return (e.g. on education) which worked to widen the gap and such mixed effects of the prices could also affect the prices of the unmeasured characteristics.

Remembering the criticism concerning the interpretation of the residual terms, we will briefly look at the gender specific and wage structure components. On the whole, the "wage structure" terms work to push women down the wage distribution while the improvement of the female skills relative to men and their movement up the male residual distribution worked to close the gap. The "gender specific" components (sum 1+4) are negative and larger than the "wage structure" components (sum 2+5), resulting in a closure of the gap. Improvement in measurable skills of women relative to men account for almost all the "gender specifics" influence on the observed gap and for 53% of the influence on the offered gap. The changes in the rates of return to observed skills are responsible for 50% to 27% of the "wage structure" effect (for the observed wage and the offered wage definition respectively). However, though a few of the terms composing these factors are significant, neither the "gender specific" nor the "wage structure" components are. We already noted that the closure of the wage gap itself is not significantly different from zero.

In conclusion, the gender wage gap in Israel is significant but it doesn't seem to have changed during the period of investigation. There were a few changes in the components influencing the wage gap that significantly worked to close or widen it, but when breaking the change in the gap into the two sub- periods (1982- 1990 and 1990- 1997) some of these components become negligible. Thus we have decided to concentrate on the changes that occurred in the gender wage gap during the entire period.

The "gender specific" factors seem to work to narrow the gap. This was mainly the result of the improvement in the human capital of women relative to men, especially in experience and occupational structure. The gap was also closing due to the progress of women in the male residual distribution. A few interpretations could be proposed (as noted above), but this progress is insignificant. The wage structure effect is to widen the gap, mainly because of the changes in the rates of return on education and the growth in the residual dispersion. The other changes in the rates of return on human capital characteristics are small and insignificant.

On the whole, the shifts in observed skills and prices explain most of the change in the gender earnings differential, while the overall effect of the change in the residual (the "rank" plus the "residual inequality" terms) is small. The closure (though insignificant) of the earnings differential between men and women seems to be chiefly the result of female improving their skills relative to men, and is not due to a reduction in discrimination or a more favoring wage structure.

The results seem to indicate a stability of the gender earnings differentials in Israel. Female average human capital characteristics do not significantly differ from those of men (although there may be differences in unmeasured skills), and the gap is primarily caused by unexplained differences in rates of return between men and women. The improvement of female skills and their better position in the male residual distribution acts only to offset wage structure effects working against them.

Table 1: Results of the Participation in the Labor Force Regressions

	male:	female:

	1982	1990	1997	1982	1990	1997
Disraelb	0.0701764	0.333372	0.0869438	-0.01782	0.204307	0.070772
	0.865	5.49	1.53	-0.309	4.354	1.562
School3	0.3580228	0.5432774	-0.0397617	-0.00181	0.358641	-0.11726
	2.719	3.568	-0.208	-0.02	3.33	-0.802
School4	0.9138057	0.723976	0.2728381	0.510558	0.437322	0.310796
	6.088	4.656	1.439	5.179	3.954	2.187
School5	0.982077	1.130715	0.5151339	0.838883	0.735125	0.58699
	6.863	7.549	2.835	9.086	7.126	4.442
School6	0.7439511	1.014916	0.5793505	1.342706	0.997091	0.753725
	4.772	6.511	3.155	12.81	9.323	5.669
School7	0.3253567	0.6470867	0.389295	1.464924	1.326903	1.022266
	2.324	4.281	2.145	12.528	11.907	7.535
Person13	-0.0959792	-0.1028362	-0.1601442	-0.2678	-0.1844	-0.22321
	-3.457	-4.866	-7.567	-11.361	-10.422	-12.313
Age	0.2141665	0.1741064	0.1583284	0.139811	0.178784	0.193009
	6.831	6.874	6.811	6.262	9.385	10.39
Age2	-0.0025765	-0.001968	-0.0020326	-0.00195	-0.0022	-0.00248
	-6.976	-6.488	-7.313	-7.385	-9.62	-11.053
Marital1	1.033505	0.7108924	0.7201251	-0.23905	-0.10721	0.207242
	10.639	9.344	9.878	-3.337	-1.885	4.12
Constant	-4.351766	-4.192963	-2.842624	-2.42516	-3.79237	-3.7056
	-6.951	-8.258	-6.001	-5.234	-9.812	-9.777
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LR chi^2	292.42	305.58	240.61	826.43	527.56	524.58

z values appear in small letters.

Table 2: Results of the Earnings Functions

Male **Female**

	1982	1990	1997	1982	1990	1997
Exp	0.019243	0.03343	0.020804	0.022863	0.022334	0.029196
	4.009	6.323	4.293	4.529	5.122	6.743
Exp2	-0.00022	-0.00045	-8.6E-05	-0.00042	-0.00036	-0.00039
	-2.414	-4.52	-0.81	-3.988	-3.97	-3.947
Disraelb	0.035904	-0.00778	0.191897	0.02108	0.057569	0.158676
	1.386	-0.294	7.734	0.755	2.392	7.303
School3	0.116791	0.05817	0.077046	-0.1173	0.075907	0.019615
	1.884	0.618	0.669	-1.607	0.945	0.196
School4	0.128137	0.142429	0.171658	0.062433	0.117123	0.091997
	1.881	1.414	1.493	0.776	1.355	0.934
School5	0.289058	0.181179	0.208345	0.198283	0.232047	0.19969
	4.196	1.696	1.83	2.355	2.601	2.025
School6	0.446239	0.401494	0.32074	0.4233	0.433128	0.342572
	5.992	3.679	2.774	4.398	4.496	3.365
Dscht5y6	-0.28194	-0.19752	-0.38111			
	-1.958	-1.541	-1.652			
School7	0.611534	0.665211	0.440504	0.536454	0.560262	0.463399
	8.101	6.315	3.775	5.228	5.302	4.338
Dscht5y7	-0.38554	-0.35911	-0.16666			
	-4.115	-4.148	-1.797			
Occup2	-0.02631	0.032734	-0.15719	-0.08797	-0.08609	-0.16128
	-0.575	0.764	-3.611	-1.72	-2.25	-4.587
Occup3	0.024538	0.162523	0.002526	0.055133	0.074802	0.130276
	0.474	3.678	0.055	0.444	0.984	2.13
Occup4	-0.23109	-0.11018	-0.31622	-0.25452	-0.23902	-0.32561
	-5.034	-2.368	-6.881	-4.645	-5.595	-9.035
Occup5	-0.3077	-0.12155	-0.466	-0.44862	-0.38518	-0.72471
	-4.609	-2.286	-9.958	-5.709	-6.695	-18.193
Occup6	-0.44229	-0.26103	-0.94972	-0.54531	-0.43834	-0.80917
	-7.963	-4.977	-7.012	-8.177	-8.888	-2.56
Occup7	-0.41909	-0.27894	-0.46368	-0.41127	-0.51358	-0.68281
	-4.274	-2.485	-10.915	-1.551	-3.357	-9.137
Occup8	-0.23993	-0.13113	-0.62337	-0.43444	-0.44718	-0.8459
	-5.036	-2.944	-11.743	-4.422	-5.916	-13.82
Occup9	-0.19905	-0.05042	-0.53814	-0.66412	-0.54273	-0.87746
	-3.965	-1.063	-10.537	-7.527	-7.012	-8.482
Occup10	-0.35893	-0.2249	-0.78309	-0.89254	-0.55657	-0.80488
	-5.697	-3.063	-14.528	-8.019	-4.849	-16.819
Constant	2.99335	2.822739	3.123624	2.7422	2.640376	2.750258
	28.979	17.214	22.163	20.414	18.129	20.778
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Mills Lambda	-0.46573	-0.43549	-0.46145	0.179239	0.182971	0.118918
	-5.547	-4.232	-4.699	2.599	2.43	1.514
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Wald chi^2	712.67	841.3	974.9	785.33	704.53	1412.74

z values appear in small letters.

Table 3: Juhn et al. Decomposition 1982-1997

	D1997-D1982	2.5%	97.5%

	Observed:			
1)	**Gender specific** $(\Delta x_{t'} - \Delta x_t)\beta_t$	-0.0406527	-0.0820527	-0.0013262
	Experience	-0.0187777	-0.0292604	-0.0099152
	Origin	-0.0024838	-0.0007298	0.007139
	Education	0.0097873	-0.0076007	0.0263042
	Occupation	-0.0341461	-0.0691926	-0.0009207
2)	**Wage structure** $\Delta x_{t'}(\beta_{t'} - \beta_t)$	0.0100361	-0.0324952	0.0500928
	Experience	0.0038357	-0.0011405	0.0086719
	Origin	0.0009558	-0.0032001	0.0055089
	Education	0.0101569	0.0020373	0.0187404
	Occupation	-0.0049124	-0.0451574	0.0368418
3)	**Selectivity**	-0.0093646	-0.0199948	0.0008836
	Residual:			
	Observed wage			
4a)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0004471	-0.0511953	0.049217
5a)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0101098	-0.0027897	0.0201315
	Offered wage			
4b)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0363539	-0.1688526	0.1170566
5b)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0277325	0.0050371	0.0535553
	Total change in observed gap	-0.0301751	-0.0810661	0.015879
	Total change in offered gap	-0.0390946	-0.1802296	0.119173
	Sum 1+4a (gender specific)	-0.0410998	-.1091688	.0190059
	Sum 2+5a (wage structure)	0.0201459	-.021116	.058751
	Sum 1+4b (gender specific)	-0.0770066	-.2177758	.0933769
	Sum 2+5b (wage structure)	0.0377686	-.0070236	.0849024

Table 4: Juhn et al. Decomposition 1982-1990

		D1990-D1982	2.5%	97.5%
	Observed:			
1)	**Gender specific** $(\Delta x_{t'} - \Delta x_t)\beta_t$	-0.0042356	-0.0287091	0.0217557
	Experience	-0.0146393	-0.0254502	-0.0050911
	Origin	0.0013018	-0.0006507	0.0046628
	Education	0.0070768	-0.0101091	0.0253581
	Occupation	0.002025	-0.0116164	0.0150751
2)	**Wage structure** $\Delta x_{t'}(\beta_{t'} - \beta_t)$	0.0090585	-0.018988	0.035684
	Experience	0.0047497	-0.0000415	0.0111716
	Origin	0.0011705	-0.0007956	0.0041302
	Education	-0.0019629	-0.0126401	0.0075542
	Occupation	0.0051011	-0.0227716	0.0304359
3)	**Selectivity**	-0.0009376	-0.0118673	0.0094892
	Residual:			
	<u>Observed wage</u>			
4a)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0050438	-0.0545483	0.0499147
5a)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	-0.0042602	-0.0166105	0.006187
	<u>Offered wage</u>			
4b)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	0.022593	-0.1427631	0.1756563
5b)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	-0.0006724	-0.0259563	0.0286655
	Total change in observed gap	-0.0054188	-0.0556909	0.0437032
	Total change in offered gap	0.0267434	-0.1413058	0.1808241
	Sum 1+4a (gender specific)	-0.0092794	-.0642874	.0505854
	Sum 2+5a (wage structure)	0.0047983	-.0264655	.03126
	Sum 1+4b (gender specific)	0.0183574	-.1499918	.1683918
	Sum 2+5b (wage structure)	0.0083861	-.0287087	.0456266

<u>Table 5: Juhn et al. Decomposition 1990-1997</u>

		D1997-D1990	2.5%	97.5%
	Observed:			
1)	**Gender specific** $(\Delta x_{t'} - \Delta x_t)\beta_t$	-0.0377753	-0.0793285	0.0010865
	Experience	-0.006962	-0.0192001	0.0044053
	Origin	-0.0002563	-0.002502	0.0018515
	Education	0.0042007	-0.0116248	0.0224413
	Occupation	-0.0347578	-0.0719351	0.0013511
2)	**Wage structure** $\Delta x_{t'}(\beta_{t'} - \beta_t)$	0.0023358	-0.0394322	0.0412191
	Experience	0.0019095	-0.0022565	0.0062493
	Origin	0.0012235	-0.0039564	0.0067706
	Education	0.0106296	0.0016632	0.0208962
	Occupation	-0.0114268	-0.0530208	0.0280171
3)	**Selectivity**	-0.0084269	-0.0179134	-0.000294
	Residual:			
	<u>Observed wage</u>			
4a)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	0.006817	-0.0380363	0.050875
5a)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0121497	-0.0003347	0.0230914
	<u>Offered wage</u>			
4b)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0660132	-0.2218259	0.095687
5b)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0354712	0.0116038	0.0641993
	Total change in observed gap	-0.0247562	-0.0680126	0.0177605
	Total change in offered gap	-0.065838	-0.2194033	0.0988581
	Sum 1+4a (gender specific)	-0.0309583	-0.0907815	0.0292011
	Sum 2+5a (wage structure)	0.0144855	-0.0309859	0.0543673
	Sum 1+4b (gender specific)	-0.1037885	-0.2634637	0.0631491
	Sum 2+5b (wage structure)	0.037807	-0.0113338	0.0879689

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Appendix 1

The Definitions of the Variables

Exp	Potential years of experience: age- years of schooling- 6
Disraelb	A dummy variable equals one if the individual was born in Israel, zero otherwise
School1	A dummy variable equals one if the individual did not attend school
School2	A dummy variable equals one if the individual attended school 1-4 years

School1 and School2 are the education left- out reference groups

School3	The same as above, 5-8 years
School4	9-10
School5	11-12
School6	13-15
School7	16+
Dscht5y6	An interaction dummy variable equals to one if the individual attended school for 11-12 years and the last school attended is a Talmudic school.
Dscht5y7	The same as above but attended school for 16+ years
Occup1	Scientific and academic professionals. Occup1 is the left- out reference group of the occupational set of dummy variables.
Occup2	Other free professionals, technicians etc.
Occup3	Managers
Occup4	Clerks
Occup5	Sales workers, agents, etc.
Occup6	Service workers
Occup7	Farm workers
Occup8	Skilled workers in industry, transportation, construction
Occup9	Skilled workers in industry, transportation, construction
Occup10	Unskilled workers in industry, transportation, construction

(when all the occupational dummies are zero the individual is working as scientific or academic professional)

Person13	Number of persons aged 0-13 years old in the household
Age	The individual's age
Marital1	A dummy variable equals one if the individual is married, zero otherwise (divorced, widowed, single and in 1990 and 1997 also separated)

Appendix 2

Characteristics Means:

	male			female		
	1982	**1990**	**1997**	**1982**	**1990**	**1997**
Exp	23.70414	21.83817	21.28685	21.06164	21.07894	20.77937
Disraelb	0.325989	0.505516	0.511398	0.389041	0.532309	0.505271
School3	0.209532	0.113869	0.06421	0.117123	0.093538	0.039157
School4	0.17446	0.135146	0.099924	0.134932	0.100316	0.072289
School5	0.261241	0.355004	0.330167	0.29726	0.326254	0.329443
School6	0.135342	0.184397	0.24848	0.230822	0.235427	0.279368
Dscht5y6	0.004946	0.005516	0.0019			
School7	0.176709	0.19543	0.245061	0.164384	0.218708	0.266943
Dscht5y7	0.011241	0.012608	0.011778			
Occup2	0.116007	0.122143	0.112462	0.247945	0.270221	0.175075
Occup3	0.069245	0.102049	0.093465	0.010959	0.020334	0.028615
Occup4	0.153777	0.120173	0.108663	0.35137	0.311794	0.307229
Occup5	0.032824	0.061466	0.109423	0.039726	0.054677	0.182982
Occup6	0.078237	0.076438	0.007219	0.182877	0.181202	0.00113
Occup7	0.01214	0.008668	0.205927	0.00274	0.004067	0.021084
Occup8	0.227518	0.233649	0.067629	0.022603	0.026661	0.035768
Occup9	0.151079	0.148148	0.086626	0.034932	0.025757	0.009036
Occup10	0.049011	0.025217	0.070669	0.015753	0.009489	0.093374
Lambda	0.222081	0.325709	0.335943	0.696729	0.648355	0.541281

Appendix 3

Mean Wages:

	male			female		
	1982	1990	1997	1982	1990	1997
Observed wage (logarithm)	3.299028	3.362354	3.388108	3.077387	3.146132	3.196642
	0.538732	0.543594	0.609592	0.561992	0.5164195	0.601096
Offered wage	3.402457	3.504196	3.54313	2.952506	3.027502	3.132274
	0.5286917	0.5314243	0.5990554	0.5931413	0.5341271	0.6088792
Observed wage residual*	0.00013	0.00027	0.00006	-0.00383	-0.07413	-0.13043
	0.4572145	0.4548091	0.4988357	0.490897	0.4740411	0.4905478
Offered wage residual**	0.00013	0.00027	0.00006	-0.45319	-0.47511	-0.44457
	0.4572145	0.4548091	0.4988357	0.4835082	0.461181	0.4937608

* According to the OLS regression model assumptions, E(u)=0
**The observed and offered wage residuals for men are the same

Standard errors appear in small letters.

Appendix 4

Juhn et al. Decomposition 1982-1990

		D1990-D1982	2.5%	97.5%
	Observed:			
1)	**Gender specific** $(\Delta x_{t'} - \Delta x_t)\beta_t$	-0.0126304	-0.0380116	0.0119746
	Experience	-0.0184645	-0.0326433	-0.0053547
	Origin	-0.0002823	-0.0028282	0.001796
	Education	0.000432	-0.0196787	0.0192998
	Occupation	0.0056843	-0.004373	0.0156936
2)	**Wage structure** $\Delta x_{t'}(\beta_{t'} - \beta_t)$	0.0174533	-0.0109112	0.0458178
	Experience	0.0085749	-0.0023174	0.0212918
	Origin	0.0027546	-0.0016069	0.0082058
	Education	0.0046819	-0.0099909	0.0201249
	Occupation	0.0014418	-0.0252058	0.0257613
3)	**Selectivity**	-0.0009376	-0.0118673	0.0094892
	Residual:			
	<u>Observed wage</u>			
4a)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0100756	-0.0581746	0.045343
5a)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0007716	-0.0143213	0.0106205
	<u>Offered wage</u>			
4b)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	0.0410071	-0.1168096	0.1987217
5b)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	-0.0190865	-0.051749	0.0032207
	Total change in observed gap	-0.0054188	-0.0556909	0.0437032
	Total change in offered gap	0.0267434	-0.1413058	0.1808241
	Sum 1+4a (gender specific)	-0.022706	-0.0755142	0.0353363
	Sum 2+5a (wage structure)	0.0182249	-0.0158404	0.0472815
	Sum 1+4b (gender specific)	0.0283767	-0.1348411	0.1775924
	Sum 2+5b (wage structure)	-0.0016323	-0.0441894	0.0333368

<u>Juhn et al. Decomposition 1990-1997</u>

		D1997-D1990	2.5%	97.5%
	Observed:			
1)	**Gender specific**	0.0039174	-0.0418689	0.0445231

	$(\Delta x_{t'} - \Delta x_t)\beta_t$			
	Experience	-0.0049633	-0.018605	0.0096307
	Origin	0.0063173	-0.0010235	0.0139983
	Education	0.001882	-0.0082543	0.0117018
	Occupation	0.0006814	-0.0422439	0.0377778
2)	**Wage structure**	-0.0393569	-0.0770386	0.0036289
	$\Delta x_{t'}(\beta_{t'} - \beta_t)$			
	Experience	-0.0000891	-0.0065882	0.0059702
	Origin	-0.0053501	-0.0116128	0.0002306
	Education	0.0129483	0.003113	0.0244922
	Occupation	-0.046866	-0.0849887	-0.0035702
3)	**Selectivity**	-0.0084269	-0.0179134	0.0002694
	Residual:			
	<u>Observed wage</u>			
4a)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0019959	-0.0515151	0.0465971
5a)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0209626	0.008861	0.0343387
	<u>Offered wage</u>			
4b)	**Rank** $(\Delta\theta_{t'} - \Delta\theta_t)\sigma_t$	-0.0650482	-0.2280232	0.1033641
5b)	**Residual inequality** $\Delta\theta_{t'}(\sigma_{t'} - \sigma_t)$	0.0345062	0.0055448	0.0626645
	Total change in observed gap	-0.0247562	-0.0680126	0.0177605
	Total change in offered gap	-0.065838	-0.2194033	0.0988581
	Sum 1+4a (gender specific)	0.0019215	-0.065208	0.0614133
	Sum 2+5a (wage structure)	-0.0183943	-0.058198	0.0307972
	Sum 1+4b (gender specific)	-.00611308	-0.2293125	0.1231556
	Sum 2+5b (wage structure)	-.00048507	-0.0536604	0.045387