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Is the Israeli Labor Market Segmented?
Revisiting the Mixture Regression Model.

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Abstract

We use a mixture regression model to identify segmentation in the Israeli labor market, and propose a new method for assigning workers to simulated segments. We identified a low-wage segment and a high-wage segment, as well as a third segment with a large wage variability that we interpret as “noisy” observations. We found quantitatively small but qualitatively reasonable differences in workers’ characteristics between the low-wage and high-wage segments, while the coefficient differences were much larger, indicating that much of the wage disparity in Israel is due to unobserved factors rather than to observable characteristics. Some policy-relevant insights are derived.

JEL codes: J31, C30

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Introduction

The tent protests across Israel in the summer of 2011 highlighted a widespread perception that achieving a middle-class lifestyle in Israel is increasingly difficult. The protesters focused on rising socioeconomic inequality in Israel. An increase in inequality can affect the middle class in two main ways: it can reduce its size, moving people either up or down the income distribution, and it can increase the gap between the middle class and the upper class. It seems like the latter was the main concern of Israeli protesters.

The first question that comes to mind in this context is what exactly is the middle class? The simplest way to define the middle class is as a range (not necessarily symmetric) of incomes around the median (Birdsall et al., 2000). Other definitions include references to wealth and occupation (Atkinson and Brandolini, 2011). All these definitions are arbitrary, and choosing one definition over another may yield a different conclusion. Some methodologies enable analyses of changes in the middle class without explicitly defining it. These include polarization measures, which examine the between-group inequality compared to the within-group inequality in a population that is made of an arbitrary number of groups (Esteban and Ray, 1994), as well as examination of changes in entire distributions (Burkhauser et al, 1999).

For developing countries, it is common to treat all those above a certain income or consumption level as the middle class (Ravallion, 2010). This apparently assumes that the upper class is negligible or not interesting. In Israel, it is also quite common to relate to two classes only. Lubell (2011) mentions the concept of "two States of Israel" – one economically dynamic, at the forefront of the modern global economy, and with a high standard of living; the other struggling to get by. Earlier, the concept of “first Israel” and “second Israel” was related to Jews of Ashkenazi (western) origin and those of Sefaradi (eastern) origin. Although Haberfeld and Cohen (2007) found that earnings differences between Ashkenazi men and

other gender and ethnic groups have not narrowed since the 1970s, it is safe to say that divisions across origins are coming close to be a matter of the past in Israel. This paper explores the question, to what extent is the "two Israels" idea manifest in the labor market? Specifically, we use the idea of labor market segmentation to ask to what extent wage earners in Israel can be divided into the "haves" and the "have-nots." We will also allow for more than two labor market segments, without pre-specifying the number of segments, in order to examine the existence of a middle class.

In neoclassical labor economics, the labor market is treated as one single, heterogeneous market, where the differential productivity of workers explains differences in wages. That is, workers are paid in proportion to their productivity. In contrast, labor market segmentation theory suggests that in the simplest case, there are two labor markets: the primary labor market has good jobs, good working conditions, and high returns to human capital, but barriers to entry; the secondary labor market has bad jobs, bad working conditions, and low returns to human capital.

Much of the literature on the topic has focused on trying to find evidence of segmentation as a way of disproving the neoclassical theory. However, it is also possible for the two ideas to complement each other. Specifically, it might be the case that what prevents poor people from getting good jobs are indeed conventional productivity variables, such as education and experience, as neoclassical theory suggests. But even so, the labor market might still be usefully characterized as segmented if the wage functions of those in the primary labor market and those in the secondary labor market are different enough. We use segmentation theory here to characterize inequality in the Israeli labor market, rather than to attempt to prove the applicability of one theory over the other to Israel.

Knowing whether the labor market is segmented is important for labor market policy because a given set of policy instruments might not affect all workers equally if the labor

market is segmented, or might not even affect certain workers at all. For example, the focus on schooling and training as tools to increase wages of the less-skilled may not be adequate if the returns to human capital are low in the less-skilled segment of the labor market. Hence, it is not only important to know whether the labor market is segmented; it is even more important to characterize the different segments. This is the purpose of this paper. In doing so, we apply the mixture regression model as has been done elsewhere in the literature (e.g., Battisti, 2013). However, assigning workers to segments based on the maximum estimated posterior probability turned out to be inconsistent with the estimated segment shares. We propose an alternative, probabilistic, post-estimation assignment procedure, in which all workers are assigned to all segments after being weighted with their appropriate worker-specific and segment-specific posterior probabilities. This procedure allows us to obtain policy-relevant insights about the existence and the characteristics of labor market segmentation in Israel. In particular, we find that much of the wage disparities are within rather than between population groups. We also identify a number of interesting interactions between schooling, ethnic minorities, and wages.

In the next section we review the literature on labor market segmentation. After that we present the methodology to be used in the empirical analysis. The data are described next, and then we present the empirical results. The final section summarizes the findings and discusses their implications.

Literature on labor market segmentation

Dickens and Lang (1985) lay out the two hypotheses that, if satisfied, would demonstrate the existence of a segmented labor market and cast doubt on the neoclassical model. The first is that the labor market can be described well by the dual market typology; that is, that most jobs resemble either "good" (primary sector) jobs or "bad" (secondary) jobs,

rather than having a continuum of jobs and workers in the economy. The second is that rationing of primary sector jobs takes place. They develop a switching regressions technique, which makes separate inferences for different labor market segments using a separate sorting equation to predict each observation's propensity to be in one segment or another. With this method, they ask whether two wage equations fit the data significantly better than one and test for the existence of barriers to enter the primary sector. Using data from the thirteenth wave of the American Panel Study of Income Dynamics, they find empirical support for both hypotheses underlying labor market segmentation. They find that workers in standard Metropolitan Statistical Areas (that is, workers who live near cities), married workers, more educated workers, and whites are less likely to be in the secondary sector.

Roig (1999) applies the method suggested by Dickens and Lang (1985) to Spanish data and also finds evidence of a dual structure of the Spanish labor market, along with evidence that some workers find it much easier to find a job in the primary sector than others do. Pailhe (2003) applies this method to data from the formerly planned Central European countries of the former Czechoslovakia, Poland, and Hungary and also finds significantly different coefficients for two different sectors of the economy, with some workers having more access to the primary sector – that is, the sector with higher returns to human capital – than others.

Sousa-Poza (2004) uses three different methods to test for segmentation in the Swiss labor market. First, he performs cluster analysis on Swiss Labor Force Survey (SLFS) data from 2000 and does not find evidence of a secondary labor market in Switzerland. He then uses the Dickens and Lang (1985) switching model on the same SLFS data and does find evidence of segmentation. Finally, he applies a discrete choice model to the first three waves of the Swiss Household Panel (SHP) to measure low-wage mobility, estimating the probability of those in low-wage jobs in 1999 moving to high-wage jobs by 2001. He finds

that a higher percentage of workers remain in low-wage jobs than would be expected if there were not barriers to the primary sector. People with low education were more likely to remain in low-wage jobs, and people in large firms were more likely to move to the high-wage market, but otherwise, reasons for wage mobility were not explained by observed characteristics of workers or industries.

Pittau and Zelli (2006) use a mixture regression model, which allows the distribution of a random variable to be expressed as a mixture of several different distributions (see also Laird, 1978; Heckman and Singer, 1984). As opposed to the switching regression of Dickens and Lang (1985), it does not require each observation to strictly belong to one segment, but allows each observation to belong to each segment with some probability. It also has the advantage that the number of segments can be changed easily, and inference can be made on the appropriate number of segments. They find that a mixture of three or four normal segments fits the data well for Italian per-capita income distributions. Battisti (2013) uses Italian data to find evidence of multiple wage equations and further evidence that movement into the primary sector is more difficult than general movement among job positions. Pittau et al. (2010) used mixture models to study income distribution in a panel of countries. Mixture regression has been used to find segmentation in heterogeneous populations in other fields, including marketing (Wedel et al., 1993), health economics (Deb and Trivedi, 1997; Conway and Deb, 2005; Deb et al., 2011), transportation (Park and Lord, 2009), ecology (Cubaynes et al., 2012) and political science (Davis, 2013).

Methodology

In this section we describe the mixture regression procedure, in which a wage equation is used to characterize the data, and observations are allowed to have a probability distribution over a number of different wage equations.

Suppose that the labor market is composed of S different segments with wages in each segment having a unique distribution, and assume that log-wages are normally distributed with segment-specific means and variances. Therefore, the density function of a worker's log-wage conditional on belonging to segment s is:

$$(1) \quad f(w_i | s; \beta_s, \sigma_s) = (2\pi\sigma_s^2)^{-\frac{1}{2}} \exp\left(-\frac{[w_i - \sum_j \beta_{j,s} x_{i,j}]^2}{2\sigma_s^2}\right)$$

where w_i is the i^{th} individual's log-wage, $x_{i,j}$ is the j^{th} ($j=1, \dots, J$) explanatory variable of individual i , $\beta_{j,s}$ is the corresponding regression coefficient in the s^{th} segment, and σ_s^2 is the residual variance of log-wage in the s^{th} segment. While each individual belongs to one and only one segment, the assignment of individuals to segments is unknown. Let μ_s be the weight attached to segment s . These weights can be interpreted as the unconditional probabilities that an individual belongs to each segment. Then we get the unconditional density function for a “finite mixture” with S segments (Pittau and Zelli, 2006):

$$(2) \quad f(w_i | \boldsymbol{\beta}, \boldsymbol{\sigma}) = \sum_s \mu_s (2\pi\sigma_s^2)^{-\frac{1}{2}} \exp\left(-\frac{[w_i - \sum_j \beta_{j,s} x_{i,j}]^2}{2\sigma_s^2}\right)$$

where $\boldsymbol{\beta}$ is a matrix consisting of all regression coefficients of all segments and $\boldsymbol{\sigma}$ is a vector consisting of all residual standard deviations. Flachaire and Nuñez (2007) note that under reasonable regularity conditions, any probability density can be consistently estimated by a mixture of normal densities, hence the normality assumption is not as restrictive as one may intuitively think.

Given n independent observations that are distributed as (2), the likelihood function of the mixture model is written as:

$$(3) \quad L = \prod_{i=1}^n \left[\sum_S \mu_s (2\pi\sigma_s^2)^{-\frac{1}{2}} \exp\left(-\frac{[w_i - \sum_j \beta_{j,s} x_{i,j}]^2}{2\sigma_s^2}\right) \right]$$

This likelihood function can be maximized using the EM algorithm (Wedel et al., 1993; Pittau et al., 2010; Battisti, 2013). Since the estimation requires a priori choice of the number of segments, the model can be estimated with several alternative numbers of segments and the explanatory power of the alternatives can be compared in terms of formal statistical criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Battisti 2013).¹ Given the estimates of β , σ and μ (the vector of segment weights), it is possible to compute the posterior probability that observation i belongs to segment s , with Bayes' theorem:

$$(4) \quad p_{i,s} = \frac{\hat{\mu}_s f_{i,s}(w_i | x_{i,j=1\dots J}, \hat{\sigma}_s^2, \hat{\beta}_{j=1\dots J,s})}{\sum_{s=1}^S \hat{\mu}_s f_{i,s}(w_i | x_{i,j=1\dots J}, \hat{\sigma}_s^2, \hat{\beta}_{j=1\dots J,s})}$$

The interpretation of (4) is the following: The probability that observation i belongs to segment s equals the probability that any observation is in segment s times the probability of obtaining the parameter estimates we obtained, were this observation truly in segment s ,

¹ Cubaynes et al. (2012) found both AIC and BIC criteria superior to a likelihood-based alternative.

divided by the probability of obtaining the parameter estimates we obtained, for all segments.²

These posterior probabilities could then be used to assign each observation to the segment for which the posterior probability of membership is highest, in order to compare the segments in terms of their observed characteristics.

² Bayes' Theorem is most simply expressed by $\Pr(A|X) = \Pr(X|A)\Pr(A)/\Pr(X)$, where $\Pr(A|X)$ is the probability of the event (A) given a positive test (X), $\Pr(X|A)$ is the probability of a positive test, given the event, $\Pr(A)$ is the unconditional probability of the event, and $\Pr(X)$ is the unconditional probability of a positive test. In our case, the "event" is observation i belonging to segment s and the "positive test" is the set of parameter estimates. The following table explains the corresponding notation of equation (4) and Bayes' Theorem:

General notation	Notation in equation (4)	Explanation
$\Pr(A X)$	$p_{i,s}$	Probability that observation i is in segment s (implied: given the parameter estimates obtained). This is the posterior probability.
$\Pr(X A)$	$f_{i,s}(w_i x_{i,j=1..J}, \hat{\sigma}_s^2, \hat{\beta}_{j=1..J,s})$	Probability that the parameter estimates obtained would be obtained, given that i belongs to s .
$\Pr(A)$	$\hat{\mu}_s$	Unconditional (prior) probability that any observation belongs to s .
$\Pr(X)$	$\sum_{s=1}^k \hat{\mu}_s f_{i,s}(w_i x_{i,j=1..J}, \hat{\sigma}_s^2, \hat{\beta}_{j=1..J,s})$	Probability of obtaining the parameter estimates obtained, over all segments.

Data

Data for this analysis are taken from the Combined 2010 Income Survey of Israel's Central Bureau of Statistics (CBS). The file combines data from two surveys so that the combined sample is representative of the Israeli population.³ In both surveys, every adult living in a sampled household is questioned. In 2010, the two surveys combined to provide data on 36,331 individuals in 15,171 households. Of these, 17,019 were wage-earning employees, and complete information was available for 16,897.⁴ The average hourly wage in this sample was 46 NIS (Table 1).⁵

The following variables, as well as their interactions, are used as explanatory variables.⁶ Their descriptive statistics are shown in Table 1.

- Gender: We would expect female workers to be overrepresented in the secondary labor market, since it is known that women, on average, earn lower wages than men do, for a variety of reasons, including choices to work in less remunerative occupations and

³ The first is an income survey that is conducted along with the annual Labor Force Survey, which samples households throughout the country. The second is the annual Household Expenditure Survey, which also samples households throughout the country and asks about income (State of Israel, 2012).

⁴ Three observations were dropped because they lacked wage data, 13 were dropped because they lacked data on educational background, and 106 were dropped because they lacked data on ethnic background. 607 workers did not report industry of occupation, and those were excluded when necessary.

⁵ Hourly wage was calculated as $([\text{monthly wage}] * 12) / ([\text{weekly hours worked}] * 52)$.

⁶ We also tried to distinguish between ethnicity groups within the Jewish population, and between ultra-orthodox Jews and others, but these distinctions did not turn out significant in the empirical analysis.

industries, fewer years of work experience, and discrimination (e.g., Blau and Kahn, 1997).

- Age: Since we do not have direct data on workplace experience, age will act a proxy, with older workers likely to have more experience and more access to the primary sector.
- Years of schooling: The secondary labor market is usually characterized by low levels of education (Sousa-Poza 2004).
- Nationality: In Israel, we expect Arabs to be underrepresented in the primary sector, as they might face discrimination, lower quality of education, and other barriers to the primary job market (Haberfield and Cohen 2007).
- Geographic periphery status: The CBS assigned each household a number, on a scale of 1 to 5, indicating how far the family lived from the center of the country. A number 1 indicates a household considered "very peripheral," and a 5 indicates "very central." Following Krueger and Summers (1988), we hypothesize that those in the periphery will have less access to primary sector jobs.
- Industry and occupation: Krueger and Summers (1988) show that the industry a person works in and their occupation help determine their wage, independent of the person's human capital. Past studies of segmentation in other labor markets, such as Sousa-Poza (2004), show industry playing a central role in segmentation. We would expect professional and managerial occupations to garner higher wages than other occupations. However, it is difficult to hypothesize which industries would provide more or fewer jobs in the primary sector. The CBS data include a categorical variable indicating the worker's industry that takes one of fifteen values, including "industry unknown." For regressions that included dummy variables for occupation and industry, observations that had "industry unknown" or "occupation unknown" were dropped.

Empirical Results

We used the command *fmm*, for finite mixture modeling, in Stata 11 (Deb, 2007) to estimate the models, and the related command *fmmlc* (Luedicke, 2011) for post-estimation.

Mixture regression results

Table 2 includes the mixture regression results for the two-segment and three-segment specifications. In the two-segment specification, less than 18% of the sample observations are assigned to segment 1 and the remaining 82% to segment 2. At the bottom of the table we report predicted values of log-wages, computed at the sample means. It can be seen that segment 2 is the high-wage segment. The two wage equations differ substantially from each other. For example, the female wage penalty is statistically significant only in segment 2. The same is true for the returns to schooling among Arabs. The standard deviation of wages in segment 1 is more than twice as large as the standard deviation of wages in segment 2.

The segment 1 wage equation in the three-segment specification is quite similar to the segment 1 wage equation in the two-segment specification, both in terms of its size (17% of the sample) and in terms of the coefficients. It still emerges as the low-wage segment, and its wage variability is large. Of the remaining two segments, segment 2, with 34% of the sample observations, has a lower predicted wage than segment 3, with 49% of the sample observations. The coefficients of the wage equations of segments 2 and 3 are quite different. A female wage penalty for Jewish females exists only in segment 3, while for Arab females it is statistically significant only in segment 2. The male Arab wage penalty is statistically significant only in segment 3. The returns to schooling for Jewish males and females are much larger in segment 3, while the returns to schooling for Arab females are significant only in segment 2.

Judging by the values of AIC, BIC and the value of the likelihood function, the three-segment specification is preferred over the two-segment specification. The fact that the majority segment in the two-segment specification is now split into two different segments adds flexibility to the model and allows different effects of explanatory variables in segments 2 and 3. For example, the male Arab wage penalty is not significant in segment 2 of the two-segment specification, while it is significant in segment 3 of the three-segment specification. On the other hand, the schooling wage premium of Arab males is significant in segment 2 of the two-segment specification, while it is insignificant in segments 2 and 3 of the three-segment specification and even significantly negative in segment 1.

Simulating the segments

The posterior probability of each observation to belong to each segment is computed using (4), and each observation is then assigned to the segment for which the posterior probability of belonging is highest. Thus, the sample is divided into “simulated segments”. Table 3 shows the variable means in each simulated segment. Beginning with the two-segment specification, it can be seen that average wage is higher in segment 1, as opposed to the prediction using the overall sample means. This implies that the population composition of the segment leads to a higher predicted wage. In fact, table 3 shows that segment 1 includes considerably fewer Arabs and slightly more educated workers. The fact that Arabs have lower schooling, on average (Shavit and Bronstein, 2011), and that the return to schooling in segment 1 is statistically significant only for Jewish workers, explains the higher predicted wage in segment 1. No other considerable differences are observed between the simulated-segment means of segments 1 and 2. Note, however, that the fraction of observations assigned to segment 1, 8%, is much lower than the estimated relative size of the

segment, 18% (table 2), and this casts some doubt about the adequacy of this method of assignment of observations to segments.

In the three-segment specification, segment 1, now including 9% of the sample, is no longer the high-wage segment. Its average wage is much lower than the average wage in segment 3 and not so much higher than the average wage in segment 2. Segment 1 has fewer Arab workers, but other than that, the variable means in all three segments are not very different from each other. This may lead to the conclusion that the Israeli labor market is not so much segmented by observable worker attributes but rather by unobservable factors.

However, there is still concern regarding the deviation of the population fractions of the assigned segments from their estimated values. In fact, the way the assigned segments are constructed may introduce assignment errors in the sense that, in the case of the two-segment specification, two observations with posterior probabilities of 0.99 and 0.51, respectively, are grouped together in the same assigned segment, despite the fact that for the second observation there is an almost equal probability that it actually belongs to the other segment. Consequently, we propose an alternative method of generating assigned segments, based on weighting the observations by posterior probabilities rather than assigning by the highest probability. Specifically, we include all observations in each of the simulated segments, where each observation is weighted by the posterior probability of the relevant segment, so that the sum of weights within each simulated segment is equal to the estimated unconditional probabilities μ_s .

The variable means of the “weighted simulated segments” are reported in table 4. Not surprisingly, the differences in the variable means across the segments are in general smaller than those of the assigned segments in table 3. In addition, in the three-segment specification, the average wage in the intermediate wage segment (segment 1) is now closer to the average wage of the high-wage segment (segment 3) than to the average wage of the low-wage

segment (segment 2). Recall that segment 1 is not only the smallest among the three. It also has a considerably larger wage variability than the other two segments. This leads to the conclusion that segment 1 of the hired labor force includes both high and low wages that do not fit well the wage equations of either the low-wage segment or the high-wage segment.

The 3-segment specification of the mixture regression model helps, therefore, to “purge” the observations with wages that are difficult to assign based on observable characteristics. Segments 2 and 3 represent, in this case, low-wage and high-wage employees, respectively. The segment-specific means in table 4 show the contributions of observable characteristics to the wage disparity. Although they are quantitatively small, the differences between the means indicate that age and schooling are associated with a higher wage. Females are equally represented in the two segments, while Arabs are over-represented in the low-wage segment. Living in the periphery is associated with lower wages, and the same is true for working in construction, commerce, hospitality, health, and domestic services sectors. On the other hand, working in the finance, real estate, public services, and education sectors is associated with higher wages. Academic, technical, managerial and clerical occupations imply higher wages, while sales, professional and unskilled occupations imply lower wages.

Summary and discussion

Our empirical analysis has shown that the mixture regression model can identify different segments in the Israeli labor market. The three-segment model differentiated between a low-wage segment, a high-wage segment, and a third segment with both high and low wages that cannot be assigned to either of the other two segments. One interpretation of this result is that the model allows “purging” of “noisy” observations, those with unexpectedly low or high wages, conditional on their observed characteristics. Given this

interpretation, the three-segment model allows a clearer distinction between low-wage and high-wage jobs.

Applying the common method of assigning observations to simulated segments using the maximal estimated posterior probability, we found that the assigned sample shares of the simulated segments are considerably different than their estimated population shares. This result leads to the conclusion that this method might lead to systematic assignment errors. Instead, we propose weighting all observations by their estimated posterior probabilities and including all weighted observations in each of the simulated segments. This leads, by definition, to simulated segments with sample shares that are identical to the estimated sample shares. Application of this classification method yielded simulated segments that are not dramatically different from those obtained using the conventional method, but still lead to some different insights. For example, Arabs were equally likely to be assigned to the high-wage and low-wage assigned segments, while they were more likely to be in the low-wage weighted segment than in the high-wage one. The same is true for residents of the periphery.

Altogether, the weighted simulation method yielded quantitatively small but qualitatively reasonable differences between the attributes of workers in the low-wage segment and the high-wage segment. The differences between the two segments in terms of their wage equation coefficients, or the returns to those attributes, were much larger. For example, Jewish females and Arab males suffer considerable wage penalties in the high-wage segment, while Arab females suffer wage penalties in the low-wage segment. Returns to schooling are considerably higher for Jewish workers in the high-wage segment, while they are positive for Arab females only in the low-wage segment, and do not exist for Arab males in either segment. Altogether, the results indicate that much of the wage disparities in Israel are due to unobserved factors rather than to observable characteristics.

The results lead to some interesting policy-relevant findings on the links among schooling, ethnic minorities, and wages. Male Arabs, for example, do not enjoy returns to schooling, regardless of their wage segment. Hence, they can earn at most as much as uneducated male Jewish workers in the low-wage segment, but much lower than any male Jewish worker in the high-wage segment. Female Jewish workers can earn as much as male Jewish workers in the low-wage segment, but much lower than an equally-educated and otherwise identical male Jewish worker in the high-wage segment. Female Arab workers earn less than any other worker in the low-wage segment if they have no schooling, but can compensate for that disadvantage if they acquire sufficient schooling. If they happen to be in the high-wage segment, on the other hand, additional schooling seems to be worthless for them in that segment.

This last result is particularly interesting and relevant for public policy, because it implies that while schooling is advantageous for female Arab workers, it is not sufficient to lift them out of the low-wage trap. The challenge of policy, in this case, is to find ways to integrate female Arabs into the high-wage segment and at the same time find ways to make their schooling valuable in that market segment. This is an example of the advantage of using the mixture regression model for analyzing wage differentials.

One remaining challenge that deserves further research is to understand how observationally-equivalent workers are assigned to the different segments. In the Israeli case, it is common to talk about “connected” and “unconnected” workers. The former include public employees, who perhaps do not enjoy high wages but are compensated by very generous fringe benefits and ultimate job security, workers in public utilities and banks that have extremely powerful unions, as well as others whose family or friends hold influential positions. It is an even more important challenge for public policy to make sure that the ability to find a job that pays well will be based principally if not solely on merit.

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Table 1: Descriptive statistics of the sample

Category	Variable	Label	Mean
	Hourly wage	Hourly Wage	46.0
	Ln(hourly wage)	Log of hourly wage	3.6
	Schooling	Years of schooling	13.9
	Age	Age	40.3
Nationality	Arab	Arab	10.7%
Gender	Female	Female	50.3%
Nationality /Gender	Female*Jewish	Female Jew	46.6%
Nationality /Gender	Female*Arab	Female Arab	3.0%
Location	Very peripheral	Lives in distant periphery (1=yes)	3.7%
Location	Peripheral	Lives in periphery	8.2%
Location	Intermediate	Lives between center and periphery	29.5%
Location	Central	Lives in center	14.3%
Location	Very central	Lives in a close center	44.3%
Industry	Agriculture	Agriculture	1.1%
Industry	Manufacturing	Manufacturing	15.1%
Industry	Utilities	Utilities	0.7%
Industry	Construction	Construction	4.7%
Industry	Commerce	Motors, retail, wholesale	12.0%
Industry	Hospitality	Hospitality	4.6%
Industry	Transportation	Transportation	6.4%
Industry	Finance	Banking, finance, insurance	4.0%
Industry	Real Estate	Real Estate	13.2%
Industry	Public	Public administration	5.0%
Industry	Education	Education	13.5%
Industry	Health	Health care	10.9%
Industry	Community	Community services	3.8%
Industry	Domestic	Domestic services	2.3%
Industry	Unknown industry	Industry unknown	2.9%
Occupation	Academic	Academic	13.6%
Occupation	Technical	Technical	14.7%
Occupation	Managerial	Managerial	5.7%
Occupation	Clerical	Clerical	18.6%
Occupation	Sales	Sales	20.5%
Occupation	Agricultural	Professional agricultural	0.6%
Occupation	Professional	Professional manufacturing	15.9%
Occupation	Unskilled	Nonprofessional	7.5%
Occupation	Unknown occupation	Occupation unknown	2.7%

Table 2: Mixture regression results - dependent variable is ln(hourly wage)

Variable	Two-segment		Three- segment		
	Seg. 1	Seg. 2	Seg. 1	Seg. 2	Seg. 3
Constant	-0.143 (0.3163)	1.991*** (0.0637)	-0.289 (0.3150)	2.466*** (0.1320)	1.885*** (0.1610)
Age	0.100*** (0.0120)	0.042*** (0.0025)	0.106*** (0.0125)	0.028*** (0.0043)	0.043*** (0.0059)
Age squared/100	-0.090*** (0.0144)	-0.039*** (0.0031)	-0.101*** (0.0152)	-0.029*** (0.0043)	-0.034*** (0.0065)
Female*Jewish	-0.303 (0.2417)	-0.106** (0.0482)	-0.057 (0.2380)	0.006 (0.0629)	-0.303*** (0.0761)
Female*Arab	-0.168 (0.6572)	-0.486*** (0.1091)	0.181 (0.6800)	-0.645*** (0.2340)	-0.301 (0.4590)
Male*Arab	0.380 (0.3008)	-0.092 (0.0630)	0.558* (0.2900)	-0.068 (0.0960)	-0.288*** (0.1030)
Schooling*Male* Jewish	0.043*** (0.0120)	0.040*** (0.0031)	0.044*** (0.0123)	0.018*** (0.0046)	0.054*** (0.0041)
Schooling*Female* Jewish	0.052*** (0.0132)	0.035*** (0.0025)	0.038*** (0.0129)	0.010*** (0.0023)	0.059*** (0.0048)
Schooling*Male*Arab	0.013 (0.0221)	0.035*** (0.0048)	-0.043* (0.0230)	-0.003 (0.0080)	0.008 (0.0080)
Schooling*Female* Arab	0.054 (0.0448)	0.054*** (0.0074)	-0.001 (0.0483)	0.045*** (0.0163)	0.010 (0.0301)
Periphery/occupation/industry	yes	yes	yes	yes	yes
Sigma	0.928	0.376	0.910	0.244	0.355
Probability weight	0.177	0.823	0.172	0.342	0.486
Predicted log-wage	3.387	3.688	3.269	3.464	3.764
AIC	3364971		3254460		
BIC	3365516		3255282		
Log Likelihood	-1682414		-1627123		
Observations	16,004		16,004		

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Segment-specific means based on assigned segment

Segment	Two-segment		Three- segment		
	Seg. 1	Seg. 2	Seg. 1	Seg. 2	Seg. 3
Hourly Wage	57.99	44.85	39.77	30.73	58.43
Age	39.90	40.54	37.44	41.39	40.32
Schooling	14.32	13.78	13.82	13.62	13.98
Female	0.488	0.515	0.543	0.503	0.516
Arab	0.049	0.117	0.062	0.117	0.116
Very Central	0.492	0.434	0.470	0.433	0.438
Central	0.128	0.143	0.132	0.139	0.146
Intermediate	0.281	0.300	0.293	0.302	0.296
Peripheral	0.061	0.086	0.067	0.086	0.085
Very Peripheral	0.038	0.037	0.039	0.039	0.035
Agriculture	0.012	0.011	0.011	0.013	0.009
Manufacturing	0.149	0.158	0.133	0.161	0.157
Utilities	0.006	0.007	0.006	0.007	0.008
Construction	0.029	0.051	0.032	0.053	0.049
Commerce	0.131	0.124	0.132	0.122	0.126
Hospitality	0.063	0.047	0.072	0.049	0.043
Transportation	0.055	0.068	0.048	0.070	0.067
Finance	0.050	0.041	0.041	0.038	0.045
Real Estate	0.160	0.135	0.142	0.140	0.134
Public	0.033	0.050	0.038	0.046	0.053
Education	0.145	0.133	0.166	0.115	0.143
Health	0.101	0.114	0.110	0.122	0.106
Community	0.047	0.038	0.049	0.040	0.036
Domestic	0.019	0.024	0.019	0.024	0.024
Academic	0.165	0.136	0.148	0.122	0.149
Technical	0.153	0.148	0.156	0.138	0.154
Managerial	0.071	0.059	0.049	0.054	0.066
Clerical	0.165	0.194	0.174	0.184	0.200
Sales	0.229	0.211	0.241	0.213	0.206
Agricultural	0.006	0.006	0.005	0.007	0.006
Professional	0.123	0.169	0.126	0.182	0.159
Unskilled	0.088	0.079	0.102	0.099	0.061
Sample share	0.081	0.919	0.087	0.393	0.520

Table 4: Segment-specific means based on weighted segments

Segment	Two-segment		Three- segment		
	Seg. 1	Seg. 2	Seg. 1	Seg. 2	Seg. 3
Hourly Wage	52.00	44.60	46.02	32.92	54.99
Age	40.94	40.39	40.07	40.52	40.61
Schooling	14.14	13.76	13.98	13.61	13.92
Female	0.504	0.515	0.520	0.512	0.511
Arab	0.080	0.118	0.084	0.126	0.111
Very Central	0.460	0.434	0.454	0.427	0.441
Central	0.141	0.143	0.141	0.138	0.146
Intermediate	0.288	0.301	0.292	0.308	0.294
Peripheral	0.074	0.086	0.076	0.089	0.083
Very Peripheral	0.037	0.037	0.038	0.038	0.036
Agriculture	0.010	0.011	0.010	0.011	0.011
Manufacturing	0.156	0.157	0.148	0.159	0.159
Utilities	0.007	0.007	0.007	0.006	0.007
Construction	0.039	0.051	0.040	0.055	0.048
Commerce	0.125	0.125	0.128	0.127	0.122
Hospitality	0.048	0.048	0.053	0.050	0.044
Transportation	0.063	0.068	0.062	0.068	0.068
Finance	0.046	0.041	0.044	0.038	0.044
Real Estate	0.149	0.135	0.142	0.136	0.136
Public	0.045	0.050	0.047	0.047	0.051
Education	0.137	0.133	0.144	0.123	0.138
Health	0.111	0.113	0.111	0.117	0.111
Community	0.043	0.038	0.043	0.039	0.037
Domestic	0.021	0.024	0.022	0.025	0.024
Academic	0.156	0.134	0.149	0.121	0.146
Technical	0.156	0.146	0.155	0.135	0.155
Managerial	0.068	0.058	0.060	0.053	0.064
Clerical	0.180	0.194	0.183	0.190	0.196
Sales	0.214	0.211	0.221	0.218	0.204
Agricultural	0.005	0.006	0.005	0.006	0.006
Professional	0.143	0.170	0.145	0.181	0.161
Unskilled	0.077	0.080	0.082	0.095	0.068
Observations	16004	16004	16004	16004	16004