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# Residential Location and the Male-Female Gap in Labor Market Outcomes—A Lesson from Newcomers to Israel

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## **Abstract**

We estimated two dynamic programming models, one for men and one for women, on a sample of immigrants who arrived in Israel from the Former Soviet Union (FSU) between 1989 and 1995. Following the literature, we assume that the household maximizes its expected utility based only on the husband's human capital. Therefore, the family's residential location decision is based on the husband's labor market opportunities. We study the potential effect of this assumed behavior on the labor market's gender gaps. In the model estimated for men, we endogenize the decisions regarding residential location, employment location, and occupational choices. In contrast, in the model estimated for women the family's residential location is taken as given. Using the estimated parameters from the two models and a number of counterfactual simulations, we are able to decompose the observed gender wage gap into two parts—one based on behavioral differences and the other based on the lower labor market returns for women. The simulations indicate that if women had the same labor market returns and the same preferences as men, their outcomes would have been similar to those of men. Moreover, the simulations show that even without any changes in their labor market conditions, women would have gained in terms of both job quality and wages if the family's residential location was based on their human capital.

# 1 Introduction

A massive wave of highly educated immigrants arrived in Israel from the Former Soviet Union (FSU) during the period 1989-1995. The labor market outcomes of the female immigrants in this wave in Israel were inferior to those of the males. Even after a number of years in Israel, there was still a substantial gender gaps in both wages and employment. The aim of this paper is to explain the sources and consequences of this gap. One common explanation is that labor market returns differ by gender. Another explanation, which we consider here, is the potential mismatch between the family's residential location and the wife's labor market opportunities.

Following the literature, we assume that the household chooses its residential location by concentrating on utilizing the husband's human capital. Based on this assumption, we develop and estimate a dynamic programming model in which married women make choices about participation and commuting, while taking the residential location of the family as given. We also estimate a model for married men (an extended version of the model that was developed in Buchinsky, Gotlibovski and Lifshitz (2014); hereafter BGL). In this model, as in BGL, men make decisions not only about participation and commuting, but also about the family's residential location. The two models make it possible to investigate the potential impact of the aforementioned assumption on the gender gaps in wages and employment among immigrants. We use a retrospective longitudinal dataset of male and female engineers who arrived in Israel from the FSU between 1989 and 1995. The male and female engineers had very similar human capital upon arrival (in terms of education and experience). This unique sample of two groups of immigrants with similar background help us to investigate the sources of the observed gender gap.

It is important to note at the outset that we do not possess the data needed to directly investigate the family's joint decisions. Therefore, we estimate separate models for men and women. Nonetheless, the dataset includes detailed information about the individual's choices and outcomes, together with limited information about their spouse's labor market outcomes.

In BGL, we examined the migration patterns of male immigrants using the same survey. Since the sample provided very little information about the labor outcomes of the individuals' spouses, it was necessary to assume that the family chooses its residence solely based on the husband's labor market opportunities. Consequently, the family's decisions about the wife's labor supply are made only after the residential location decision. Given this assumption, the model provided very strong predictions and an excellent fit to the data, which provides support for the assumption. In the current study, we focus on labor market outcomes of

married female immigrants in Israel, while maintaining the assumption that the household chooses its residential location based on the husband's human capital.

Given this setting, we decompose the differences in labor market outcomes between men and women into their various underlying factors. This is done on the basis of a number of illuminating counterfactual simulations. The simulations also provide circumstantial evidence that the assumed decision making process within the family is supported by our data.

For this study we estimate two dynamic programming models: one for men and other for women. We assume, as in BGL, that the family's residential location decision is based solely based on the husband's human capital. Based on this assumption, in the first model (only men), we allow the individual to make optimal choices in every six-month period with respect to: (a) residential location; (b) employment; and (c) region of employment. We refer to this model as the *augmented labor supply model* (or ALSM). In the second model (only women), we assume that the family's residential location is taken as given, and therefore the individual can optimize only with respect to (a) employment and (b) region of employment. We refer to this model as the *labor supply model* (LSM). In both models, an individual can choose to work in one region and reside in another, but then he/she incurs commuting costs.

Both models also take into account the potential effects of regional amenities, differences in regional housing prices, and existing social networks. We also incorporate stochastic job offers and job terminations. Finally, we control for unobserved heterogeneity in a manner similar to Keane and Wolpin (1997), namely through the presence of individual types.

One of the study's main goals is to quantify the factors—those based on behavior versus those based on the labor market—underlying the pronounced gaps in labor market outcomes between male and female immigrants in Israel. We therefore decompose the overall effects accordingly. This is achieved by means of counterfactual simulations in which we decompose the overall differences between the outcomes of men and women. We use several alternative combinations of the model's parameters and the data, thus providing a comprehensive decomposition in the spirit of the Oaxaca decomposition.

The simulations clearly show that gaps in labor market outcomes between spouses are not a result of differences in observed human capital. Rather, if women had the same labor market returns and the same preferences as men, their outcomes would have been similar to those of men. Moreover, we conduct a simulation in which we didn't change the job market parameters, but we allow women to make decisions regarding residential location. The results of this counterfactual suggest an increase of more than 100% in the proportion of women working in white-collar occupations and a much lower proportion in the non-employment status. This counterfactual indicates that, even without any changes in their

labor market conditions, women would have gained in terms of both job quality and wages if the residential location of the family was decided based on their human capital.

The rest of the paper is organized as follows: Section 2 presents the data and in particular the gender differences in the data. Section 3 surveys the literature on the labor market participation of women and particularly married women. Section 4 describes the basic model and its various alternatives. Section 5 presents the results, including a number of important counterfactual simulations. Section 6 concludes.

## 2 Data and Motivation

The data are taken from a survey conducted by the Brookdale Institute in Jerusalem among immigrants from the FSU who declared, upon arriving in Israel, that they had trained and worked as an engineer in the FSU. This is the same survey used in BGL; however, while only the data for men were used in BGL, here we extend the analysis to include women. The interviews were conducted face-to-face and in Russian. A total of 1,432 male and female immigrants were interviewed between June and December of 1995. The survey's most serious drawback is that it gathered little information about the immigrant's spouse, even if s/he was also an engineer. This, of course, makes it impossible to model the couple's joint decision making. The analysis is restricted to married engineers between the ages of 25 and 55 at the time of arrival, yielding a sample of 412 females and 614 males.

As part of the survey, the respondents provided information about their occupational and educational background in the FSU, as well as a host of post-arrival variables. This allowed us to construct a continuous history of the residential location since time of arrival. Table 1 displays selected descriptive statistics for the married women and men. The women's mean monthly earnings at the time of the survey (excluding the non-employed) range from 1,800 to 2,800 NIS, varying with years since arrival, whereas the men's mean monthly earnings are much higher, ranging from 2,600 to 4,300 NIS. The earnings of men also grow much faster than those of women over time.<sup>1</sup> The mean monthly housing costs at the time of the survey are about 1,000 NIS and are similar between men and women, as expected, in view of the fact that the cost of housing is borne by the family. About 60% of the individuals reported owning their dwelling.<sup>2</sup>

The mean age of the female immigrants upon arrival is about 42, while that for the males

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<sup>1</sup>All earnings observations are for 1995, at which time the exchange rate was approximately three NIS per U.S. dollar.

<sup>2</sup>The monthly housing costs were constructed in the same manner as in BGL: rent for renters and mortgage payments for owners. There were a few individuals who reported both a mortgage payment and rent; in that case we used the rent. This usually occurred when the individual had bought a house, but had not yet moved in.

is about 46. The mean years of education is particularly high: about 16 for females and 16.5 for males. The spouse's level of education is also high, which suggests strong and positive assortative mating on education. The wives have an average of 15 years of education (as compared to an average of 14.5 for female immigrants from the FSU) while the husbands have an average of 15.7 years of education (as compared to 14.6 for male immigrants from the FSU).<sup>3</sup> The female immigrants arrived with 13.9 years of labor market experience as engineers in the FSU, while the males arrived with 16.3. About 78% of the women and 73% of the men originated from three republics in the FSU: Ukraine, Belarus, and Russia. Most of the immigrants arrived in Israel during a short period of time, with more than 70% arriving by the end of 1992.

Overall, the women and men in the sample have very similar levels of observed human capital, which is expected since both groups trained as engineers in the FSU. Thus, the large gender wage gap in the sample cannot be explained by differences in (observed) human capital. However, in Israel, the occupational choices of the men differed significantly from those of the women, despite their similar backgrounds in the FSU.

Figure 1a-1c depict the proportion of men and women in each of three occupation categories: non-employed, white collar and blue collar. The patterns of employment differ significantly between men and women. First, the non-employment rate for women exceeds that for men during the initial years following arrival. However, after 4.5 years in Israel the rates converge. Second, the proportion of men employed in white-collar occupations is larger than that of women, with the gap increasing over time. There are also some noticeable differences in the blue-collar occupations: The proportion of women increases throughout the sample period, while that of men increases initially, but subsequently declines. This is due to the transition of some of the men from blue-collar to white-collar occupations, a pattern that is not observed among women. Furthermore, while there is virtually no part-time employment among men, a significant number of women are employed in part-time blue-collar jobs. This pattern can be clearly seen in Figure 2a-2d and is discussed below, together with the predictions of the model.

To detect any differences that may exist in employment patterns between men and women, Table 2 presents the employment distributions for women (Panel A) and for men (Panel B) over the entire sample period, according to the spouse's education level. For women, we differentiate between full-time and part-time employment in blue-collar occupations. Table 2 reveals two important differences between men and women. First, the conditional distribution of employment for women depends crucially on the husband's level of education, while the conditional distribution of employment for men shows no clear pat-

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<sup>3</sup>For more details about this immigration wave see Cohen-Goldner, Eckstein and Weiss (2008, 2010).

tern of dependence on their wives' level of education. Second, the rate of non-employment among men is significantly lower than among women across all the education levels of their spouses.

In order to determine whether the pattern of married female employment described above is unique to this sample of immigrants, Table 3 presents the employment and wage distributions in 1995 (the year in which the data on wages was collected) for married native Israelis and for FSU immigrants that arrived after 1990. To make the two samples comparable with respect to level of education, we restrict our attention to families in which both spouses have at least 14 years of education. The patterns that emerge from the two samples are very similar in the case of both women and men. There are far fewer women in white-collar employment even though their levels of education are similar to those of their male counterparts. Furthermore, the relative wages of women and men in the two samples are comparable. Specifically, the wages of men in both samples dominate those of the women, with similar magnitudes of disparity. Interestingly, there is a larger gender wage gap in the white-collar occupations among natives than among immigrants. The table also shows a large wage gap between native Israelis and immigrants.

To further compare the employment patterns among men and women, we carried out a number of binary probit regressions in which the dependent variable takes a value of one if the individual is in the relevant employment status (i.e., non-employed, white collar or blue collar) and zero otherwise. The results are presented in Panel A (for women) and Panel B (for men) in Table 4.<sup>4</sup> In all the regressions, we control for age, spouse's education, and spouse's type of employment (where the omitted category for the spouse is non-employment). Clearly, there are major differences between men and women in the marginal effect of the spouse's employment status, even after controlling for the spouse's education. For example, a woman is far more likely to be not-employed if her husband is employed (by 32 percentage points if the husband is in a white-collar occupation and by almost 26 percentage points if he is in a blue-collar occupation). In contrast, whether the wife is employed in a blue-collar or a white-collar occupation has little effect on the husband's employment outcomes.

This might be reflecting the fact that the husband's employment is the dominant factor when the family decides on residential location. Thus, it is likely to be the case that for the husband to accept a white-collar job and locate the family residence at a commutable distance from his workplace, his wife must remain not-employed, at least temporarily.

According to the literature on assortative mating, we would expect the human capital

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<sup>4</sup>All regressions were estimated based on the last period of the sample (which is the only period for which the occupation of the spouse is available). Also, the average education of the men's spouses (in the men's sample) is 15.7 years, while the average education of the women's spouses (in the women's sample) is 15 years.

(both observed and unobserved) of two partners to be positively correlated (Greenwood et al. (2014), Gihleb and Lifshitz (2020)). The results in Table 4 indeed show that the husband's characteristics contribute to determining a woman's occupation type but not vice versa. The asymmetry between the partners suggests that the potential effect of assortative mating is overcome by the need to adjust to the new country and maximize household utility, even at the cost of not fully utilizing the wife's human capital, at least temporarily.

Unfortunately, the data do not make it possible to determine whether this asymmetry is an outcome of the family's preferences or is simply due to the greater bargaining power of the husband relative to his wife. Nevertheless, the similarity in the levels of education and experience in the FSU between men and women seems to indicate that women and men had similar employment patterns before immigrating to Israel.

Note that there is some indication of positive sorting by marriage, such that when one of the spouses is employed in a white-collar occupation, his/her spouse is more likely to be as well. Nevertheless, the effect of a man's occupation on his spouse's occupation is larger than in the other direction. The impact of employment in a blue-collar occupation on the spouse's occupation also differs significantly between men and women where the employment of a man in a blue-collar occupation has a huge positive effect on his wife's likelihood of also working in a blue-collar occupation, while the reverse effect is much smaller.

The two panels of Table 5 (Panel A for women and Panel B for men) describe the transitions between employment statuses between period  $t$  and period  $t + 1$  (a period of six months in our case) over the entire sample period. Once again, the patterns differ considerably between men and women. For both genders, the proportion remaining in a white-collar occupation, conditional on being in a white-collar occupation in the previous period, is over 97%. However, in the case of non-employment, the probability of a man who was not-employed in period  $t$  being not-employed in  $t + 1$  is less than 47% while for women it is about 17 percentage points higher. This result provides further evidence that a woman's experience in the labor market in Israel differs significantly from that of a man.

### 3 Literature Review

There is only limited research in the literature that is directly related to the connection between the family's residential location decision and the labor market outcomes of each spouse. Nonetheless, there is of course a massive literature on the gender gap in labor market outcomes, joint employment decisions and the difference in behavior between men and women in the labor market. Although this literature does not relate directly to the family's residential location decision, it does shed light on the incentives facing the family in

making that decision.

### 3.1 Residential Location Decision and Spouse's Labor Market Outcomes

Gemici (2011) is closest in spirit to the joint decision model we would have analyzed if data had been available on the respondent's spouses. In her model, couples choose their residential location (which is also their work location) through a bargaining process. Using PSID data, she finds that although inter-regional migration involves compromises by both spouses, couples move more often in response to the man's opportunities. This is because, at least in part, women experience lower wage offers, a lower arrival rate of offers, and a lower variance of wage offers. As a result, an inter-regional move results in higher wages for married men, but far less so for married women. In fact, they are less likely to be employed following a move. Thus, part of the gender wage gap can be explained by the joint decision making within the household regarding migration and employment. This conclusion is consistent with the assumption made in BGL and in the current study.

Tenn (2010) investigated the role of the wife in the decision to migrate across geographic regions in the U.S. He finds that the family migration decision is primarily determined by the husband's benefit from migration rather than the wife's, since it is difficult to balance two careers simultaneously and the husband's job is given greater priority. As long as households make major decisions that prioritize the husband's career over the wife's, the labor market outcomes of married women will not converge to those of married men.

This finding is also supported by Epstein and Heizler (2006) in the case of Israel. Using a representative sample of 503 households of recent FSU immigrants in Israel, the authors report that about 40% of the sample chose their residential location based on job opportunities. However, the likelihood of a man earning above the minimum wage was found to be significantly higher than that of a woman.

Mok (2007) examines the question of whether the residential location choices of two-earner households are based on the incomes of both spouses. The results clearly reject the hypothesis in the case of childless families but not in the case of households with children. Importantly, the results suggest the need to address intra-household dynamics when modeling location choice.

Residential choices and the corresponding mobility decisions are also investigated in Stolpovsky (2015). She examines the couple's decision of whether to move to a new location using PSID data for the period 1985-1991 and finds that the well-known income pooling hypothesis is unambiguously rejected for retired couples.

Sakanishi (2007) develops a model in which household location is determined by the husband's choice, while the wife's employment decision is conditional on the location chosen. This is essentially the same assumption adopted in the current paper.

Inoa, Picard and de Palma (2014) consider a setting in which the household's residential location decision involves several decision makers. This is a difficult task, especially in the case of dual-earner households in which the spouses work at different locations. They note that even though this has become quite a common situation in France (and elsewhere), there is almost no research devoted to unravelling the joint decision process. Using a reduced-form approach, they find that differences in the value of commuting time between the spouses is a key factor in the intra-household decision process. Their method is closely related to the collective approach used by Chiappori (1992) to model the residential location choices of dual-earner households. While the analysis falls short of estimating a fully structural model, the reduced-form analysis adopts flexible specifications using a three-nested Logit model that can be closely related to structural estimates.

Fosu (2000) suggests that the labor force participation preferences of married women vary significantly across regions of the U.S. He provides some evidence of what he refers to as regional "social economy". This coincides with our finding that employment of women varies considerably across the seven regions of Israel, despite the country's small size. The impact of the spatial distribution of employment on residential location is also addressed in Boustan and Margo (2009). While they do not directly address the employment of married women relative to that of married men, their model leads to a phenomenon of employment mismatch. That is, what may be a suitable location for the wife may not be for the husband and vice versa.

Black, Kolesnikova and Taylor (2014) also investigate the relatively large variation in labor supply of married women across U.S. cities. They primarily focus on differences in commuting time as a potential explanation and make no assumption about the variation in housing prices nor do they control for it. They find that labor force participation rates of married women are negatively correlated with commuting time. Furthermore, they find that, in general, metropolitan areas with larger increases in commuting time between 1980 and 2000 also displayed slower growth in the labor force participation of married women.

The study of residential location and labor market outcomes extends beyond the economics and sociology literature and is also examined in, for example, the geography literature. For example, Prashker, Shiftan, and Hershkovitch-Sarusi (2008) and Sermons and Koppelman (2001) provide a comprehensive analysis of the effect of socioeconomic variables - family characteristics and differential values of commuting time between men and women, on the residential location choice. Plaut (2006) analyzes the relationship between the commut-

ing decisions of spouses in dual-income households and finds that the choice of commuting distance is more sensitive to the husband's income.

### **3.2 Labor Market Gaps and Spouse's Joint Employment Decisions**

The literature mentioned above provides evidence that a family's residential location choice is based on the human capital of the spouse with the highest expected returns in the labor market. In view of the substantial gender wage gap in Israel, this spouse is likely to be the husband.

Dagan-Buzaglo, Hasson and Ophir (2014) report that in Israel the average monthly salary of a Jewish woman is about 59% less than that of a Jewish man. Even after controlling for the difference in work hours, the average hourly wage of women is still 18% less than that of men. Although the overall gender wage gap stems largely from occupational sorting, such that women and men are concentrated in different sectors and occupations, men earn more in every occupation dominated by either men or women. A result that is specifically relevant to our study concerns the gender wage gap among engineers: the median monthly salary of a man who is employed full-time as an engineer or an architect was higher than that of a comparable woman by about 67% in 2008. It is likely that as a result of a man's higher wage, families will give priority to utilizing the husband's human capital, and thus will choose a residential location based on his job opportunities.

Mandel and Birgier (2016) found that gender inequality has declined in Israel and at a similar rate to that in other OECD countries. Nonetheless, occupational sex segregation has remained relatively stable in Israel since the late 1970s.

Blau and Kahn (2017) provide a comprehensive review of the literature and arrive at several important conclusions that are relevant to the current study. First, the gender wage gap has narrowed over time and by 2014 a full-time female worker in the U.S. earned about 21% less than a male worker on average on an annual basis, and 17% less on a weekly basis. Second, even after controlling for occupation, industry and other employment characteristics, the gender wage gap remains substantial, at about 8%. Finally, there is a relatively large gender wage gap at the top of the distribution and between 1980 and 2010 it narrowed much less than in other parts of the distribution. This suggests that there remains a "glass ceiling" for women in high-earning occupations.

Barbulescu (2020) is based on a sample of over 1,000 graduates from a large European MBA program and has direct implications for the current study. The individuals were asked about their thoughts and expectations at different points during their job search, as well as their employment outcomes. It was found that, among other things, women are less likely than men to apply for finance and consulting jobs, even though they offer the highest

salaries, and are far more likely to apply for general management positions. The differences are explained, at least in part, by women’s preference for jobs with better anticipated work-life balance, their lower identification with stereotypically masculine jobs (particularly in finance) and their lower expectations of job offer success in such stereotypically masculine jobs.

Duleep and Sanders (1993) provide further support for our assumption about the roles of women and men in family decision making. They find that immigrants to the U.S. from European and Asian countries employ similar labor market strategies, where the husband goes out to work first to accumulate U.S.-specific human capital. Women tend to work more in households where the husband does not earn enough to support the family.

## 4 The Model

### 4.1 Features, Assumptions and Goals

As in BGL, we present a partial equilibrium model in which housing prices and wages are taken to be exogenous. In BGL, we provided ample support for these assumptions.<sup>5</sup> An excellent description of this approach is presented in Weiss (2000) who provides a summary of events in the labor market in Israel during the period of mass immigration from the FSU. He states that:

*Another important lesson is that even a large wave of immigration can be absorbed in the labor market without marked effects on wages or employment of natives. This is a consequence of two related trends, entry of additional capital and gradual entry into high skill occupations, that together kept the aggregate capital labor ratio constant, if labor is correctly measured. Specifically, the estimated individual wage profiles of natives and immigrants can be used to create a quality adjusted labor aggregate, that takes into account the different productivity of immigrants and natives and the changes in this gap as the immigrants are gradually matched. If one uses this quality adjusted number of workers, the capital labor ratio has remained roughly constant.*

We make no attempt to explain the economy-wide response to the mass immigration from the FSU to Israel during the early 1990s. The main goal is to examine the effects of the family’s residential location choice on the gender gaps in labor market outcomes. As mentioned above, there were two identical samples of engineers available to us, one for each gender. While we

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<sup>5</sup>See specifically Section 4.1 of BGL.

had some information about the respondent's spouse (such as occupation at the time of the survey), it was not sufficient to make direct inferences about the family's joint labor market decisions. Hence, we had to make an assumption about the structure of the decision process. Following the literature and, in particular, Gemici (2011) and Tenn (2010), we assume that the household chooses its residential location to utilize the husband's human capital, while the wife's labor market participation decision is made subsequently. We adhered to this assumption for both models - the one for men and the one for women. While one can estimate alternative models based on somewhat different sets of assumptions about the role of the man and the woman in the household, it is impossible to provide any meaningful inferences. The evidence is simply circumstantial and thus for the most part only suggestive. Nevertheless, under this assumption (which is supported by the literature) we were able to evaluate the effect of this setup on a woman's outcomes relative to those of a man.

It is important to note that all the relevant initial variables, including human capital, age, occupation, engineering experience and republic of origin in the FSU, are as of the time of arrival. All the immigrants had to leave the FSU abruptly because of the rapidly growing anti-Semitism in the FSU and Israel was essentially the only country that offered them free entry (see Cohen and Haberfeld (2007)).<sup>6</sup> Furthermore, the window of opportunity to leave the FSU was expected to be short-lived. Indeed, 70% of the immigrants in our sample arrived in Israel by 1992, and the remainder shortly thereafter. Thus, the usual initial conditions problem is of no consequence in our study and therefore all the relevant variables at the time of arrival are assumed to be exogenous.<sup>7</sup> Finally, a close examination of the sample shows that the distributions of all the observed variables remain virtually identical from 1989 to 1995. This appears to indicate the absence of any selection bias due to the exact timing of the move to Israel.

## 4.2 The Augmented Labor Supply Model (ALSM)

We first summarize the model estimated for men which we refer to as the Augmented Labor Supply Model (or ALSM).<sup>8</sup> We then introduce the restricted version, estimated for women, in which an individual decides only on her labor supply but not her residential location, which we refer to as the labor supply model (or LSM). It is worthwhile emphasizing

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<sup>6</sup>Even the United States, which allowed free entry to refugees from the FSU prior to 1989, only permitted entry for the purpose of family reunification after 1989.

<sup>7</sup>For further support of this assumption, see Cohen-Goldner, Eckstein and Weiss (2012) and Section 4.4 of BGL.

<sup>8</sup>Note that the ALSM is an extended version of the model that we estimated in BGL. See details in sub-section 4.4.

that while we cannot test one model against the other, the assumptions made imply that the ALSM model cannot apply to both women and men. Hence, to be consistent, if it were to be the case that the ALSM applies to men, it must also be the case that the LSM applies to women.

In the case of the ALSM, we assume that the residential/work locations are determined by the maximizer (i.e. the man), subject to certain characteristics of his spouse. In each period (semester), the individual maximizes the expected discounted present value of his/her utility up until the age of 65 (the mandatory retirement age in Israel during the sample period) by choosing: (a) region of residence; (b) employment status; and (c) region of employment. Neither saving nor borrowing is allowed.<sup>9</sup> There are a total of seven regions (i.e.,  $R = 7$ ): Tel Aviv, the Sharon, the Shfela, Haifa, the Galilee, the Negev, and Jerusalem. There are four employment choices (i.e.,  $K = 4$ ): non-employment ( $k = 1$ ), white-collar employment ( $k = 2$ ), full-time blue-collar employment ( $k = 3$ ) part-time blue-collar employment. ( $k = 4$ ).<sup>10</sup> In order to control for unobserved heterogeneity, we assume that there are ( $J = 3$ ) fixed discrete types of individuals.<sup>11</sup> The model's parameters are generally allowed to vary by type.

The per-period value of non-employment for individual  $i$  of type  $j$  at time  $t$  in the region of residence  $r$  is given by

$$u_{i1rt}^j(z_{it}, t) = b_r(\varepsilon_{i1rt}) + \tau_r(x_i, \mu_{ir}) - hc_{trj}(x_i) - \gamma_j I(r_t \neq r_{t-1}), \quad (1)$$

where  $z_{it}$  denotes the individual's state vector at time  $t$ , and  $b_{1r}(\varepsilon_{i1rt})$  is the per-period consumption value of non-employment in region  $r$ , which is given by

$$b_r(\varepsilon_{i1rt}) = b_{1r}I(t = 1) + \exp(\varepsilon_{i1rt}), \quad \text{for } t = 1, \dots, T. \quad (2)$$

The term  $b_{1r}I(t = 1)$  accounts for the fact that the first period differs systematically from all others in Israel, where  $I(\cdot)$  is the usual indicator.

The second term in (1),  $\tau_r(x_i, \mu_{ir})$ , represents the individual's per-period preference for residing in region  $r$ . It is a function of the individual's characteristics  $x_i$ , and region-specific characteristic,  $\mu_{ir}$ , which accounts for the immigrant's valuation of the region's amenities. In

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<sup>9</sup>This assumption is extreme though standard in the modeling of dynamic labor supply. When utility is linear and additive in consumption, the problem is reduced to that of wealth maximization, as is basically assumed here. For immigrants, this assumption reflects both the lack of financial resources (from the FSU) and the low initial income that limited their ability to save, as well as the lack of credit accessibility that prevented them from borrowing (special mortgages were available for immigrants and therefore that was introduced into the model).

<sup>10</sup>following the data, in the model estimated for men, we eliminate the option of ( $k = 4$ ).

<sup>11</sup>Adding more than three types had virtually no effect on the explanatory power of the model.

general, the republic of origin tends to shift the residential location decision towards regions, with a concentration of immigrants from the same republic. The third term,  $hc_{trj}(x_i)$ , is the per-period total cost of housing in region  $r$ . The last term,  $\gamma_j$ , is the individual's type-specific costs of moving from one region to another, which are incurred if the individual were to change residential location between  $t$  and  $t + 1$ . The term  $\varepsilon_{i1rt}$  is i.i.d. white noise (see below for further explanation).

The per-period value of working in a white-collar occupation for individual  $i$  of type  $j$  who works in region  $r'$  and resides in region  $r$  is given by:

$$u_{i2rt}^j(z_{it}, t) = 6 \cdot w_{kr't}(x_i, x_{i2t})e^{\varepsilon_{i2r't}} + \tau_r(x_i, \mu_{ir}) - hc_{trj}(x_i) - \gamma_j I(r_t \neq r_{t-1}) - tc(r', r), \quad (3)$$

where the deterministic components of the wage offer function in region  $r'$ ,  $w_{2r't}$ , are assumed to be a function of the individual's characteristics. The multiplicative stochastic term in the wage function follows the well-known Mincer-type specification.<sup>12</sup> Note that the next three terms are identical to those in (1), while the last term represents the cost of commuting if the individual resides in region  $r$  and works in region  $r'$ .

The specification of per-period utility in the blue-collar occupations is similar to that in the white-collar occupations, with one significant difference: a blue-collar worker can only work in the region where she resides (an unavoidable assumption since blue-collar workers were not asked where they work).<sup>13</sup>

Hence, the per-period utilities for full-time blue-collar workers are given by:

$$u_{i3rt}^j(z_{it}, t) = 6 \cdot w_{3rt}(x_i, x_{i3t})e^{\varepsilon_{i3rt}} + \tau_r(x_i, \mu_{ir}) - hc_{trj}(x_i) - \gamma_j I(r_t \neq r_{t-1}). \quad (4)$$

### 4.3 The Labor Supply Model (LSM)

Under the restricted version, namely the LSM,  $\gamma_j$  in 1 cannot be identified since the individual views residential location as given. The same applies to  $\tau_r(x_i, \mu_{ir})$  and  $hc_{trj}(x_i)$ . That is, from the point of view of the maximizing individual any change in residential location is exogenous. In that case, the per-period value of non-employment for individual  $i$  of type  $j$  at time  $t$  in the region of residence  $r$  is given by:

$$u_{i1rt}^j(z_{it}, t) = b(\varepsilon_{i1rt}). \quad (5)$$

<sup>12</sup>The wage function is multiplied by 6 because earnings are reported monthly, and a semester, the period used in the analysis, is six months long.

<sup>13</sup>This restriction is consistent with the results of Presman and Arnon (2006) who study commuting patterns in Israel. Also more generally in Israel, women commute to their job significantly less than men, probably because of their more important role in other aspects of the household.

The per-period value of working in a white-collar occupation for individual  $i$  of type  $j$  who works in region  $r'$  and resides in region  $r$  is given by:

$$u_{i2rt}^j(z_{it}, t) = 6 \cdot w_{kr't}(x_i, x_{i2t})e^{\varepsilon_{i2r't}} - tc(r', r), \quad (6)$$

that is, they choose only where to work and accordingly incur the cost of commuting  $tc(r', r)$ .

In the restricted model, the per-period values of working in the blue-collar occupations for full-time employment and part-time employment, respectively, are given by:

$$u_{i3rt}^j(z_{it}, t) = 6 \cdot w_{3rt}(x_i, x_{i3t})e^{\varepsilon_{i3rt}} - \gamma_j I(r_t \neq r_{t-1}),$$

and

$$u_{i4rt}^j(z_{it}, t) = 6 * w_{4rt}(x_i, x_{i3t})e^{\varepsilon_{i4rt}} - \gamma_j I(r_t \neq r_{t-1}),$$

where  $w_{4rt}(x_i, x_{i3t}) = \psi \cdot w_{3rt}(x_i, x_{i3t})$ ,  $\psi$  is the proportion of the deterministic part of the full-time wage paid to a part-time employee. In addition, the error terms for wages in blue-collar occupations, i.e.,  $\varepsilon_{i3rt}$  and  $\varepsilon_{i4rt}$ , need not be the same.

## 4.4 Other Features

The state vector  $z_{it}$  consists of a number of predetermined variables (which change deterministically) and the set of stochastic elements. That is,  $z_{it} = (x'_i, x'_{it}, \varepsilon_{it})$ , where  $\varepsilon_{it} = (\varepsilon_{i1rt}, \varepsilon_{i2rt}, \varepsilon_{i3rt}, \varepsilon_{i4rt})$  (or  $\varepsilon_{it} = (\varepsilon_{i1rt}, \varepsilon_{i2rt}, \varepsilon_{i3rt})$  when working in a part-time blue-collar job is not possible). The vector  $x_i$  includes all of the variables known upon arrival from the FSU: age on arrival, education, engineering experience, the republic of origin and the number of children under age 21. Finally, the vector  $x_{it}$  contains all the variables that vary over time.

The stochastic components of  $\varepsilon_{it}$  are assumed to be independent and identically distributed across regions and employment sectors. Nevertheless, within an employment sector the stochastic terms are allowed to be serially correlated within the same region of employment, that is:

$$\varepsilon_{ikrt} = \rho \varepsilon_{ikrt-1} + \nu_{ikrt}, \quad (7)$$

for  $k = 2, 3, 4$ , where  $\nu_{ikrt}$  is white noise. In addition, the  $AR(1)$  coefficient  $\rho_k$  is allowed to differ across employment sectors, but is constrained to be identical across all regions.

It is important to note that we do not estimate the discount factor  $\delta$  but rather set it to be  $\delta = 0.985$  per semester, which is equivalent to an annual discount rate of 0.97.<sup>14</sup>

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<sup>14</sup>It is well known from the literature that estimating  $\delta$  is problematic and we make no attempt to do so.

We allow the type probabilities to vary with the education of the spouse in order to account for possible assortative mating. That is, the probability of a woman being of type  $j$  ( $j = 0, 1, 2$ ) when the husband's education level is  $m$  is given by:

$$p_j(d_m^{ed}) = \exp(\phi_{1j} + \phi_{mj}d_m^{ed}) / (1 + \exp(\phi_{1j} + \phi_{2j}d_2^{ed}) + \exp(\phi_{1j} + \phi_{3j}d_3^{ed})),$$

for  $m = 1, 2, 3$ , and  $d_m^{ed}$ ,  $m = 1, 2, 3$  are dummy variables that take the value one if the spouse has level of education  $m$ , and zero otherwise. The omitted categories are type 0 and education level 1.<sup>15</sup> We re-estimated the BGL model for men (the ALSM in this paper), allowing for a similar structure of the type probabilities (and restrict the data to married men only).

The probability of receiving a job offer in sector  $k$  in region  $r$  at time  $t$  for an individual working in the same occupation and the same region as in time  $t-1$  is  $P_{krt} = 1 - \lambda_{kr}$ , for  $k = 2, 3, 4$ , where  $\lambda_{kr}$  denotes the involuntary dismissal probability. That is,<sup>16</sup>

$$\lambda_{kr} = \lambda_k = \frac{\exp\{\eta_k\}}{1 + \exp\{\eta_k\}}, \quad \text{for } k = 2, 3, 4.$$

An individual may also receive offers in other sectors and/or other regions. We specify these probabilities to be:

$$P_{k'r'it} = \begin{cases} \psi_k \exp(A_{k'r'it}) / \{1 + \exp(A_{k'r'it})\} & \text{if } t = 1 \\ \exp(A_{k'r'it}) / \{1 + \exp(A_{k'r'it})\} & \text{otherwise,} \end{cases}$$

where

$$A_{k'rit} = \lambda_{0k'r'} + \lambda_{1k=2(S=15,16)}S_i + \lambda_{2k=2(s>16)}S_i + \lambda_{3k=2}I(\text{Non-emp at } t-1) + \lambda_{4k}\text{age}_i \quad (8) \\ + \lambda_{5(k=2)}x_{oi}^{Eng} + \lambda_{6k}\text{time}_i + \lambda_{7k}TP_{1i} + \lambda_{8k}TP_{2i},$$

$\text{age}_i$  denotes age on arrival in Israel,  $S_i$  denotes the years of completed schooling in the FSU,  $\text{time}_i$  denotes the years since arrival in Israel,  $x_{oi}^{Eng}$  is experience as an engineer accumulated in the FSU, and  $TP_{ji} = 1$  if the individual is of type  $j$ , and  $TP_{ji} = 0$  otherwise, for  $j = 1, 2$  (the excluded type is type 0).

It is important to note that an individual can receive a job offer in any of the regions,

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Rather, we simply adopt a value for  $\delta$  that is generally reported in the literature for similar applications.

<sup>15</sup>Education level 1 includes individuals with up to 14 years of education; education level 2 includes those with 15 or 16 years of education, and education level 3 includes those with 17 or more years of education.

<sup>16</sup>In the estimation, we also allow the parameter  $\eta_k$ , and hence  $\lambda_{kr}$ , to vary by type.

in any period and in any of the employment sectors. Finally, while an individual can search under the LSM for a full-time or part-time job in the blue-collar sector only in her region of residence, in the white-collar sector she can search in any of the seven regions.

## 4.5 Further Parameterization of the Per-Period Value Functions

The per-period preference for residing in region  $r$  is parameterized to be a simple linear function of the republic of origin and other family characteristics, that is,

$$\begin{aligned}\tau_r(x_i, \mu_{ri}) &= \tau_r^1(\mu_{ri}) + \tau_r^2(x_i), \quad \text{where} \\ \tau_r^1(\mu_{ri}) &= \tau_0 + \tau_{1r}R_{1i} + \tau_{2r}R_{2i} + \tau_{3r}R_{3i}, \\ \tau_r^2(x_i) &= \tau_{4r}NK_i,\end{aligned}\tag{9}$$

where  $NK_i$  is the number of children under 21 who were living with the family at the time of the survey.  $R_{li} = 1, l = 1, 2, 3$ , for each of the three republics (Ukraine, Belarus and Russia, respectively), and 0 otherwise.<sup>17</sup> The term  $\tau_r^2(x_i)$  accounts for the fact that having children may affect the individual's choice of region in which to live.

The housing costs in region  $r$  are specified to be a linear function of family size, and the unobserved discrete type. That is,

$$hc_{trj}(x_t) = 6 * \exp(\gamma_{0r} + \gamma_1NK_i + \gamma_3TP_{1i} + \gamma_4TP_{2i}) / (1 + rp_r)^{T-t}, \tag{10}$$

where  $TP_{ji} = 1$ , for  $j = 1, 2$ , if the individual is type  $j$ , and 0 otherwise. The excluded type is type 0. The terms  $rp_r$  are parameters that represent the per-period rate of price increase in region  $r$ , for  $r = 1, \dots, 7$ . They account for the fact that housing prices vary differentially across the regions throughout the sample period.

The deterministic components of the wage offer functions in a white-collar occupation in region  $r$  are given by:

$$\begin{aligned}\ln w_{j2rit}(x_i, x_{it}) &= \beta_{02r} + \beta_{12}S_iI(S_i = 15, 16) + \beta_{22}S_iI(S_i > 16) + \beta_{32}x_{oi}^{Eng} + \\ &+ \beta_{42}x_{i2t} + \beta_{52}I(\text{age}_i \geq 40) + \beta_{62}TP_{1i} + \beta_{72k}TP_{2i},\end{aligned}\tag{11}$$

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<sup>17</sup>The excluded category is all other republics in the FSU. Hence,  $\tau_{0r} = \tau_0 - (\tau_{01} + \tau_{02} + \tau_{03})$  corresponds to that category.

while in a blue-collar occupation they are given by:

$$\begin{aligned} \ln w_{j3rit}(x_i, x_{it}) &= \beta_{03r} + \beta_{13}S_iI(S_i = 15, 16) + \beta_{23}S_iI(S_i > 16) + \\ &\quad + \beta_{33}x_{i3t} + \beta_{43}TP_{1i} + \beta_{53}TP_{2i}, \end{aligned}$$

where  $S_i$  is the level of education defined in (8),  $x_{oi}^{Eng}$  denotes the years of experience accumulated in the FSU, and  $x_{ikt}$  denotes the years of experience accumulated in Israel. We allow for differential returns on education between those with less than 16 years of education and those with more.<sup>18</sup> Note that we control for unobserved heterogeneity in the wage functions in both sectors, as well as in the regional housing cost function. This allows for unrestricted correlations between the unobserved components of these functions. Finally, moving costs are also specified to be type-specific.

## 5 The Results

### 5.1 The Parameter Estimates

We estimated the two versions of the model described in Section : the ALSM for men and the LSM for women. The parameter estimates for the ALSM are presented in Tables B.1 through B.7 in Appendix B while those for the LSM are provided in Tables A.1 through A.7 in Appendix A.

The parameters for the value of non-employment in the first period after arriving in Israel, namely  $\alpha_r$ ,  $r = 1, \dots, 7$ , which appear in Table A.1 and Table B.1, have the same relative importance across regions in both the LSM and the ALSM. Nevertheless, the magnitude is somewhat different. We see that Jerusalem is highly valued by both groups, while the Shfela is highly valued by women but not by men. Note that the preference for residing in a particular region crucially depends on the republics of origin of the FSU immigrants already living there (Table B.1) . In general, the results indicate that immigrants from the FSU prefer to live near individuals who come from the same republic in the FSU.

Table A.2 and Table B.2 present the parameter estimates for employment in a white-collar occupation, i.e.,  $\beta_{02r}$ ,  $r = 1, \dots, 7$ , which indicate that there is some variation in wages across regions. There are two important differences between the parameters for women in the LSM and those for men in the ALSM. First, there is much less variation in the region-specific

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<sup>18</sup>This is because the number of years of education is a reflection of the individual's type of engineering degree.

parameters for women than for men. Second, the estimates indicate that women’s wages are 15%-45% lower than those of men across all regions. This is consistent with the pattern observed in the data for both native Israelis and immigrants from the FSU. There are also relatively moderate returns within occupation type for having a higher level of education. As is also the case for men, there appears to be no return on experience accumulated in the FSU ( $\beta_{32}$ ) for women, although there is a substantial return on the experience acquired in Israel ( $\beta_{42}$ ). The magnitude of the returns is very similar for men and women. Note that the estimated commuting costs are lower for women than for men. However, due to the lower wages of the women, they commute less than men as the lower wages make long distance commuting less efficient.

The estimates for blue-collar employment in the two models are presented in Tables A.3 and B.3, respectively. Note first that wages are much lower in blue-collar occupations than in white-collar occupations across all regions. Nevertheless, the return on experience accumulated in Israel is quite similar in white-collar and blue-collar occupations. Similar to the results for white-collar occupations, the estimates of  $\beta_{03r}$ ,  $r = 1, \dots, 7$  for the ALSM and LSM show that women earn 30% less on average than men. Note also that the estimate for  $\psi$  (the proportion of the deterministic part of the full-time wage paid to a part-time employee) is 0.626, a relatively large proportion of the full time equivalent.

Tables A.4 and A.5 present the estimates for job-arrival and job-loss probabilities, respectively, for women in the LSM. Similarly, Tables B.4 and B.5 present those same estimates for men in the ALSM. First, note that in the case of the white-collar occupations there are relatively small differences in the estimated parameter for job-loss probability between the two models, although there are significant differences in the probability of losing a job across the estimated individual types. In the blue-collar occupations, the likelihood of a woman losing her job is much higher compare to the likelihood of a man.

The implied overall probability of receiving a job offer is much larger for men. The role of education is quite similar in both models, yet the region-specific constant terms vary significantly between the models for women and men, though not in any systematic way. The lower job offer probabilities for women, as estimated by the model, might reflect bias against women in the Israeli labor market, yet it can also reflect the fact that women do not look for jobs as intensively as men.

Tables A.6 and B.6 provide the estimates of the type-specific probabilities, which are allowed to depend on the spouse’s level of education in both models.

Clearly, women’s type probabilities crucially depend on the husband’s level of education. For example, Woman’s probability of being Type 1, which characterize with higher returns

in the white-collar wage and job-offer functions<sup>19</sup>, is only 0.05 if her husband has less than 15 years of education, but 0.792 if her husband has at least 17 years of education. In contrast, the type probabilities in the ALSM do not depend on the level of the wife’s education. For example, Type 1 probabilities are estimated to be: 0.61, 0.62, and 0.67 for the three possible levels of the wives’ education. In other words, while the coefficients from the ALSM are statistically significant they have no economic effect on the predicted type probabilities.<sup>20</sup>

The pronounced asymmetry between the dependence of the wife’s type on the husband’s level of education and the lack of dependence in the other direction, appears to contradict the prediction of the assortative mating theory, according to which we would expect the human capital (both observed and unobserved) of two partners to be positively correlated and thus influence the labor market outcomes of both. The results indeed show that the husband’s characteristics contribute to determining a woman’s labor market outcomes but not vice versa. This is also consistent with the evidence presented in Section 2, where we found that it takes much longer for a woman to find a job and that they tend to be employed in part-time and full-time blue-collar jobs, even though they are as educated as their spouses. Those results provide additional support for our choice of models. However, we can not rule out the possibility that the lack of dependence of the husband’s type on his wife’s education stems from the fact that the labor market outcomes of the wives are not correlated with their education, at least soon after arriving in Israel.

Finally, Tables A.7 and B.7 provide the estimates for the *measurement error* and *classification error* rate. The results clearly indicate that it is crucial to account for possible measurement errors, which are all statistically significant and relatively large. The classification error rate is also quite large (about 37%) in both models.<sup>21</sup>

## 5.2 The Model’s Predictions

Tables 6 through 9 present the predictions of the LSM alongside the actual data for a number of key variables. Table 6 and Figures 2a-d present the actual and predicted employment statuses by semester. The model captures the exact curvature of the employment alternatives trajectory and predicts the level and change in the non-employment rate with a high degree of accuracy. The model also predicts employment in blue-collar occupations quite well for both full- and part-time employment, but somewhat under-predicts the growth in employment in white-collar occupations. It is worthwhile noting that even by the end of the sample period only about 15% of the women are working in white-collar occupations,

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<sup>19</sup>see Table A.2. and B.2 for the estimated type parameters

<sup>20</sup>This does not stem from the model estimated. When we estimate the LSM for men and the ALSM for women we get similar results.

<sup>21</sup>See BGL for more details about the measurement and classification errors.

despite the fact that all the women in the sample are highly educated and of prime working age. For men, almost 27% are working in white-collar occupations by the end of the sample period.

The fact that very few women in the sample work in white-collar occupations is also the main reason that it is harder for the model to predict the employment share in white-collar occupations by region, as is evident from Table 7. Nevertheless, the model correctly predicts the average employment shares in the white-collar occupations in each region.

The model's predictions of employment shares for blue-collar workers in the seven regions of the country are relatively accurate. Although the individuals in the sample were trained as engineers in the FSU, over 64% of the women in the sample were still working in blue-collar occupations at the end of the sample period. Table 8 clearly shows that the model accurately captures the employment shares in each of the regions, as well as the turning points in employment shares over the sample period. Over the entire sample period, the mean predictions of employment shares by region deviate only marginally from those in the data. Recall that it is assumed that a blue-collar worker works and resides in the same region. Given the much lower wages in the blue-collar occupations, there is little incentive for women employed in them to commute long distances.

Table 9 presents the joint work/residential location data for women in white-collar occupations. The model correctly predicts that, on average, about 70% of them reside in the same region in which they work. Moreover, the women who do commute tend to work in adjacent regions. Thus, a large share of the white-collar workers reside in the regions adjacent to Tel Aviv, i.e., the Sharon and the Shfela, and work in Tel Aviv. Overall, the model does very well in predicting the employment shares in these regions, but is not as accurate in predicting the exact region from among those three. The model does quite well in predicting the larger employment shares in the Negev and the Galilee, as well as predicting that very few individuals commute to these two regions.

### **5.3 Decomposition of the Differences in Labor Market Outcomes between Women and Men**

We conduct a number of alternative counterfactual simulations that make it possible to decompose the overall differences in labor market outcome for men and women into their various factors. In each simulation, we use different sets of parameter estimates from the LSM for women and the ALSM for men, along with the data sets for men and for women. We then compare the employment and wage outcomes for these alternative counterfactuals. This Oaxaca-like decomposition makes it possible to provide a clear mapping of the possible

sources for observed differences in labor market outcomes between men and women.

Table 10 presents the employment and wage outcomes of the various simulations. Column (1) and (2) report the observed data for women and men, respectively, while Column (3) and (4) present the predictions of the ALSM for men and the LSM for women, respectively. Column (5) presents the predictions of the first counterfactual: the ASLM's predictions for the female sample. That is, we use the labor market parameters and commuting costs estimated for women using the LSM while allow women to choose the family's residential location. The parameters for the cost of housing (rent) and cost of moving were taken from the estimation of the ALSM, since consistent estimates for those parameters could not be obtained under the LSM. The parameters for the benefits of residing in a particular residential location (tastes) were set to be equal across regions since our underlying assumption did not make it possible to estimate them for women. This means that the term  $\tau_r(x_{it}, \mu_{ir})$  in (eq. 1, 3 and 4) was omitted<sup>22</sup>. The simulation allows us to assess the impact on labor market outcomes of the restriction imposed in the LSM model that women do not choose the family's residential location.

Comparing column (5) to column (3) reveals that even when we restrict the simulation for women to the estimated parameters that correspond to their labor market, the women would do much better if they could choose the family's residential location. Under this scenario, they have higher employment rates, especially in the white-collar occupations, in which their employment more than double.

Column (6) reports the predictions for women from the LSM model using the wage, job arrival and job dismissal parameters from the ASLM model estimated for men. This is used to determine the extent to which differential returns in the labor market are responsible for the gender gap. Note that in this simulation the residential location is still taken as given by women and that women in blue-collar occupations can only work full-time (as is also the case for men). The counterfactual predictions suggest that if women had the same returns as men in the labor market, their probability of being employed in a white-collar occupation would increase by 4.8 percentage points. Their wages improved substantially: by 37% in white-collar occupations and by 54% in blue-collar occupations (and by 39.4% in the case of a full-time job in blue-collar occupations). The huge difference in returns by gender cannot be explained by differences in the observable human capital of men relative to women, and thus may indicate discrimination against women. Alternatively, it may be the case that the difference stems from the fact that women work in different sub-occupations within each

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<sup>22</sup>We simulated the same scenario, where the women's taste parameters are set to the values of men. The result of this simulation improved women's performance even further compared to the simulation in column (5): Non-employment dropped by more than 10 pp, blue-collar employment increased by 13 pp, while White-collar employment slightly decreased by 2.5 pp.

sector, or from other unobserved differences in characteristics between men and women or in their labor market behavior.

Comparing column (6) to column (4) shows that even though a woman’s probability of being employed in a white-collar occupation increases substantially if she faces the same returns as men, a significant gender gap nonetheless remains. Woman’s average probability of being employed in a white-collar occupation would increase from 10.1% to 12.8%, but that is still far below a man’s probability (21.7%). The same is true for the gender wage gap: a woman’s average wage in a white-collar occupation increases from 3,259 NIS to 4,600 NIS, yet that is still well below a man’s wage (5,097 NIS).

To identify the source of the remaining gaps, in the last simulation (column 7) we allow women to solve a similar maximization problem to that solved by men and with the same parameters as estimated for men, except that we equalize the benefits from residing in a particular residential location (tastes), as in column (5). Thus, the women can choose the family’s residential location in this simulation. Comparing the results in column (7) to the results in column (4) (for men), we can see that the gender wage gap almost vanishes and that the employment gap narrows substantially (with only a 3.2 percentage point gap in white-collar occupations remaining). The result of the simulation in column (7) therefore suggests that if women had the same labor market returns and the same preferences as men and chose the family’s residential location, then their outcomes would have been very similar to those of men.<sup>23</sup> This is not particularly surprising, given the similar levels of human capital among the women and the men in the samples.

## 5.4 Implications of Model Choice—Random Allocation Simulation

In order to investigate which of the two models (ALSM vs. LSM) is the most applicable for each gender, we conduct a set of counterfactual simulations that we will refer to as *random allocation* simulations. This involves randomly assigning an individual to a region of residence in the first period of the model and then simulating the model according to the originally estimated parameters, while the region of residence assigned in the first period is kept fixed. This will make it possible to determine the extent to which men and women would change their behavior given an arbitrary assignment by region. We focus our attention on two important outcomes of the model: employment choices and the distribution of wages.

Table 11 shows that under random allocation the proportion of women in white-collar occupations rises from 10% to over 13%. This is largely at the expense of women in blue-collar occupations, while the proportion of non-employed women increases from 36.7% to

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<sup>23</sup>We got virtually the same results when we used the parameters for taste that were estimated for men instead of equalizing the tastes among all the regions.

37.3%. The situation of men worsens under random allocation in all employment categories: there are more non-employed and a lower proportion in white-collar occupations. If women indeed solve a more restricted labor supply decision, subject to residential location that is sub-optimal for them, then indeed we would expect them to fare quite well under the random allocation. On the other hand, since we assume that men optimize also with respect to residential location, we would expect them to be worse off under random allocation, as was indeed the case.

To further understand the implications of our choice of models, we now restrict our attention to the results for wages reported in Table 12 and 13. Overall, the wages for women under random allocation are slightly better in white-collar occupations and slightly worse in blue-collar occupations. In contrast, the wages for men are significantly worse in both. These results would be expected if in reality the residential location decision is based on the husband's human capital.

Note that it is hard to pinpoint the exact reasons leading to the observed results, since the composition of individuals' characteristics differ substantially across the various employment categories. To overcome this, we present a detailed breakdown of the results in Table 13, in order to highlight the changes in wages for each gender as a result of the reallocation between the employment categories. Overall, the results in Table 12 stem from the fact that there was reallocation across sectors. The two panels of Table 13 present the results for women and men, respectively. Each panel presents the wage outcomes for all the possible cross-tabulations between the employment choices under the relevant model and those under the corresponding random allocation. The cross-tabulations are presented for both the ALSM (in the top part of each panel) and the LSM (in the bottom part of each panel).

For example, line 2 of Panel A in Table 13 shows that the average wage of women who chose to work in white-collar occupations in the base model (LSM) and made the same choice under random allocation is 3,379 NIS as compared to 3,445 NIS under the random allocation counterfactual of that model. This represents an average increase of 2.0% for this group of women. For the women who chose to work in a full-time blue-collar job in both models, the average wage decreased by 1.3% (from 2,323 NIS to 2,293 NIS). In contrast, Men's average wage decrease both in white-collar occupations (-4.9%; from 5,280 NIS to 5,023 NIS) and in blue-collar occupations (-5.3%; from 3,290 NIS to 3,115 NIS). The changes in the occupation distribution and wages as a result of the random allocation simulation provide further support for the assumption that the residential location is chosen to utilize the husband's human capital<sup>24</sup>.

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<sup>24</sup>In order to rule out the possibility that the vastly different results for men and women under the random allocation simulation are artificial and stem merely from the fact that we consider different models for men

## 6 Summary and Conclusions

Following the literature, we assume that the household maximizes its potential outcomes by concentrating on utilizing the husband's human capital. Therefore, the family's residential location decision is based on the husband's labor market opportunities and in turn on his husband's human capital, while the wife takes the household residential location as given when she decides about her labor market engagement. We construct a model to assess the implications of this assumed decision making process on women's labor market outcomes and the gender gaps in wages and employment, based on a sample of engineers who immigrated from the FSU to Israel during the period 1989-1995. This is accomplished through counterfactual simulations and the results are used in the decomposition of differences in labor market outcomes between men and women into various underlying factors.

Several insights emerge from the data itself. First, the progress of the women in the labor market lagged considerably behind that of the men in terms of both employment opportunities and wages. Second, while a significant number of women are employed in part-time blue-collar jobs, there are virtually no men employed in part-time jobs whether blue-collar or white-collar. Furthermore, the employment patterns for both the men and women in the sample are parallel to those of highly educated native Israelis.

We estimate two dynamic labor supply models that incorporates the features suggested in the literature, particularly the literature on the Israeli labor market. In the model estimated for women, women take the residential location of the family as given, we term this model the labor supply model (LSM). The LSM model is a restricted version of the model estimated for men, which we term the augmented labor supply model (ALSM).

In both models, we control for several (unobserved) individual types. We find that the type probabilities for a woman crucially depend on her husband's level of education, while the wife's education does not have any meaningful economic impact on the type probabilities of her husband. This provides additional support for the crucial dependence of the wife's choices on her husband's, and our choice of models. We conduct a number of counterfactual simulations that shed light on the impact of the decision-making framework on women's

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and women in the simulation we conducted additional estimation. We estimated the LSM for men as well and conducted the random allocation simulation for men under that model. The results clearly indicate that the patterns observed in the random allocation counterfactual simulation are not driven by model selection. The labor market outcomes for men deteriorate dramatically under that simulation. This is in complete contrast to the results we obtained for women in the simulation results provided here. The unemployment for men more than double itself (from 19% under the LSM to 40% under the random allocation simulation) and the likelihood to work in the white-collar sector decreases by about 50%, from 25.7% under the LSM to only 13.4% under the random allocation simulation. The likelihood to work in the blue-collar sector also decreases also by about 9 percentage points, from 55.2% under the LSM to 46.4% under the random allocation simulation.

labor market outcomes per se and also relative to men.

It is important to note that we cannot generate direct evidence concerning the role of each spouse in the family's decision-making process since the data does not make it possible to investigate the family's joint decision process. This is because the datasets provided only limited information about the individual's spouse. Based on our assumption regarding the decision making of the two spouses, we run different models for men and women and arrive at different results for each. For example, in white-collar occupations there is much less variation in the region-specific parameters among women than among men. Furthermore, the estimates reflect a large disparity in wages between men and women that ranges from 15% to 55% in all regions of the country and in both white-collar and blue-collar occupations. Finally, we find that for both men and women there is no return on experience brought over from the FSU, although there is a high return on experience acquired in Israel.

Counterfactual simulations are used to decompose the wage disparity between men and women into its specific components. It is found that it is more difficult for women to obtain job offers in both blue-collar and white-collar occupations and that the jobs they do get pay significantly lower wages than the jobs offered to men. Moreover, we find that the women would have fared better if they had been the ones to choose the family's residential location. Under that scenario, they would have higher employment rates, especially in the white-collar occupations, in which their employment more than double. Finally, it is found that if women chose the family's residential location, and were treated like men in the marketplace, their labor market outcomes would be very similar to those of men.

There are several decision-making mechanisms within the family that might generate the observed data. However, to be able to advance on this important issue one must have data on the decisions of all members of the household. We certainly hope to address this issue with suitable data in the future.

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**Table 1: Descriptive Statistics**

Variable	Mean		St. Dev.		Obs.	
	Females	Males	Females	Males	Females	Males
Employed	.80	.89	-	-	412	614
Months in Israel	46.62	50.04	(16.98)	(16.50)	412	614
Age	42.38	46.21	(8.02)	(8.34)	412	614
Years of education	15.89	16.46	(1.26)	(1.61)	412	614
Previous experience as engineers	13.9	16.30	(8.05)	(8.40)	398	610
Children under 21 living at home	1.20	1.70	(.80)	(.69)	412	614
Years of education of spouse	15.73	14.98	(2.30)	(2.07)	412	614
From Ukraine	.31	.31	-	-	412	614
From Belarus	.11	.11	-	-	412	614
From Russia	.36	.31	-	-	412	614
Year of Arrival:						
1989	.01	.01	-	-	-	-
1990	.33	.42	-	-	-	-
1991	.26	.20	-	-	-	-
1992	.13	.14	-	-	-	-
1993	.16	.14	-	-	-	-
1994	.11	.09	-	-	-	-
Monthly earnings:						
Semester 2	1,825	2,552	(1,018)	(575)	10	12
Semester 5	1,965	2,903	(613)	(727)	25	29
Semester 8	2,316	3,579	(1,371)	(1,482)	28	31
Semester 10-12	2,781	4,307	(1,041)	(2,024)	128	242
Monthly housing costs:						
Semester 2	1,229	1,539	(329)	(1,833)	19	11
Semester 5	962	1,100	(452)	(406)	36	29
Semester 8	952	950	(433)	(392)	42	31
Semester 10-12	1,032	1,015	(545)	(599)	149	241

**Note:** The variable Children under 21 is measured at the time of the survey in 1995. All other Variables (except Monthly earning and Housing cost) are measured at the time of immigration. Experience as engineers are for those who worked as Engineers before immigration.

**Table 2: Occupation, by Spouse's Education****a. Women's Employment**

<b>Husband's Education</b>	<b>14</b>	<b>15,16</b>	<b>17</b>
Non-employment	32.49	35.90	32.36
White-collar	0.91	11.77	19.42
Blue-collar - full-time	53.18	42.50	39.56
Blue-collar - part-time	13.43	9.83	8.66

**b. Men's Employment**

<b>Wife's Education</b>	<b>14</b>	<b>15,16</b>	<b>17</b>
Non-employment	22.71	21.00	21.97
White-collar	17.39	24.67	18.06
Blue-collar	59.90	54.32	59.97

**Table 3: Wage Statistics in Israel**

Gender	Occupation	Natives		Immigrants	
		%	Wage	%	Wage
Male	Non-employment	5.4	—	18.8	—
	White-collar	65.9	10,018	26.9	6,244
	Blue-collar	22.7	7,598	54.3	3,597
Female	Non-employment	12.0	—	31.1	—
	White-collar	40.4	5,306	11.1	3,825
	Blue-collar	47.6	3,698	57.8	2,493

**Table 4: Occupation Probabilities by Spouse’s Characteristics, Probit Estimates**

**A. Women’s Employment**

Variable	Employment Status					
	White-Collar		Blue-Collar		Non-Employed	
	Estimates	Marginal Effect	Estimates	Marginal Effect	Estimates	Marginal Effect
Constant	-1.5713		-.2763		.1631	
	(.8250)		(.6054)		(.6704)	
Age at arrival	-.0375	-.0074	.01335	.0047	-.0075	-.0019
	(.0113)	(.0022)	(.0084)	(.0029)	(.0093)	(.0024)
Education of Spouse	.0896	.0177	-.0360	-.0126	.0029	.0007
	(.0404)	(.0079)	(.0296)	(.0103)	(.0327)	(.0084)
<b>Husband employed in:</b>						
White-collar	.9339	.1841	.5636	.1969	1.2378	.3175
	(.3671)	(.0718)	(.2331)	(.0797)	(.2523)	(.0598)
Blue-collar	.3667	.0402	.9584	.3347	1.0196	.2615
	(.2038)	(.0723)	(.2134)	(.0689)	(.2167)	(.0514)

**B. Men’s Employment**

Variable	Employment Status					
	White-Collar		Blue-Collar		Non-Employed	
	Estimates	Marginal Effect	Estimates	Marginal Effect	Estimates	Marginal Effect
Constant	.5449		-.1925		-2.4016	
	(.4977)		(.4573)		(.6013)	
Age at arrival	-.0412	-.01257	.01920	.0071	.0308	.0055
	(.0068)	(.0019)	(.0061)	(.0022)	(.0084)	(.0015)
Education of Spouse	.02586	.0079	-.01961	-.00473	.0007	.0001
	(.02808)	(.0086)	(.0254)	(.0094)	(.0320)	(.0058)
<b>Wife employed in:</b>						
White-collar	.3783	.1155	-.2283	-.0848	-.1186	-.0213
	(.1826)	(.0552)	(.1711)	(.0633)	(.2219)	(.0399)
Blue-collar	.1052	.0321	.0624	.02318	-.2602	-.0468
	(.1436)	(.0438)	(.1286)	(.0477)	(.1597)	(.0287)

**Table 5: Transition Frequencies between Employment Statuses**

**A. Women's Employment Transitions**

Occupation at $t$	Occupation at $t + 1$				
	Non-Empl.	White Collar	Blue Collar, FT	Blue Collar, PT	Total
Non-employment	642 (63.13)	52 (5.11)	245 (24.09)	78 (7.67)	1,017 (100.0)
White-collar	7 (2.12)	318 (96.66)	4 (1.22)	0 (0.00)	329 (100.0)
Blue-collar, FT	73 (6.21)	8 (0.68)	1,084 (92.17)	11 (0.94)	1,176 (100.0)
Blue-collar, PT	22 (8.21)	7 (2.61)	22 (8.21)	217 (80.97)	268 (100.0)

**B. Men's Employment Transitions**

Occupation at $t$	Occupation at $t + 1$			
	Non-Empl.	White Collar	Blue Collar	Total
Non-employment	481 (46.16)	112 (10.75)	449 (43.09)	1,042 (100.0)
White-collar	16 (1.69)	925 (97.78)	5 (0.53)	946 (100.0)
Blue-collar	144 (5.72)	57 (2.26)	2,318 (92.02)	2,519 (100.0)

**Table 6: Distribution of Employment Status by Semester****A. Actual**

Employment Status	Semester									
	1	2	3	4	5	6	7	8	9	10
Non-employed	.864	.498	.341	.303	.252	.220	.188	.170	.120	.097
White-collar	.015	.053	.076	.103	.141	.157	.173	.198	.187	.194
Blue-collar - FT	.090	.349	.474	.480	.496	.498	.527	.518	.582	.602
Blue-collar - PT	.031	.100	.109	.114	.111	.125	.112	.114	.111	.107

**B. Predicted**

Employment Status	Semester									
	1	2	3	4	5	6	7	8	9	10
Non-employed	.858	.563	.410	.320	.253	.205	.180	.151	.112	.097
White-collar	.014	.035	.059	.078	.096	.108	.129	.150	.215	.219
Blue-collar - FT	.098	.315	.422	.484	.526	.559	.566	.575	.566	.574
Blue-collar - PT	.031	.088	.109	.118	.126	.129	.126	.123	.107	.110

**Table 7: Work Location for White-Collar Workers by Semester****A. actual**

Region	Semester										Mean
	1	2	3	4	5	6	7	8	9	10	
Tel Aviv	.000	.263	.297	.314	.311	.326	.304	.292	.256	.333	.303
Sharon	.000	.158	.074	.086	.089	.087	.087	.104	.163	.061	.097
Shfela	.200	.105	.222	.143	.111	.109	.109	.104	.070	.061	.111
Haifa	.200	.053	.037	.057	.089	.109	.174	.166	.186	.242	.135
Galilee	.400	.158	.185	.171	.133	.109	.087	.125	.139	.152	.135
Negev	.200	.263	.185	.200	.222	.195	.217	.188	.163	.121	.192
Jerusalem	.000	.000	.000	.029	.045	.065	.022	.021	.023	.030	.027

**B. Predicted**

Region	Semester										Mean
	1	2	3	4	5	6	7	8	9	10	
Tel Aviv	.361	.374	.354	.336	.309	.274	.240	.210	.194	.198	.259
Sharon	.078	.082	.093	.091	.082	.078	.070	.069	.068	.069	.077
Shfela	.136	.127	.139	.150	.167	.172	.191	.191	.205	.224	.181
Haifa	.174	.166	.161	.156	.155	.171	.183	.195	.176	.184	.174
Galilee	.087	.094	.088	.083	.085	.088	.097	.109	.114	.128	.101
Negev	.137	.132	.137	.156	.172	.181	.191	.201	.218	.180	.182
Jerusalem	.027	.025	.028	.028	.030	.035	.028	.025	.025	.017	.026

**Table 8: Work Location for Blue-Collar Workers by Semester****A. Actual**

Region	Semester										Mean
	1	2	3	4	5	6	7	8	9	10	
Tel Aviv	.160	.088	.097	.107	.098	.080	.051	.045	.044	.047	.078
Sharon	.140	.137	.142	.125	.098	.096	.113	.122	.116	.113	.120
Shfela	.280	.330	.314	.324	.328	.330	.362	.346	.355	.406	.339
Haifa	.060	.099	.102	.120	.108	.112	.119	.102	.087	.085	.105
Galilee	.180	.170	.137	.125	.152	.138	.158	.167	.174	.160	.153
Negev	.120	.094	.106	.102	.108	.143	.124	.135	.152	.123	.118
Jerusalem	.060	.082	.102	.097	.108	.101	.073	.083	.072	.066	.087

**B. Predicted**

Region	Semester										Mean
	1	2	3	4	5	6	7	8	9	10	
Tel Aviv	.034	.071	.103	.102	.103	.097	.070	.056	.038	.029	.075
Sharon	.136	.129	.139	.137	.107	.128	.128	.136	.114	.124	.127
Shfela	.271	.300	.304	.332	.327	.301	.314	.340	.344	.371	.326
Haifa	.136	.135	.119	.117	.112	.112	.122	.111	.106	.105	.116
Galilee	.203	.177	.160	.146	.150	.148	.186	.185	.189	.200	.170
Negev	.135	.141	.134	.112	.136	.138	.116	.123	.144	.114	.129
Jerusalem	.085	.047	.041	.054	.065	.076	.064	.049	.061	.057	.057

**Table 9: Residential-Work Location for White-Collar Worker (in %)****A. Actual**

Place of Residence	Work Location							
	Tel Aviv	Sharon	Shfela	Haifa	Galilee	Negev	Jerus.	Total
Tel Aviv	5.96	1.63	1.63	0.00	0.00	0.00	0.00	9.21
Sharon	2.17	6.50	0.00	0.00	0.00	0.00	0.00	8.67
Shfela	22.22	1.36	8.94	0.54	1.63	0.00	0.00	34.69
Haifa	0.00	0.27	0.00	6.50	2.17	0.00	0.00	8.94
Galilee	0.00	0.00	0.00	6.23	9.76	0.00	0.00	15.99
Negev	0.00	0.00	0.54	0.00	0.00	19.24	0.00	19.78
Jerusalem	0.00	0.00	0.00	0.00	0.00	0.00	2.71	2.71
Total	30.35	9.76	11.11	13.28	13.55	19.24	2.71	100.00

**B. Predicted**

Place of Residence	Work Location							
	Tel Aviv	Sharon	Shfela	Haifa	Galilee	Negev	Jerus.	Total
Tel Aviv	8.66	1.85	3.95	0.00	0.00	0.00	0.00	14.46
Sharon	10.26	5.22	0.09	0.16	0.01	0.00	0.00	15.75
Shfela	6.90	0.38	14.08	0.08	0.03	0.18	0.00	21.65
Haifa	0.00	0.18	0.00	12.91	1.79	0.00	0.00	14.88
Galilee	0.00	0.00	0.00	4.20	8.27	0.17	0.02	12.65
Negev	0.12	0.04	0.01	0.03	0.02	17.82	0.07	18.11
Jerusalem	0.00	0.00	0.01	0.00	0.00	0.01	2.48	2.50
Total	25.95	7.67	18.14	17.39	10.12	18.16	2.57	100.00

**Table 10: Labor Market Outcomes for Women’s and Men’s Counterfactuals**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Data	Data	LSM	ALSM	ALSM	LSM	ALSM
	Women	Men	Women	Men	Women <sup>25</sup>	Women <sup>26</sup>	Women <sup>27</sup>
Employment:							
Non-employed	34.4	21.7	36.7	21.7	29.0	26.5	25.4
White-collar	12.2	21.7	10.1	21.7	21.1	12.8	19.0
Blue-collar	53.4	56.6	53.2	56.6	50.0	60.7	55.6
Wage White-collar:							
Mean	3,227	4,991	3,259	5,097	3,186 <sup>28</sup>	4,600	4,890
Median	3,000	4,566	3,000	4,651	2,935	4,192	4,460
St. deviation	1,233	2,189	1,372	2,283	1,341	2,073	2192
Wage Blue-collar: Full-Time Job							
Mean	2,374	3,325	2,284	3,309	2,691 <sup>29</sup>	3,262	3,221
Median	2,200	3,037	2,116	2,999	2,491	2,987	2,913
St. deviation	836	1,276	939	1,522	1,180	1,403	1,462

**Table 11: Counterfactual Simulation - Random Allocation Occupational Choices**

Occupation	Data	Model	
		Base	Random
<b>A. Women</b>			
Non-employed	34.35	36.70	37.33
White-collar	12.21	10.09	13.35
Blue-collar, FT	43.48	43.08	39.78
Blue-collar, PT	9.96	10.13	9.54
<b>B. Men</b>			
Non-employed	21.68	21.66	25.81
White-collar	21.66	21.67	17.18
Blue-collar	56.67	56.67	57.01

<sup>25</sup>Wage, job arrival, job dismissals, type distribution and commuting costs parameters taken from women’s model

<sup>26</sup>Wage, job arrival, job dismissals and type’s distribution parameters taken from the men’s model

<sup>27</sup>All parameters except for tastes taken from the men’s model

<sup>28</sup>The average wage for the women who were predicted to work in the white-collar sectors also under the original LSM is 3,303.

<sup>29</sup>The average wage for the women who were predicted to work full-time in the blue-collar sectors also under the original LSM is 2,769.

**Table 12: Counterfactual Simulation - Random Allocation Wages**

Wage Statistics	Data		Model			
	White	Blue	Base		Random	
			White	Blue	White	Blue
<b>A. Women</b>						
Mean	3,227	2,170	3,259	2,073	3,326	2,022
Median	3,000	2,000	3,000	1,908	3,053	1,847
St. deviation	1,233	917	1,372	982	1,414	973
<b>B. Men</b>						
Mean	4,955	3,298	5,097	3,309	4,831	3,150
Median	4,561	3,037	4,651	2,299	4,401	2,868
St. deviation	2,172	1,266	2,283	1,522	2,174	1,411

**Table 13: Random Allocation Counterfactual Simulation - Wage Statistics**

Choice under Original Model		Choice under Random Allocation							
		Non-Emp.		White-Collar		Blue-Collar FT		Blue-Collar PT	
		Base model	Random simul.	Base model	Random simul.	Base model	Random simul.	Base model	Random simul.
<b>A. Women</b>									
1.	Non-Employed	-	-	-	3,201	-	2,057	-	990
2.	White	3,051	-	3,379	3,445	3,233	2,143	3,291	1,004
3.	Blue, FT	2,144	-	2,270	3,295	2,323	2,293	2,395	1,094
4.	Blue, PT	1,031	-	1,091	3,396	1,108	2,380	1,120	1,132
<b>B. Men</b>									
1.	Non-Employed	-	-	-	4,663	-	2,986		
2.	White	4,913	-	5,280	5,023	5,040	3,269		
3.	Blue, FT	3,146	-	3,434	4,738	3,290	3,115		

Figure 1: Occupational Choices for Men and Women

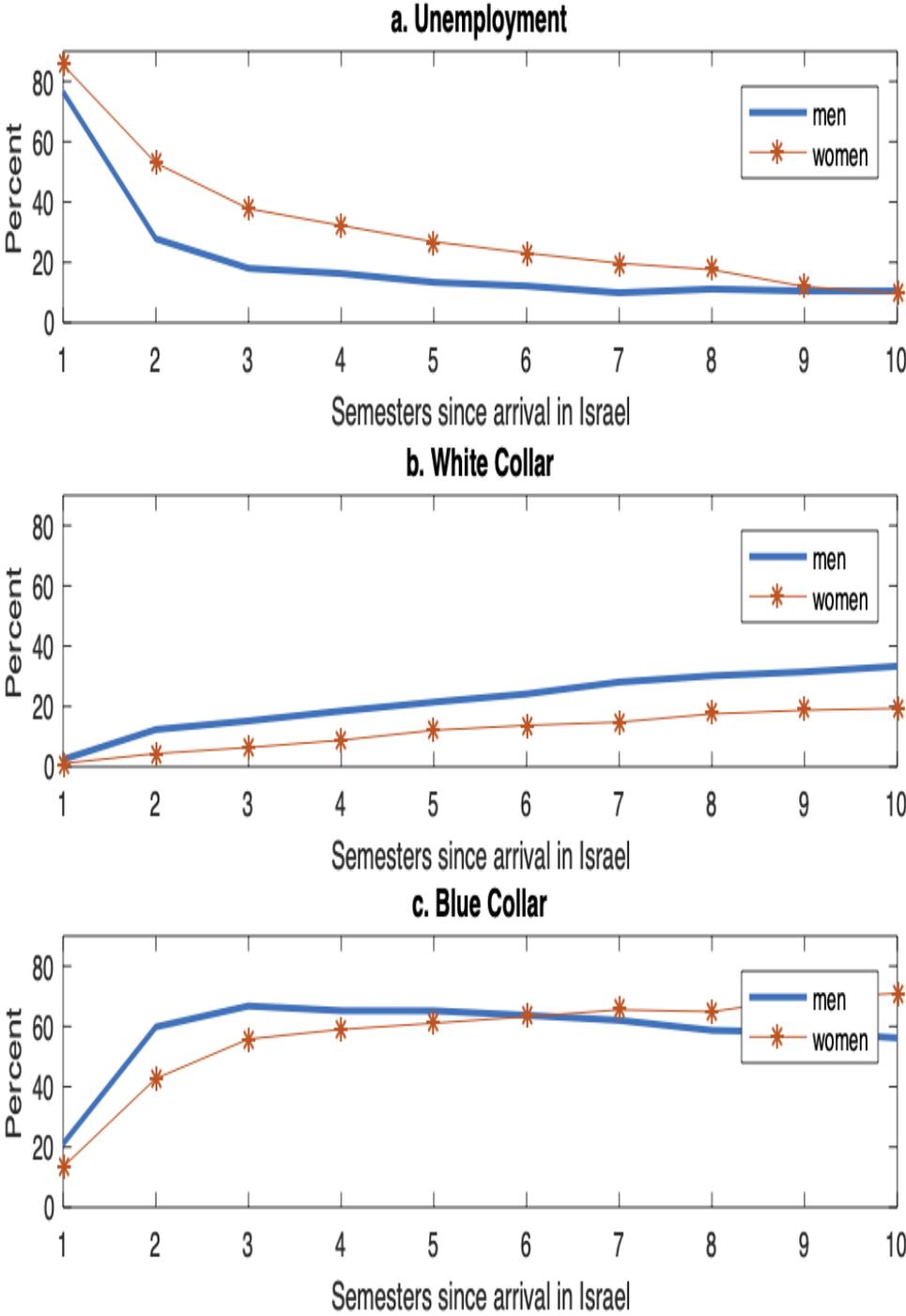
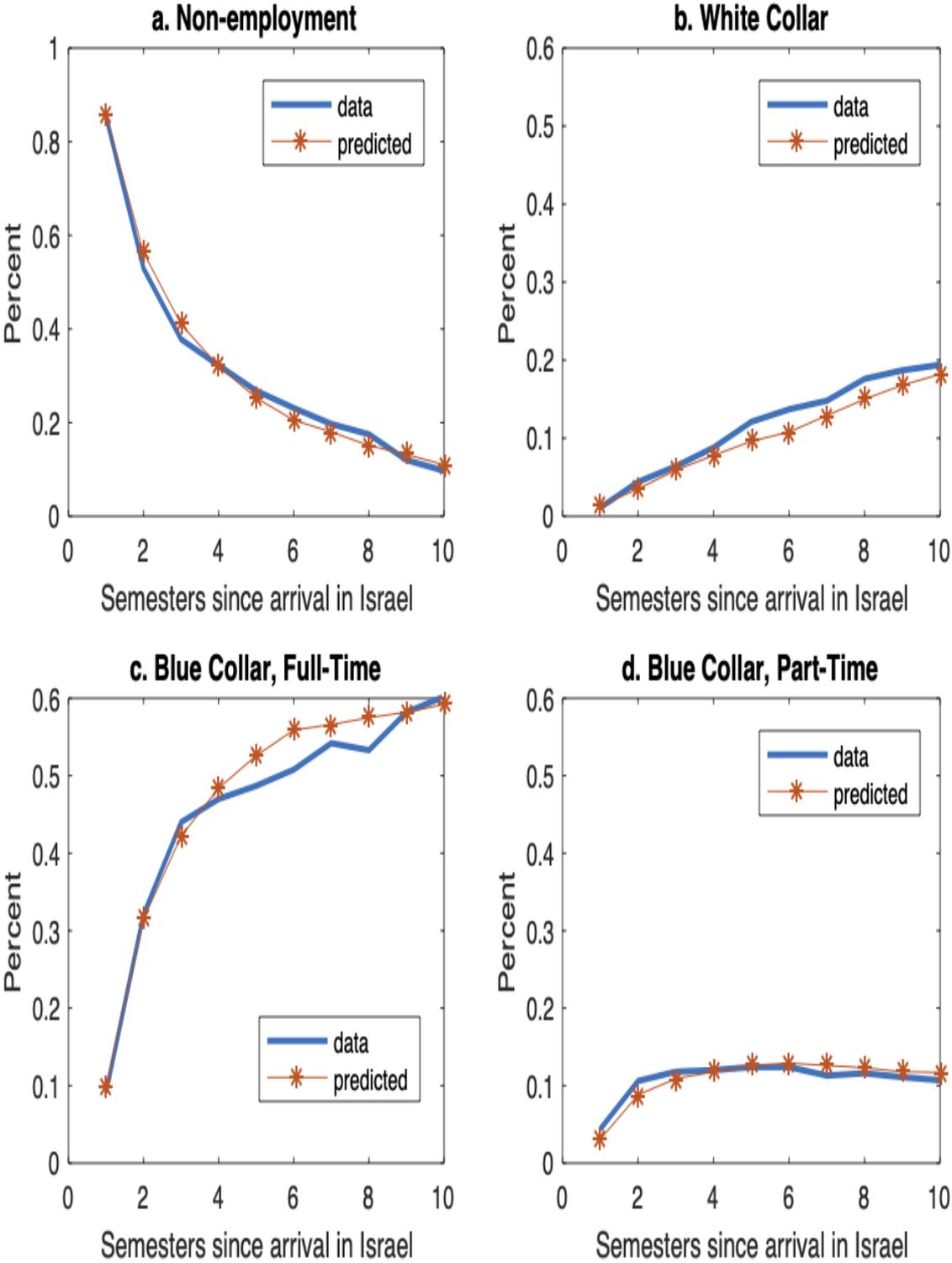


Figure 2: Distribution of Employment Status, By Semester



# Appendix A–Labor Supply Model (LSM) for Women

**Table A.1: Utility of Non-Employment**

No.	Variable	Estimate	St. Err.						
Value of non-employment, $b_r(\varepsilon_{i1rt})$ :									
$b_{1r}$ (for t=1)									
1	Tel Aviv	2,351	491.3						
2	Sharon	493	91.2						
3	Shfela	2,704	43.8						
4	Haifa	1,789	384.9						
5	Galilee	1,113	205.1						
6	Negev	1,179	19.3						
7	Jerusalem	8.142	528.8						
$\sigma_{\varepsilon_1}^2$									
8.	All regions	3.3	.002						

**Table A.2: Utility from Employment in the White-Collar Occupation**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Log wage, $\ln w_{j2rit}(x_i, x_{i2t})$ :									
		$\beta_{02r}$							
1	Tel Aviv	7.852	.024						
2	Sharon	7.777	.012						
3	Shfela	7.894	.013						
4	Haifa	7.857	.002						
5	Galilee	7.640	.012						
6	Negev	As in 2	-						
7	Jerusalem	As in 2	-						
<hr/>									
		$\beta_{12}(\text{for } S=15,16)$		$\beta_{22}(\text{for } S>16)$		$\beta_{32}$			
8	All regions	.044	.827	.128	.034	-.324	.0022		
<hr/>									
		$\beta_{42}$		$\beta_{52}$		$\beta_{62}$		$\beta_{72}$	
9	All regions	.035	.0008	-.167	.104	.147	.002	-.236	.000
<hr/>									
Traveling costs $tc(r, r')$ :									
		$tc_1$		$tc_2$		$tc_3$		$tc_4$	
10	All regions	8,370	305.1	322,948	10,332.6	72,596	8250.1	14,696	.7
<hr/>									
Error structure:									
		$\rho_2$		$\sigma_{v_2}^2$					
11	All regions	.620	.054	.325	.034				
<hr/>									

$$\ln w_{2rit}(x_i, x_{i2t}) = \beta_{20r} + \beta_{21}I(S_i = 15, 16) + \beta_{22}I(S_i > 16) + \beta_{32}x_{0i} + \beta_{42}x_{i2t} + \beta_{52}I(\text{age}_i \geq 40) + \beta_{62}TP_{1i} + \beta_{72}TP_{2i} + \epsilon_{2rit},$$

$$\epsilon_{2rit} = \rho_2 \epsilon_{2rit-1} + \nu_{2rti},$$

$$TC_1 = TC_{1,2}, TC_{1,3}, \quad TC_2 = TC_{1,4} = TC_{1,5}, TC_{1,6}, TC_{1,7}, TC_{2,5}, TC_{2,6}, TC_{2,7}, \\ , TC_{3,4}, TC_{3,5}, TC_{3,6}, TC_{3,7}, TC_{4,6}, TC_{4,7}, TC_{5,6}, TC_{5,7}, TC_{6,7},$$

$$TC_3 = TC_{2,3}, TC_{2,4}, \quad TC_4 = TC_{4,5}.$$

**Table A.3: Utility from Employment in the Blue-Collar Occupation**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Log wage, $\ln w_{j3rit}(x_i, x_{i3t})$ :							
$\beta_{03}$							
1	Tel Aviv	7.384	.018				
2	Sharon	7.532	.001				
3	Shfela	7.471	.022				
4	Haifa	7.670	.001				
5	Galilee	7.449	.289				
6	Negev	7.434	.036				
7	Jerusalem	7.369	2.257				
$\beta_{13}(for S = 15, 16)$ $\beta_{23}(for S > 16)$ $\beta_{33}$							
8	All regions	.012	.003	.024	.024	.039	.088
$\beta_{43}$ $\beta_{53}$							
9	All regions	-.152	.001	.299	.010		
$\psi$							
10	Part-time fraction	.626	.030				
Error structure:							
$\rho_3$ $\sigma_{V_3}^2$							
101	All regions	.627	.000	.248	.006		

$\tau_r(x_i, \mu_{ir})$ : As in table A.1,  $hc_{trj}(x_i)$ : as in table A.1,

$$\ln w_{3rit}(x_i, x_{i3t}) = \beta_{03r} + \beta_{13}I(S = 15, 16) + \beta_{23}I(S > 16) + \beta_{33}x_{i3t} \\ + \beta_{43}TP_{1i} + \beta_{53}TP_{2i} + \epsilon_{3rit}.$$

**Table A.4: Probability of Job Loss , by Type**

No.	Occupation	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
		$\eta_k$ of Type 0		$\eta_k$ of Type 1		$\eta_k$ of Type 2	
1	White-collar	-5.374	1.668	-7.613	.087	-5.158	.378
	Implied Prob.	.0046		.0005		.0057	
2	Blue-collar	-1.174	0.003	Same as above		Same as above	
	Implied Prob.	.2361		Same as above		Same as above	

$\Lambda_{kj} = \exp(\eta_{kj}) / (1 + \exp(\eta_{kj}))$  for  $k=1,2$ ;  $j=1,2,3$ .

**Table A.5: Probability of Job Arrival , by Type**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
		White-Collar, $\gamma_{02r}$		Blue-Collar, $\gamma_{03r}$			
1	Tel Aviv	-3.287	.060	.434	.015		
2	Sharon	-4.384	.301	.716	.050		
3	Shfela	-4.408	.094	.855	.016		
4	Haifa	-3.844	.630	.426	.004		
5	Galilee	-4.508	1.878	1.201	.030		
6	Negev	-2.965	1.474	.477	.021		
7	Jerusalem	-4.296	.972	.377	.025		
		$\lambda_1$		$\lambda_2$		$\lambda_3$	
8	White-Collar	.011	.000	.018	.004	-.031	.000
9	Blue-Collar	-	-	-	-	-	-
		$\lambda_4$		$\lambda_5$		$\lambda_6$	
10	White-Collar	-.037	.057	.089	.000	.376	.002
11	Blue-Collar - FT	-.0 037	.000	-	-	.177	.071
12	Blue-Collar - PT	-.066	.003	-	-	-.077	.000
		$\lambda_7$		$\lambda_8$		$\lambda_9$	
13	White-Collar	-0.028	0.001	1.710	.050	-2.086	.105
14	Blue-Collar	0	-	-1.140	.052	1.118	.080
		White-Collar $\psi$		Blue-Collar $\psi$			
15	$\psi$ (from $\psi P_{krit}$ ) for t=1	.395	.000	.405	.017		

$$P_{kirt} = \psi_k \exp(A_{kirt}) / (1 + \exp(A_{kirt})), \quad \text{if } t=1$$

$$P_{kirt} = \exp(A_{kirt}) / (1 + \exp(A_{kirt})), \quad \text{otherwise.}$$

$$A_{kirt} = \lambda_{0kr} + \lambda_{1k=1} I(S = 15, 16) + \lambda_{2k=1} I(S > 16) + \lambda_{3k=1} I(\text{Non-empat}_{t-1}) \\ + \lambda_{4k}(\text{age at arrival}) + \lambda_{5k=1}(\text{Exp. as eng. in FSU}) + \lambda_{6k}t + \lambda_{7k}t^2 + \lambda_{8k}TP_{1i} + \lambda_{9k}TP_{2i}$$

**Table A.6: Type-specific parameters and moving costs**

		Type 0		Type 1		Type 2	
		Estimate	St. Error	Estimate	St. Error	Estimate	St. Error
1	$\varphi_0$	0	-	-1.328	.137	1.404	.051
2	$\varphi_1$	0	-	1.363	.166	-1.959	.026
3	$\varphi_2$	0	-	3.901	.132	-.510	.000

$$\pi_j = \Pr(\text{Type } j) = \exp(B_j) / (1 + \exp(B_1) + \exp(B_2)), \quad j = 0, 1, 2,$$

$$B_j = \phi_{1j} + \phi_{2j}I(W_S = 15, 16) + \phi_{3j}I(H_S > 16)$$

**Implied type probabilities by husband education**

		Type 0	Type 1	Type 2
Husband education:				
	Less than 15	.187	.050	.763
	15 or 16	.383	.397	.220
	17 or more	.060	.792	.148

**Table A.7: Other Parameters**

		Estimate	St. Err.
Standard deviation of measurement errors:			
1	Wages	.377	26.6
Base classification error rate:			
2	Parameter, $\vartheta$	.754	.036
	Implied probability	.679	

$c = \exp(\vartheta)/(1 + \exp(\vartheta)) = .680 = 1\text{-classification error.}$

The wage punishment parameter estimate is zero.

# Appendix B–Augmented Labor Supply Model (ALSM) for Men

**Table B.1: Utility of Non-Employment**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Value of non-employment, $b_r(\varepsilon_{i1rt})$ :									
$b_{1r}$ (for $t=1$ )									
1	Tel Aviv	1,654	191						
2	Sharon	1,360	9.4						
3	Shfela	1,817	1.5						
4	Haifa	2,881	4.7						
5	Galilee	3,325	5.3						
6	Negev	2,287	2.0						
7	Jerusalem	7,467	8.6						
Taste For Residential location, $\tau_r(x_i, \mu_{ri})$ :									
		$\tau_0$		$\tau_1$		$\tau_2$		$\tau_3$	
8	Tel Aviv	0	-	0	-	0	-	0	-
9	Sharon	8,281	452.5	-3,394	2.3	-3,257	5.4	-5,308	4.8
10	Shfela	8,748	23.5	-5,113	2.5	2,251	2.8	-4,796	49.7
11	Haifa	-243	0.9	2,624	24.8	7,444	26.5	2,301	3.4
12	Galilee	3,597	7.0	-3,159	2.1	5,140	19.3	-1,909	8.9
13	Negev	-5,924	75.7	4,945	3.4	12,143	10.3	8,211	13.7
14	Jerusalem	0	-	0	-	0	-	0	-
Housing cost, $hc_{trj}(x_i)$ :									
		$\gamma_0$		$rp$					
15	Tel Aviv	7.024	.010	.057	.001				
16	Sharon	6.985	.027	.045	.000				
17	Shfela	6.891	.013	.045	.000				
18	Haifa	6.638	.003	.064	.000				
19	Galilee	6.305	.004	.033	.015				
20	Negev	5.817	.001	.026	.000				
21	Jerusalem	6.875	.002	.053	.000				
		$\gamma_1$		$\gamma_2$		$\gamma_3$			
22	All Regions	.051	.000	.172	.000	.388	.0000		
		$\sigma_{\varepsilon_1}^2$							
23	All regions	7.2	.002						

$$u_{i1rt} = b_r(\varepsilon_{i1rt}) + \tau_r(x_i, \mu_{it}) - hc_{trj}(x_i) - \gamma_j I(r_t \neq r_{t-1}),$$

$$b_r(\varepsilon_{i1rt}) = b_{1r} I(t = 1) + \exp(\varepsilon_{i1rt}),$$

$$\tau_r(x_i, \mu_{ri}) = \tau_r^1(\mu_{ir}) + \tau_r^2(x_i), \quad \tau_r^1(\mu_{ir}) = \tau_{0r} + \tau_{1r} R_{1i} + \tau_{2r} R_{2i} + \tau_{3r} R_{3i},$$

$$hc_{trj}(x_i) = 6 * \exp(\gamma_{0r} + \gamma_1 NK_i + \gamma_2 TP_{1i} + \gamma_3 TP_{2i}) / (1 + rp_r)^{T-t}.$$

For brevity, we do not report the estimate for  $\tau_{4,r}$  from  $\tau_r^2(x_i)$  in (9).

**Table B.2: Utility from Employment in the White-Collar Occupation**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.	Estimate	St.
Log wage, $\ln w_{j2rit}(x_i, x_{i2t})$ :									Err.
		$\beta_{02r}$							
1	Tel Aviv	8.243	.003						
2	Sharon	7.925	.002						
3	Shfela	8.165	.012						
4	Haifa	8.227	.010						
5	Galilee	8.266	.006						
6	Negev	7.960	.005						
7	Jerusalem	8.081	.001						
		$\beta_{12}(\text{for } S=15,16)$		$\beta_{22}(\text{for } S>16)$		$\beta_{32}$		$\beta_{42}$	
8	All regions	.036	.0000	.036	.0000	-.005	.0000	.036.	00000
		$\beta_{52}$		$\beta_{62}$		$\beta_{72}$		$\beta_{82}$	
9	All regions	-.00001	.00000	-.111	.000	.128	.0000	-.180	.0000
Traveling costs $tc(r, r')$ :									
		$tc_1$		$tc_2$		$tc_3$			
10	All regions	7,085	2	81,543	103	20,006	18		
Error structure:									
		$\rho_2$		$\sigma_{v_2}^2$					
11	All regions	.554	.020	.354	.000				

$\tau_r(x_i, \mu_{ir})$ : As in Table B.1,  $hc_{trj}(x_i)$ : as in Table B.1,

$u_{ikrt} = 6*(w_{krt}(x_i, x_{ikt})e^{\epsilon_{krt}} + \tau_r(x_i, \mu_{ir}) - hc_{trj}(x_i) - \gamma_j I(r_t \neq r_{t-1}) - tc(r, r'))$  for  $k = 2$ .

$\ln w_{2rit}(x_i, x_{i2t}) = \beta_{02r} + \beta_{12}I(S_i = 15, 16) + \beta_{22}I(S_i > 16) + \beta_{32}x_{oi} + \beta_{42}x_{i2t} + \beta_{52}x_{i2t}^2 + \beta_{62}I(\text{age}_i \geq 40) + \beta_{72}TP_{1i} + \beta_{82}TP_{2i} + \epsilon_{2rit}$ ,

$\epsilon_{2rit} = \rho_2 \epsilon_{2rit-1} + \nu_{2rti}$ ,

$TC_1 = TC_{1,2}, TC_{1,3}, TC_2 = TC_{1,4} = TC_{1,5}, TC_{1,6}, TC_{2,5}, TC_{2,6}, TC_{2,7}, TC_{3,4}, TC_{4,5}, TC_{3,5}, TC_{3,6}, TC_{3,7}, TC_{4,6}, TC_{4,7}, TC_{5,6}, TC_{5,7}, TC_{6,7}$ ,

$TC_3 =$

$TC_{2,3}, TC_{2,4}$ ,

**Table B.3: Utility from Employment in the Blue-Collar Occupation**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Log wage, $\ln w_{j3rit}(x_i, x_{i3t}) :$							
$\beta_{03}$							
1	Tel Aviv	7.780	.000				
2	Sharon	7.732	.074				
3	Shfela	7.812	.004				
4	Haifa	7.810	.008				
5	Galilee	7.821	.003				
6	Negev	7.807	.005				
7	Jerusalem	7.822	.066				
<hr/>							
$\beta_{13}(\text{for } S=15,16)$ $\beta_{23}(\text{for } S>16)$ $\beta_{33}$							
8	All regions	.032	.000	.031	.000	.031	.000
<hr/>							
$\beta_{43}$ $\beta_{53}$ $\beta_{63}$							
9	All regions	-.0000001	.0000000	-.104	.000	.294	.000

Error structure:

$\rho_3$ $\sigma_{V_3}^2$							
11	All regions	.578	.206	.299	.000		

$\tau_r(x_i, \mu_{ir})$ : As in Table B.1,  $h_{ctrj}(x_i)$ : as in Table B.1,  
 $\ln w_{3rit}(x_i, x_{i3t}) = \beta_{03r} + \beta_{13}I(S=15,16) + \beta_{23}I(S>16) + \beta_{33}x_{i3t} + \beta_{43}x_{i3t}^2$   
 $+ \beta_{53}TP_{1i} + \beta_{63}TP_{2i} + \epsilon_{3rit}$ .

**Table B.4: Probability of Job Loss , by Type**

No.	Occupation	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
		$\eta_k$ of Type 0		$\eta_k$ of Type 1		$\eta_k$ of Type 2	
1	White-collar	-5.662	.002	-9.015	.372	-4.311	.014
	Implied Prob.	.0035		.0001		.0132	
2	Blue-collar	-5.133	.002	Same as above		Same as above	
	Implied Prob.	.0059		Same as above		Same as above	

$\Lambda_{kj} = \exp(\eta_{kj}) / (1 + \exp(\eta_{kj}))$  for  $k=1,2; j=1,2,3$ .

**Table B.5: Probability of Job Arrival , by Type**

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
		White-Collar, $\gamma_{02r}$		Blue-Collar, $\gamma_{03r}$			
1	Tel Aviv	-3.986	.001	2.506	.001		
2	Sharon	-4.411	.004	1.434	.000		
3	Shfela	-3.862	.001	1.911	.001		
4	Haifa	-3.788	1.118	2.178	.001		
5	Galilee	-4.006	.594	1.883	.006		
6	Negev	-3.012	.008	2.083	.046		
7	Jerusalem	-3.546	.091	3.135	.008		
		$\lambda_1$		$\lambda_2$		$\lambda_3$	
8	White-Collar	.047	.000	.044	.000	0.998	.000
9	Blue-Collar	-	-	-	-	-	-
		$\lambda_4$		$\lambda_5$		$\lambda_6$	
10	White-Collar	-.0370	.000	.167	.000	-.013	.000
11	Blue-Collar	-	-	.099	.000	-.000	.000
		$\lambda_7$		$\lambda_8$			
12	White-Collar	1.817	.001	1.078	.023		
13	Blue-Collar	-1.372	.001	.687	.001		
		White-Collar $\psi$		Blue-Collar $\psi_0$			
14	$\psi$ (from $\psi P_{krit}$ ) for t=1	.053	.010	.070	.000		

$$P_{kirt} = \psi_k \exp(A_{kirt}) / (1 + \exp(A_{kirt})), \quad \text{if } t=1$$

$$P_{kirt} = \exp(A_{kirt}) / (1 + \exp(A_{kirt})), \quad \text{otherwise.}$$

$$A_{kirt} = \lambda_{0kr} + \lambda_{1k=2} I(S = 15, 16) + \lambda_{2k=2} I(S > 16) + \lambda_{3k=2} I(Non - emp_{t-1}) \\ + \lambda_{4k}(\text{age at arrival}) + \lambda_{5k}t + \lambda_{6k}t^2 + \lambda_{7k}TP_{1i} + \lambda_{8k}TP_{2i}$$

**Table B.6: Type-specific parameters and moving costs**

		Type 0		Type 1		Type 2	
		Estimate	St. Error	Estimate	St. Error	Estimate	St. Error
1	$\varphi_0$	0	-	1.979	0.03	1.315	.001
2	$\varphi_1$	0	-	0.129	.003	0.081	.001
3	$\varphi_2$	0	-	0.112	.003	-0.212	.003
4	Moving costs-all regions	90,712	26.8	101,534	13.8	46,370	16.1

$$\pi_j = Pr(\text{Type } j) = \frac{\exp(B_j)}{1 + \exp(B_1) + \exp(B_2)}, \quad j = 0, 1, 2,$$

$$B_j = \phi_{1j} + \phi_{2j}I(W_S = 15, 16) + \phi_{3j}I(W_S > 16).$$

**Implied type probabilities by wife education**

		Type 0	Type 1	Type 2
Wife education				
	Less than 15	.084	.605	.311
	15 or 16	.075	.620	.305
	17 or more	.082	.669	.249

**Table B.7: Other Parameters**

		Estimate	St. Err.
Standard deviation of measurement errors:			
1	Wages	.364	.002
2	Cost of housing ( $\kappa$ )	1.21	.001
Base classification error rate:			
3	Parameter, $\vartheta$	.764	.032
	Implied probability	.682	

$c = \exp(\vartheta)/(1 + \exp(\vartheta)) = .682 = 1 - \text{classification error}$ .  
The wage punishment parameter estimate is zero.