The Role of Women and Men in Choices of Residential and Work Locations in Israel

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Abstract

In this study we augment the comprehensive dynamic programing model developed in Buchinsky, Gotlibovski and Lifshitz (2014) with the necessary features that would allow us to examine the sample of women. The key goal of the paper is to identify and analyze the role of the wife in the decision making within the household, especially the impact of the decision making process on the vast differences in the outcomes for women and men. We use retrospective longitudinal data on immigrants who arrived in Israel from the Former Soviet Union (FSU) from 1989 through 1995. The results suggest that women and men take different responsibilities within the household, and thus the family concentrates on finding residential locations that are especially fit for utilizing the human capital of the husband rather than that of the wife. This family strategy leads to weak performances of the women in the labor market. A series of counterfactual simulations indicates that, given their observed characteristics, women could have gained a lot if they were to behave in a manner similar to their male counterparts. The labor market outcome gaps between the spouses is not a result of different levels of observed human capital. In fact, if the women were to behave and were treated in the marketplace like men, their labor market outcomes would have been better than those for men. According to a new index that we propose, we find that the female losses are on average about 60% of their current wages, namely, if the women were to choose the residential locations of the family their wages would increase by about 60% on average.

1 Introduction

There has been growing literature recently in economics regarding joint decisions within the family and in particular the role of the women (see the literature review). We concentrate our study on the of the choice of the place of residence, one of the most important choices made by families. We examine the role that each spouse plays in making this choice and the influence of this choice on their labor outcomes. While the structure of our data sets does not allow us to directly model the joint decisions in the family, we are able to drive implications that can be then tested by the data.

The study employs retrospective longitudinal data on immigrants who arrived in Israel from the Former Soviet Union (FSU) during the period from 1989 through 1995. We model and estimate the underlying decision making process regarding several choices, including the choice of residential location. This permits us to closely investigate the impact of this specific decision on the very pronounced gaps in employment opportunities and wages for male and female immigrants from the FSU in Israel.

In an earlier paper, i.e. Buchinsky, Gotlibovski and Lifshitz (2014) (hereafter BGL), we examined the migration patterns of male immigrants using the same data source. Despite the fact that most of the individuals in the sample were married, the sample provided very little information about the individuals' spouses. Therefore, it was absolutely necessary for us to assume that the key decision maker in the family is the husband (or that the family targets its residential location decisions toward the labor market outcomes of the husband), while the wife optimizes after the initial set of decisions (i.e., residential of the family and possibly the work location of the husband) has already been made. In general, the model in BGL provides very strong predictions. Moreover, the fitness of the model is exemplary.

Using a sequence of policy counterfactual simulations we examined in BGL the impact of the incentives that the Israeli government introduced in order to induce individuals to move to the northern and southern parts of Israel (the Galilee and the Negev, respectively). Nevertheless we were unable to address several important questions in that study. One important question that was left unanswered is: What is the role of women in the decision making process of the families of the new immigrants in Israel? Also, to what extent the family decisions evolve around the comparative advantages of the spouses in the Israeli labor market? Could the families in our sample have gained had they followed a different pattern of choices by the family? To what extent can the government influence the decisions of the families that would provide welfare gains for the individuals? In this study we concentrate our attention on examining the role of women in the family decision making process. We focus on the residential location decisions and assess the influence of these decisions on the labor market outcomes of the spouses. To do that we estimate two alternative models based on the sample of women and compare the results obtained to those obtained based on the sample for men.[1]

The model for women is an extension of on the comprehensive dynamic programming model developed in BGL. We augment that model with a number of necessary features in order to be able to address issues that are unique to the female labor force. We also consider a restricted version of the model in which women do not make the residential decision, but rather take it as given. We estimate both models using data similar to the one used in BGL, only for women rather than men. This is a retrospective longitudinal data set from a group of individuals that arrived in Israel in large numbers from the former Soviet Union (FSU) from 1989 to 1995.

According to this model, the individuals make optimal choices every period (six months) about: (a) residential location; (b) employment; and (c) the region of employment. In this model an individual can choose to work in one region and reside in a different region, but then he/she has to incur commuting costs. As in BGL, the model takes into account the potential effects of regional amenities, differences in regional prices, and existing social networks. We also incorporate stochastic job offers and job terminations. Additionally, we control for unobserved heterogeneity in manner similar to Keane and Wolpin (1997), namely through the presence of individual types.

The results of the estimation reveal that men and women behave quite differently, and thus the parameter estimates are quite different for the two groups. Moreover, as is explained in detail below, it seems that the most relevant model for women is what we call the *restricted model*, while the most relevant model for men is what we refer to as the *full model*. In BGL we made an explicit assumption that the family optimizes first with respect to the male. The results obtained in this study indeed confirm that assumption. The female optimization is indeed a restricted (or constrained) optimization that is made after the residential location of the family has already been made.

As mentioned above, a key goal of the paper is to identify and analyze the role of the female in the decision making within the household and especially the impact of the decision making process on the vast differences in the outcomes for women and men. Hence, the most important element of the paper is provided in several counterfactual simulations that we conduct. In these simulations we decompose and examine the overall differences between the outcomes of women and men. We use several alternative combinations of the model's parameters and data source, providing a comprehensive decomposition procedure that isolates the potential causes for the observed differences between women and men.

The simulations clearly show that labor market outcome gaps between the spouses is

[1]For men, we re-estimate the model for men discussed at length in BGL. We add few modifications to make the estimation for the male and female samples comparable. These are described in detail below.

not a result of different levels of observed human capital. Given the characteristics of the women in our sample, if they were to behave and were treated in the market place like men, their outcomes would have been better than those for men. On the other hand, these simulations and two other simulations that we conducted - (1) random allocation of the family's residential location; and (2) maximization of the wage stream instead of the utility - clearly indicate crucial differences for women and men in the the Israeli labor market. The results suggest that women and men take different responsibilities within the household, and thus the family concentrates on finding residential locations that are especially fit for utilizing the human capital of the husband rather than that of the wife. The simulation results also seem to indicate that the Israeli market is more favorable to men and thus gives the families the incentives to behave in the particular order described above.

This family strategy leads to weak performances of the women in the labor market. We propose an index that provides a measure for the magnitude of the labor market losses that women incur due to this strategy and find that their losses are on average about 60% relative to their current wages, namely, if the women were to choose the residential locations of the family, their wages would increase by about 60% on average.

The rest of the paper is organized as follows. In Section 2 of the paper we explain the data used in this study. In particular, we provide information about the specific features of the data sets for men and women, that give rise to the formulation of the current study. Section 3 provides a discussion of the literature on the labor market participation of women, and particularly of married women, that puts this study in context. Section 4 of the paper is devoted to a brief description of the base model and its various alternatives. In Section 5 of the paper we provide a detailed discussion of the results. We first discuss the parameter estimates. We then follow with a detailed examination of a number of important counter-factual simulations using the various estimated models for men and women, as well as the data for female introduced in this study and the data for men from used in BGL. Finally, Section 6 provides a summary and a few concluding remarks.

2 Data and Motivation

The data used in this study are similar to that used in BGL. The main difference is that while in BGL we used data for men only, here we extend the study to include women as well. Both data sets come from the same survey, namely a survey of all immigrants from the FSU who declared, upon arriving in Israel, that they trained and worked as engineers in the FSU. The survey was conducted by the Brookdale Institute of Jerusalem and targeted these individuals. The interviews were face-to-face and in Russian. A total of 1,432 male and female immigrants were interviewed between June and *December* of 1995. We restrict the analysis here to only female engineers between the ages of 25 and 55 at the time of arrival, yielding a sample of 529 immigrants. We specifically target this population in order to investigate the differences in choices between men and women and closely examine the potential reasons for these differences. In particular, we are able to draw some implications about the bargaining power in the family and assess the role of women and men in the decision making process.

During the survey, the individuals provided information about their occupational and educational background in the FSU. They also provided detailed information about a host of variables since their arrival in Israel. This allowed us to construct a continuous history of the immigrants residential location since the time of arrival. Table 1 displays selected descriptive statistics of the data extract we use in the estimation. The women's mean monthly earnings at the time of the survey (excluding the non-employed) are between 1,900 and 2,700 NIS, depending on the length of time since arrival in Israel.[2] The mean monthly housing costs at the time of the survey are about 1,000 NIS. About 60% of the individuals reported monthly housing costs on their privately owned homes.[3] The mean age of the immigrants upon arrival is about 43, with very high mean years of education of about 16 years, and significant labor market experience in the FSU of almost 15 years. About 77% the immigrants came from three republics: Ukraine, Belarus, or Russia. Also, while the sample is for the 1989-95 period, more than 50% of the immigrants in the sample arrived by 1991.

The occupational choices for the men (in BGL) and women were quite different despite the fact that they were all engineers in the FSU, and had very similar backgrounds. Figures 1a-1c depict the share of men and women in each of the three occupation categories. For both the men and the women the graphs are based on their respective data source. That is, the data for men are for the men engineers, while that for the women are for the women engineers.

Clearly, the patterns of employment are very different for the male and female engineers. First, the non-employment rate for the female sample is always above that for their male counterparts. Only by the ninth period, i.e., 4.5 years after arrival in Israel, the non-employment rates are equated. Second, the share of men employed in the white-collar occupation sector is larger than that for the women, with the gap increasing over time. By the tenth period, the share of men in a white-collar occupation is more than 10 percent-

[2]All earnings observations are in 1995, at which time the exchange rate was approximately three NIS per U.S. dollar.

[3]The monthly housing costs were constructed in similar fashion to BGL, that is: For those who reported rent on their housing unit, we take that rent as the housing costs. For all individuals that reported paying mortgage (obtained from the government) the housing costs are taken to be the mortgage payment.

age points higher than that of women. There are also some noticeable differences in the blue-collar sector. The fraction of women in that sector increases throughout the sample period, while the fraction for men decline toward the end. This is because for men there are some transitions from the blue-collar to the white-collar sector, but almost none for women. Also, while there is virtually no part-time employment of men in the the blue-collar sector, a significant number of women are engaged in only part-time work in the blue-collar sector.

Table 2 provides information of employment shares for women (Panel a) and men (Panel b) over the entire sample period, by the education level of their spouses. For women we again distinguish between full-time and part-time employment in the blue-collar sector. An important fact that is clear from Table 2 is that the conditional distribution of employment for women depends crucially on the husbands' education. In complete contrast, the conditional distribution for mens' employment is independent of their wives' education. Furthermore, the non-employment of men is lower than that of women across all levels of their spouse's education.

To examine whether the pattern of female employment described above is unique to the sample of immigrants, we provide in Table 3 the employment and wage distributions in 1995 (the same year in which the data about wages is collected in our sample) for native born Israelis and for the immigrants from the FSU that arrived since 1990. To make the sample as close as possible to the sample of engineers, we restrict attention to only families in which both spouses have at least 14 years of education. Comparison between the two samples shows similar employment patterns for the natives and new immigrants, and for both women and men. In general, there are fewer women in the white-collar sector despite having similar educational attainments as their male counterparts. Also, the relative wages for women and men are similar across the two samples. Clearly, the wages for men in both subsamples dominate those of women, with similar patterns of disparity between the men and women. Nevertheless, there is a much larger gap between the men's and women's wages in the white-collar occupations for the natives than for the immigrants. The similarities in the patterns of employment for the natives' and immigrants' samples indicate that the integration of the husband into the labor market is no more important for immigrants than for the natives. Nevertheless, the huge gap in earnings between the natives and immigrants may also indicate that the income effect may play a more dominant role for the native Israelis.

To further investigate the relative employment patterns for men and women we ran a few binary probit regressions where the dependent variables take the value one if the individual is in the employment status under consideration (i.e., unemployed, white-collar, and blue-collar) and takes the value zero otherwise. We summarize the results in the two panels of Table 4 (Panel a for women and Panel b for men).[4] In all the regressions we control for age, education of the spouse, and the sector of employment of the spouse (the omitted category for the spouse is non-employment). Clearly, there are major differences in the marginal effect of the spouse being in a particular employment status, even after controlling for the spouse's education. For example, a woman is a lot more likely to be unemployed, by almost 32 percentage points, if her husband is employed in a white-collar occupation and 26 percentage points more likely if her husband is employed in a blue-collar occupation. In complete contrast, whether the wife is employed in either a blue-collar or a white-collar occupation has little effect on the man's employment outcomes. This is likely to be a reflection of the fact that in order for the husband to accept a white-collar job and locate the family residence in a commutable distance from his workplace, the wife has to remain unemployed, at least for a while. This is a feature that we integrate into the model as is discussed further below.

Note also the strong positive sorting of marriage exhibited in the results; when one of the spouses is employed in a white-collar occupation, his/her spouse is also more likely to be employed in a white-collar occupation. Nevertheless, there are markedly different effects for men and women; the effect of the male on his spouse is larger than that of the female on her spouse. The impact of employment in a blue-collar occupation on the spouse's occupation is also quite distinct for men and women. The employment of a man in a blue-collar occupation has huge positive effect on his wife's likelihood of working in a blue-collar occupation. In contrast, the employment of a women in a blue-collar occupation has much smaller effect of the likelihood of employment of her husband in that occupation.

This all leads us to the unavoidable conclusion that there is great deal of asymmetry in the effect of the husband and wife on the outcome of the family as a whole, namely the choice of residential location and occupation. Nevertheless, it is not a-priori clear as to the source of these apparent differences. This may be a reflection of the fact that women and men face different returns to human capital in the labor market, or simply an artifact of the greater bargaining power of husbands relative to their wives. The results presented above seem to indicate that a typical family makes its choices largely based on the husbands' opportunities in the labor market. Consequently, the wife has a restricted choice set relative to that of her husband, that is, she makes her occupational choices only after the residential location has already been chosen.

We further investigate the source of this distinction between men and women by estimat-

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

ing a few alternative competing models. The results obtained shed new light on these very clear patterns in the data. We first address this issue by allowing the woman's choices to depend on the husband's characteristics. We also re-estimated the model for men of BGL, allowing the man's choices to have similar dependence on the characteristics of his wife. For both samples we also estimate restricted versions of the model, in which we assume that when the spouse's employment choices are made the spouse takes the residential location as given. That is, we abstract from the residential location decision, assuming that it has been made by the spouse. We then use the results of the estimated models in examining the validity of this assumption for each gender. Needless to say, the above assumption cannot hold for both the men and the women, so we determine in light of the results obtained for which of the genders it is more likely to hold. Detailed discussions of the results of the various alternative models are provided below.

In the two panels of Table 5 we provide the the transitions between employment statuses between period t and period $t + 1$ over the entire sample period. The results for the women are provided in Panel a of the table, while those for men are provided in Panel b. Again, we see very distinct patterns for men and women. Common to men and women is the fact that the fraction of individuals staying in a white-collar occupation, conditional on being in a white-collar occupation in the previous period, is over 95%. But these probabilities are quite different for the non-employment category. A man who is unemployed in a given period is less then 50% likely to be unemployed in the following period. For women, this conditional probability is about 15 percentage points higher. Also, a man employed in the blue-collar occupation in a given period is less likely to remain there in the following period relative to his female counterpart. The results of Table 5 seems to be indicative that the female labor market in Israel is quite different from that of their male counterparts. However, one should be cautious with this conclusion, as we only observe the eventual choice of the individuals and not their employment offers.

3 Literature Review

There are no papers in the literature that are directly related to what we do in this study. Importantly, there is no research that investigates the potential impacts of the decision making process within the family regarding residential locations on the labor market outcomes of the spouses. Nevertheless, there is a large number of papers in the literature addressing certain aspects that are related to labor force participation of women. There has certainly been significant interest in the literature addressing the joint work decisions and the differential behavior of men and women.

Johnson (2014) investigates the causal relationship between housing prices and labor force participation of married women. The correlation between housing prices and married women's labor force participation across metro areas in the U.S. is positive, namely areas with higher housing prices tend to have higher participation rates of married women in the labor market. Nevertheless, the direction of causation is far from being clear. It may very well be the case that having more two-earner households in a certain metro area has direct effect on housing prices. To examine this question, Johnson (2014) constructs an equilibrium model of metro area locations, labor supply and land prices in which there are two key predictions. First, metro areas with (exogenously) smaller buildable land will have higher housing prices and thus greater labor force participation of married women. Second, metro areas with exogenously more prone-to-work married women will also have higher housing prices. Using geographic instruments for housing supply, he finds little evidence of a positive effect of housing prices on the participation of married women in the labor force. Interestingly, he finds support for the hypothesis that markets with higher housing prices tend to also have higher earnings for both women and men. Instrumenting for married women's labor supply also leads to inclusive results, namely there is, at most, only weak evidence for a causal effect of two-earner households on housing prices.

An important aspect of the women's sample in our study is that they tend to accept part-time jobs. This phenomenon has been documented elsewhere in the literature (e.g. Lester (1996)) and is incorporated into our estimation through the specific choice of part-time blue-collar occupation. A paper closer in spirit to ours is that of Abe (2011), in which she builds a model of family labor supply and residential choices that explicitly allow for a choice between the full-time and part-time jobs for the women. The model intends to explain differential patterns of women's participation in full-time and part-time work across regions with close geographical proximity, but with very different in housing prices. The estimation of the model is based on data that come from the Tokyo metropolitan area. The results also indicate that the high commuting costs is likely to be one of the key impediments to women's full-time employment in Tokyo.

As becomes clear below, one of the the conclusions of our study is that households first choose their residential location based on the husband's employment opportunities, while the women seem to make a "constrained" choice, namely they make their occupational choices after the residential location has been made. Similarly, Sakanishi (2007) develops a model in which household location is determined by the husband's choice, while the wife makes her employment decisions, conditional on the husband's residential location decision.

A similar venue is pursued by Black, Kolesnikova and Taylor (2014), who investigate the relatively large variation in labor supply of married women across U.S. cities. In this paper, the authors focus largely on the differences in commuting times across cities in the U.S. as a potential explanation for the variation in married women employment. The paper makes no assumption about, and does not control for, the variation in housing prices. The results support the model's predictions, namely, labor force participation rates of married women are negatively correlated with the metropolitan area commuting time. Additional support is provided by the variation in employment growth over time. That is, the metropolitan areas with larger increases in commuting time between 1980 and 2000 also had slower growth in the labor force participation of married women.

Costa and Kahn (2000) examine the residential location of power couples. They find that power couples are increasingly located in large metropolitan areas. The percent of households with college educated couples in these metropolitan areas rose from 32% in 1940, to 50% by 1990. Most of this rise stems from the increased severity of the power couples problem, namely looking for two jobs. This is largely because the job opportunities in large cities are better, especially for the more highly educated households. Using a simple duration model on U.S. data, Pingle (2006) finds that, in fact, the likelihood of migration is substantially reduced the more equal are the labor incomes of the spouses.

Diamond (2016) also finds that the rise in the U.S. college-high school graduate wage gap during the period from 1980 to 2000 coincided with significant increase in geographic sorting. Most importantly, the college graduates are more concentrated in high wage, high rent cities. The divergence in the location choices of high and low skill workers from 1980 to 2000 was caused largely by the divergence in high and low skill productivity across space. Using a structurally estimated model she is able to explain the increase in skill sorting. She finds that skill sorting is largely due to the differential changes in local labor demands. This trend has been further amplified by the endogenous increases in amenities in cities that attracted more highly skilled labor. These changes have led low skilled workers to relocate to more affordable locations in which there were reduced amenities. Consequently, there was a dramatic increase in the overall welfare inequality between college and high school graduates.

Mok (2007) examines whether or not the residential location choices of two-earner households are based on the income of both spouses. The results indicate that the hypothesis that the decisions are based on both incomes is rejected for the childless families, but is not rejected for households with children. On the methodological side, the results illustrate the need for addressing intra-household dynamics when modeling location choices.

The residential choices and corresponding mobility decisions are investigated further in Stolpovsky (2015). This paper studies the decision making of couples regarding moving to a new location. She uses data from the PSID, for the period 1985-1991, to examine the well-known income pooling hypothesis. This hypothesis is clearly rejected for retired couples. It also stands on very shaky ground when the move considered is related to the consumption of the household in question. That is, the income pooling hypothesis is generally rejected.

In an ambitious study, Steele, Clarke and Washbrook (2013) consider a model in which married, or cohabiting, individuals make their decisions jointly. Specifically, they develop a general statistical framework with which they analyze both the individuals, as well as the joint decision making, using household panel data. Despite the innovative ideas proposed in this paper, it falls short of addressing the estimation problems that arises in structural the estimation considered here. Furthermore, it does not allow for the causal interpretation that we consider in the current paper.

Smits, Ultee and Lammere (1996) examine the effect of occupational status differences between spouses on the wife's employment choices and achievement using data from twelve European countries. They find that labor force participation of a woman is the highest when her occupational status is similar to that of her spouse. Even more interesting is the finding that the husband's occupation produces both a ceiling effect and a facilitating effect on the wife's occupational achievement. While the magnitude of the effect varies across countries, the results are qualitatively very similar. It is worth noting that both of these findings are consistent with the finding of our paper as is clear from the results presented below.

Inoa, Picard and de Palma (2014) consider the household residential location decision that involves several decision-makers. This is a difficult problem, especially for dual-earner households, when spouses happen to work at different locations. They note that despite the fact that this has become quite common in France (and elsewhere), there is almost no research devoted to resolving this joint decision process. Using a reduce-form approach, they find that differences in the values of commuting times for the spouses is a key factor in the intra-household decision process. They apply a method closely related to the collective approach for household decision process of Chiappori (1992) to model the residential location choices of dual-earner households.While the analysis falls short of estimating a fully structural model, the reduce-form analysis adopts flexible specifications using a three-nested Logit model.

The question regarding employment of women is an important issue world-wide. For example, Ogawa and Ermisch (1996) use data from Japan, and find similar patterns to the European countries. They find that younger married women are more likely to take full-time paid jobs, especially when there is a presence of parents or parents-in-law. This is a reflection of the more important role that women generally take in raising the children, a role that is relieved when the woman's parents or parents-in-law provide some help.

In an earlier paper Duleep and Sanders (1993) provide similar results. They find that immigrants to the U.S. from both European and Asian countries employ similar strategies, sending the husband to work first, in an attempt to invest in his human capital that is specific to the U.S. Women tend to work more in households where the husband does not earn enough to support the family. Tenn (2010) also investigates the role of the wife in the decision to migrate in more recent time, when there is generally greater attachment of women to the labor force. He finds that wives play only a marginal role in the family migration decision. The difficulty in balancing two careers simultaneously led households to focus primarily on the husband's career. This a very similar situation to the case in our study. This is also supported by the findings of Epstein and Heizler (2006) for Israel as well. They provide strong evidence that the men choose their jobs first, while the women tend to look for their jobs only after the family decided where to reside.

Fosu (2000) suggests that labor force participation preferences of married women vary significantly across regions of the U.S., providing some evidence to what he terms as regional "social economy." This also coincides with our finding, where employment of women varies considerably across the seven regions of Israel, despite the fact that Israel is quite small in size. The general question regarding the impact of the spatial distribution of employment on residential location is also addressed in Boustan and Margo (2009). While it does not directly address the employment of married women relative to that of married men, it gives rise to the notion of employment mismatch. That is, what may be a suitable place for the wife may not be the most suitable place for the husband and vice versa. A more general characterization of the changes in the labor force participation of married women is provided in the survey article of Juhn and Potter (2006).

The literature of labor force participation extends to fields other than economics and sociology. For example, it has become a topic of interest in the geography literature as well. In particular, Prashker, Shiftan, and Hershkovitch-Sarusi (2008), and Sermons and Koppelman (2001) provide thorough discussions on the role of socio-economic variables, family characteristics and differential values for commuting time for men and women, on residential location choices. Plaut (2006) analyzes the relationships between the commuting decisions of spouses in dual-income households. Again, the paper finds that the commuting distance is more sensitive to income for women than for men.

4 The Model

4.1 General Equilibrium versus Partial Equilibrium

As in BGL, the model we consider here is a partial equilibrium model in which housing prices and wages are taken to be exogenous. In BGL we provide ample support that this approach is indeed valid. An excellent summary for that view is expressed in Weiss (2000), who provides a good summary for the labor market in Israel during the period of the 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.*

As in BGL, we make no attempt to explain in the current paper the economy-wide response to the mass immigration from the FSU, but rather examine issues that are related to the choices of the families, investigating the female part of the population of immigrants. Specifically, our goal is to model the individual women's behavior, in face of wages and prices across the various regions of the country. The variability in wages and housing prices are the main sources that allow us to distinguish between the two behavioral models that are considered in this study. Furthermore, comparison of the results from the model estimated here with those previously obtained in BGL shed new light on the decision process within the family of the new immigrants and specifically the role of women and men in the family and the economy. Papers in the literature routinely assume that the man in the family decides first, while the woman simply optimizes after the residential location and the man's occupation decisions have already been made (e.g. Diamond (2016), BGL). Here we are able to better assess whether or not this is indeed true, and evaluate the welfare implications from such decision processes.

4.2 The Structure of the Full and Restricted Models

The model employed here is essentially the same as the one used in BGL, augmented with a few important features that are unique to the female population. We summarize below the *full* model and introduce the additional features. We then introduce the *restricted* model, which amounts to the full model with no choice of residential area. We then examine the models for both men and women in an attempt to determine how the family behaves within the Israeli housing and labor markets.

For the full model, we assume that the residential-work locations are determined by the female, subject to some characteristics of the male.[5] Each period (semester) the female immigrant maximizes the expected discounted present value of her utility until the age of 65 (the mandatory retirement age in Israel during the sample period) by choosing: (a) the region of residence; (b) the employment status; and (c) the region of employment. There are a total of seven regions (i.e., $R = 7$): Tel Aviv, Sharon, Shfela, Haifa, the Galilee, the Negev, and Jerusalem. The are four employment choices (i.e., $K = 4$): non-employment ($k = 1$), employment in white-collar ($k = 2$), employment as full-time in blue-collar ($k = 3$) and employment as part-time in blue-collar ($k = 4$) . In order to control for unobserved heterogeneity, we assume that there are ($J = 3$) fixed discrete types of individuals.[6] To capture the potential dependence on the male in the family we allow the type probabilities to depend on observed characteristics of the husband. All the model's parameters are generally allowed to vary by type.

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

$$u^{j}_{i1rt}\left(z_{it}, t\right) = \mathit{\Gamma}_l + b_{1r}\left(\varepsilon_{i1rt}\right) + \tau_r\left(x_{it}, \mu_{ir}\right) - hc_{trj}\left(x_{it}\right) - \gamma_j I\left(r_t \neq r_{t-1}\right), \tag{1}$$

where z_{it} denotes the individual's state vector at time t. The parameter Γ_l is the value of leisure for individuals who do not work at all. Here $b_{1r}\left(\varepsilon_{i1rt}\right)$, is the per-period consumption value of non-employment in region r, and is given by

$$b_{1r}\left(\varepsilon_{i1rt}\right) = b_{1r}\alpha_r I\left(t = 1\right) + \exp\left(\varepsilon_{i1rt}\right), \quad \text{for } t = 1, ..., T, \tag{2}$$

where $I\left(\cdot\right)$, and $b_{1r}\alpha_r I\left(t = 1\right)$ accounts for the fact that the first period differs systematically from all other periods in Israel.[7]

The second term in (1), $\tau_r\left(x_{it}, \mu_{ir}\right)$, represents the individual's per-period preference for residing in region r. It is a function of the individual's characteristics, and regional-specific characteristic, μ_{ir}, that captures the immigrant's valuation of regional amenities. In general, the republic of origin shifts the taste for residing in a particular region in Israel depending on the concentration of immigrants from the same republic already living there, i.e., the

[5]In BGL we assume for the full model that the decisions are all made by the male in the household. Needless to say, both assumptions cannot simultaneously hold. This is discussed at length below.

[6]Adding more than three types had virtually no effect on the explanatory power of the model.

[7]See BGL for a more detail explanation for this specification.

immigrant's network effects. The third term in (1), $hc_{trj}(x_{it})$, is the per-period total cost of housing in region r. The last term in (1), γ_j, is the individual type-specific moving costs from one region to another, if the individual were to change residential location between t and $t+1$. The term ε_{i1rt} is an i.i.d. white noise (see further explanation below).

Note that under the assumption that the family follow the male in determining the residential location, then γ_j cannot be identified, because the female simply takes the residential location as given and permanent. Any change of the residential location is random from the point of view of the female in the family. In this case, that is, under the restricted model, the per-period utility of non-employment is simply

$$u_{i1rt}^{j}(z_{it}, t) = \Gamma_l + b(\varepsilon_{i1rt}), \tag{3}$$

that is, the housing costs and taste for residing in region r cannot be identified.

The per-period value of working in the white-collar sector for individual i, of type j, who works in region r' and resides in region r, is given by

$$u_{i2rt}^{j}(z_{it}, t) = 6 \cdot w_{kr't}(x_i, x_{ikt})e^{\varepsilon_{i2r't}} + \tau_r(x_{it}, \mu_{ir}) - hc_{trj}(x_{it}) - \gamma_j I(r_t \neq r_{t-1}) - tc(r', r), \tag{4}$$

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 simply follows the well-known Mincer-type specification.[8] Note that the next three terms are identical to those in (1), while the last term takes into account the commuting cost in the event that the individual resides in region r and works in region r'.

For the restricted model the specification that can be identified is reduced to

$$u_{i2rt}^{j}(z_{it}, t) = 6 \cdot w_{kr't}(x_i, x_{ikt})e^{\varepsilon_{i2r't}} - tc(r', r), \tag{5}$$

that is, the female only chooses where to work and pays the commuting costs $tc(r', r)$ if she travels to region r' from her region of residence r.

The specification of the per-period utility in the the blue-collar occupations is similar to that of the white-collar, with two crucial changes. First, a blue-collar worker can only work in her place of residence. Second, it is possible for a blue-collar worker to work in a part-time job, an option that does not exist for those who choose to work in the white-collar occupations. Note that under part-time work, the worker has some benefit from leisure as well.

It is necessary for us to impose the first restriction since blue-collar workers were asked only about their place of residence.[9]

[8] The wage function is multiplied by 6 because earnings are reported monthly. A semester, the period in this study, consists of six months.

[9] As we explain in detail in BGL, this restriction is consistent with the results of Presman and

Hence, the per-period utility is given by

$$u^j_{i3rt}\left(z_{it},t\right)=6\cdot w_{3rt}(x_i,x_{i3t})e^{\varepsilon_{i3rt}}+\tau_r(x_{it},\mu_{ir})-hc_{trj}(x_{it})-\gamma_j I\left(r_t\neq r_{t-1}\right), \tag{6}$$

and

$$u^j_{i4rt}\left(z_{it},t\right)=\varphi\Gamma_l+6\cdot w_{4rt}(x_i,x_{i3t})e^{\varepsilon_{i4rt}}+\tau_r(x_{it},\mu_{ir})-hc_{trj}(x_{it})-\gamma_j I\left(r_t\neq r_{t-1}\right), \tag{7}$$

for the full-time and part-time jobs in the blue-collar occupation, respectively, with

$$w_{4rt}(x_i,x_{i3t})=\psi\cdot w_{3\mathrm{rt}}(x_i,x_{i3t}),$$

where ψ is the fraction of the deterministic part of the full-time wage paid to a part-time employee and φ is the fraction of the utility from leisure due to the fact that the individuals works in a part-time job. Also, the error terms for the two wages in the blue-collar occupations, i.e. ε_{i3rt} and ε_{i4rt} need not be the same.

Under the restricted model the two per-period components that can be identified are given by

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

and

$$u^j_{i4rt}\left(z_{it},t\right)=\varphi\Gamma_l+6\cdot w_{4rt}(x_i,x_{i3t})e^{\varepsilon_{i4rt}}-\gamma_j I\left(r_t\neq r_{t-1}\right).$$

As in the case of BGL, the state vector z_{it} consists of a number of predetermined variables, variables that change deterministically, and the set of stochastic elements. That is, $z_{it}=(x_i',x_{it}',\varepsilon_{it})$, where $\varepsilon_{it}=(\varepsilon_{i1rt},\varepsilon_{i2rt},\varepsilon_{i3rt},\varepsilon_{i4rt})$. The vector x_i includes all the variables known upon arrival from the FSU, that is: age, education, experience as engineer and the republic of residence. The vector x_{it} contains all the varying information.

The stochastic components ε_{i1rt}, ε_{i2rt}, ε_{i3rt}, and ε_{i4rt}, are assumed to be independent and identically distributed across regions and employment sectors. Nevertheless, within a sector of employment the stochastic terms are allowed to be serially correlated within the same region of employment, that is,

$$\varepsilon_{ikrt}=\rho\varepsilon_{ikrt-1}+\nu_{ikrt}, \tag{8}$$

Arnon (2006), who study the commuting patterns in Israel. We also note that in Israel women commute to their job significantly less than men, likely because of their more important role in other aspects of the household.

for $k = 2, 3,\ 4$ ν_{ikrt} is white noise. The $AR(1)$ coefficient ρ_k is allowed to differ across employment sectors, but it is constrained to be identical across regions.

It is important to note that we do not estimate the discount factor δ. We set the discount factor to be $\delta = .985$ per semester, which is equivalent to an annual discount rate of .97.[10]

Unlike in the BGL model, here we allow the type probabilities to vary with the education of the husband. That is, the probability of being of type j if the husband is in education level m is given by

$$p_j\left(d_m^{ed}\right) = exp\left(\phi_{0j} + \phi_{mj} d_m^{ed}\right) / \left(1 + exp\left(\phi_{0j} + \phi_{2j} d_2^{ed}\right) + exp\left(\phi_{0j} + \phi_{3j} d_3^{ed}\right)\right),$$

for $m = 1, 2, 3$, where the omitted category is that of education level 1, where d_m^{ed}, $m = 1, 2, 3$, are dummy variables that take the value one if the individual is at education level m , and zero otherwise.[11]

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 in which she worked at time $t-1$ is

$$P_{krt} = 1 - \lambda_{kr}, \quad \text{for } k = 2, 3, 4$$

where λ_{kr} denotes the involuntary dismissal probability given by,[12]

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

An individual may also receive offers in the other sectors and/or in any region. We specify these probabilities to be

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

where

$$\begin{aligned} A_{k'rit} = {} & \lambda_{0k'r'} + \lambda_{1k=2(S=15,16)} S_i + \lambda_{2k=2(s>16)} S_i + \lambda_{3k=2} I\left(\text{Non-emp at } t-1\right) + \lambda_{4k} \text{age}_i \\ & + \lambda_{5(k=2)} x_{oi}^{Eng} + \lambda_{6k} \text{time}_i + \lambda_{7k} TP_{1i} + \lambda_{8k} TP_{2i}, \end{aligned} \quad (9)$$

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[10] It is well known in the literature that estimating δ is problematic. We made no attempt to estimate it. We simply adopt a value for δ that is generally reported in the literature for similar applications.

[11] Education level 1 includes all the individuals with education level of up to 14 years, level 2 includes those with 15 or 16 years of education, while education level 3 includes all those with 17 or more years of education.

[12] In the estimation, we also allow the parameter η_k, and hence λ_{kr}, to vary by type.

age_i denotes the age upon arrival in Israel, S_i denotes the years of completed schooling in the FSU, time_i denotes the time since arrival, x_{oi}^{Eng} is the experience as an engineer that the individual accumulated in the the FSU, $TP_{ji} = 1$ 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 at any period an individual may receive a job offer from any of the regions and in any of employment sectors.

Note that under the restricted model an individual can search for a full-time or part-time job in the blue-collar sector only in her place of residence. She can, though, obtain offers from any of the seven regions in the white-collar sector.

4.3 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

$$\begin{aligned} \tau_r(x_{it}, \mu_{ri}) &= \tau_r^1(\mu_{ir}) + \tau_r^2(x_{it}), \quad \text{where} \\ \tau_r^1(\mu_{ri}) &= \tau_0 + \tau_{1r}R_{1i} + \tau_{2r}R_{2i} + \tau_{3r}R_{3i}, \\ \tau_r^2(x_{it}) &= \tau_{4r}M_i + \tau_{6r}M_iNK_i + \tau_{7r}M_i\text{age}_i, \end{aligned} \tag{10}$$

$M_i = 1$ if the immigrant is married in the last period, and $M_{it} = 0$, otherwise, NK_i is the number of children under 18 in the last period, and age_i denotes the age of the wife upon arrival in Israel. Finally $R_{li} = 1$, $l = 1, 2, 3$, for each of the three republics of the Ukraine, Belarus and Russia, respectively, and $R_{li} = 0$, otherwise.[13] The term $\tau_r^2(x_{it}, \mu_{ri})$ simply accounts for the taste of the individual to be in a particular region due to having a spouse and children.

As in BGL, the survey provides information on individuals, and only some basic information about the rest of the family including the spouse. Thus, we cannot explicitly model the joint decisions in the family, which would have been our preferred strategy. Nevertheless, in order to account for the possibility that the husband and children alter the individual's taste for residing in a specific region, we introduce the term $\tau_r^2(x_{it}, \mu_{ri})$. Note that, unlike the specification in BGL, we do not include the spouse's level of education, which was found to be statistically insignificant.

The housing costs in region r are specified exactly in the same fashion as that in BGL, namely a linear function of marital status, family size, and the unobserved discrete type,

[13] The excluded category is all other republics in the FSU. Hence the $\tau_{0r} = \tau_0 - (\tau_{01} + \tau_{02} + \tau_{03})$ corresponds to that category.

that is,

$$hc_{trj}(x_{it}) = 6 * \exp\left(\gamma_{0r} + \gamma_1 M_{it} + \gamma_2 NK_{it} + \gamma_3 TP_{1i} + \gamma_4 TP_{2i}\right) / \left(1 + rp_r\right)^{T-t}, \tag{11}$$

where $TP_{ji} = 1$, for $j = 1, 2$, if the individual is type j, and $TP_{ji} = 0$, otherwise. The excluded type is type 0. The terms rp_r are parameters that represent the per-period rate of price increases in region r, for $r = 1, ..., 7$. We introduce these parameters to account for the fact that housing prices continue to rise differentially across the regions of the country throughout the sample period.

The deterministic components of the wage offer functions in a white-collar occupation in region r is

$$\begin{aligned} \ln w_{j2rit}(x_i, x_{it}) = \beta_{0,2,r} + \beta_{1,2} S_i I\left(S_i = 15, 16\right) + \beta_{2,2} S_i I\left(S_i > 16\right) + \beta_{3,2} x_{0i} + \\ + \beta_{4,2} x_{ikt} + \beta_{5,2} I\left(\text{age}_i >= 40\right) + \beta_{6,2} TP_{1i} + \beta_{7,2k} TP_{2i}, \end{aligned} \tag{12}$$

while in a blue-collar occupation it is

$$\begin{aligned} \ln w_{j3rit}(x_i, x_{it}) &= \beta_{0,3,r} + \beta_{1,3} S_i I\left(S_i = 15, 16\right) + \beta_{2,3} S_i I\left(S_i > 16\right) + \\ &\quad + \beta_{3,3} x_{ikt} + \beta_{4,3} TP_{1i} + \beta_{5,3} TP_{2i}, \end{aligned}$$

where S_i is defined in (9), x_{0i} denotes the years of experience accumulated in the FSU, and x_{ikt} denotes the years of accumulated experience in Israel. We do allow for differential returns to education for those with less than 16 and those with more than 16 years of education.[14] The individual types are the same as in (11). Note that we control for unobserved heterogeneity in the wage functions in both sectors, as well as in the regional housing costs function. This allows for unrestricted correlations in the unobserved components of these functions. Finally, the moving costs are also specified to be type specific.

4.4 The Initial Conditions

Note that all the variables in the vector x_i are measured at the time of the immigrant's arrival in Israel. These include measures of human capital, age, occupation, experience as engineer and place of residence in the FSU. As is explained extensively in BGL, all the immigrants had to leave the FSU abruptly. The fact that they chose to go to Israel was motivated largely by the growing anti-Semitism in the FSU and the fact that Israel was one

[14]This is because the number of years of education is a reflection the engineering degree the individual holds.

of the very few countries that allowed them free entry.[15]

As Cohen and Haberfeld (2007) indicate, this essentially left the Jews in the FSU with no choice but to immigrate to Israel. Also, the window of opportunity to leave the FSU was viewed as short lived. Indeed, in our sample 70% of the immigrants arrived in Israel by 1992, and the remainder shortly thereafter. Thus, the usual initial conditions problem is of no consequence in our study. Hence, all the variables in x_i are treated as exogenous.[16] Also, a close investigation of our sample provides additional empirical evidence to this effect. We find that the distributions of all observed variables for the female population of immigrants are virtually identical over the various immigration years in the sample period. This indicates that, at least based on observed variables, there does not seem to be any selection bias introduced due to the exact timing of immigration to Israel.

5 The Results

5.1 The Parameter Estimates

We estimate the two versions of the model described in Section 1. We first estimate the *full model*, and then we estimate a restricted version of the full model, the *restricted model*, in which the residential location is taken as given. As noted above, under the latter model a woman only makes two choices, namely: employment and whether or not to commute. The parameter estimates for the full model are provided in Tables A.1 through A.7 of Appendix A. Appendix B presents Tables B.1 through B.7 for the restricted model.

The parameters in Table A.1 and Table B.1, are associated with the non-employment choice, for the full and restricted models, respectively.[17] The parameters for the value of non-employment in the first period after arriving in Israel, namely α_r, for $r = 1, ...7$, have the same order of magnitude for both the restricted model and the full model, with minor

[15]Even the United States, who allowed free immigration to refugees from the FSU prior to 1989, changed its policy from 1989 onward, allowing entry to immigrants only due to family reunification.

[16] For further support of this fact see BGL and the literature cited therein. Specifically, see Cohen-Goldner, Eckstein and Weiss (2012).

[17] Note that in the restricted model, there is no taste for living in a particular area or the housing cost for living in the area. This follows the explanation given above in Section 4. Because the individual is assigned exogenously to live in an area makes it impossible to estimate the parameters that correspond to the taste. Also, since the individual is restricted to live in an area, the housing costs do not affect any decision and thus cannot be identified.

changes in the value of the estimates. This is to be expected, since the parameter estimates only reflect the value of not working in a particular area, independent of the way in which she arrived to live in that area.

Note that the taste for residing in a particular area crucially depends on the composition of the republics of origin from the earlier waves of immigration from the FSU. In general, the results indicate that the immigrants from the FSU prefer to live next to individuals who came from the same republic in the FSU. These preferences are some weaker from those obtained for men in BGL, where the estimated taste coefficients are larger in absolute terms.[18] The housing costs function we estimate for women indicate that the housing costs vary significantly over the seven regions of the country. The coefficients for the housing costs function are quite similar to those obtained for the men sample. This is not surprising, because this part of the model is based on observed costs of the individuals that are quite similar for the two samples.

Table A.2 and Table B.2 present the parameter estimates that correspond to working in a white-collar occupation. As the parameter estimates for β_{02r}, $r = 1, ...7$, indicate there are some differences in wages across the various regions. There are two important differences from the results obtained in BGL for men. First, there is a lot less variation in the region specific parameters for women than for men. Second, the estimates indicate that women's wages are 30%-40% lower than those for men across all regions. Also, the parameter estimates for the full model are somewhat larger than the corresponding parameters for the restricted model. This stems from the fact that women are more restricted in their searches for job relative to men. Thus they are more likely to accept wages that are smaller on average relative to those obtained under the full model. We also see significant premiums to having higher education. As is the case for men, there seems to be no return to the experience previously accumulated in the FSU (β_{32}). In contrast, there is a significant return to the experience acquired in Israel (β_{42}). Note that the estimated commuting costs are lower for the female sample than for their male counterparts. Since the commuting cost are not directly observed and the observed wages for women are lower than those for men, this induce lower estimate for the commuting costs for women than for men.

In Tables A.3 and B.3 we provide the estimates for the blue-collar employment alternative. Note first, that the wages in the blue-collar occupations are much lower than those in the white-collar occupations across all regions. Also, the return to education is reduced significantly in the blue-collar occupation. Nevertheless, the return to the experience ac-

[18] Alternatively, it is possible that this merely reflects the fact that the wages for women are lower than those for men.

cumulated in Israel is quite similar in the two employment alternatives. Contrary to the results for the white-collar occupation, the estimates of β_{02r}, $r = 1, ...7$, for the full model and restricted model are statistically the same. Note also that we estimate ψ (the fraction of the deterministic part of the full-time wage paid to a part-time employee) to be .751 and .719 for the full and restricted models, respectively. Comparing the results here with those for men in BGL, indicates that the average wage for women in the blue-collar sector are 30%-50% lower than for men.

In Tables A.4 and A.5 we report the estimates that correspond to the job arrival and job loss probabilities for the full model. The estimates for these two events for the restricted model are provided similarly in Tables B.4 and B.5. First note that there are only marginal differences in the parameter estimates of the job loss probability for the full model and restricted model. More interestingly, they are also quite similar to that of men. The main difference between men and women is that the implied overall probability of receiving a job offer is almost double for men relative to their female counterparts. For example, for type 0 in the blue-collar occupation they are .0053 and .0030 for men and women, respectively. Note also that there are significant differences of losing a job across the three estimated types, but the differences across types remain essentially the same for the full model and restricted model.

As for the parameter estimates associated with job arrival probability, we note that the region specific constant terms are quite different for the full model and restricted model, but not in any systematic way. . For the blue-collar sector the constant terms under the full model are are always larger than those under the restricted model. Some of the other parameter estimates are also quite different in a very meaningful fashion across the two models. For example (see estimates for λ_3), it is more likely to get a job offer after a period of non-employment under the restricted model. In contrast, the role of education is quite similar for the two models. Comparing the results for women with those for men, we note that the constants for a blue-collar occupation for men are much larger than those for women, implying greater offer probabilities for men in the blue-collar occupations. Similar differences exist for the white-collar occupations as well.

One should be careful not to misinterpret these results. The estimates are obtained based on the observed choices of the individuals, and not the individuals intension and/or exact behavior. It may simply be the case that women do not look for jobs as intensively as men. While this will translate into larger coefficients for men it is not a reflection of systematic bias against women in the Israeli labor market.

Tables A.6 and B.6 provide the estimate for the type specific probabilities. Clearly, for both the full and restricted models, the type probabilities crucially depend on the husbands level of education. This is in complete contrast to the model estimated for men in which the parameter estimates in the type probability that correspond to the wife's education are statistically and economically insignificant. This is an important finding that we discuss further below.

Finally, Tables A.7 and B.7 provide the estimates of a few other key parameters, namely the *measurement errors* and *classification error* rate. The results clearly indicate that it is crucial to account for possible measurement errors. These are all statistically significant and relatively large. The classification error rate indicate that it is quite large too, about 32%. These estimates are quite robust to model specification (i.e., they are very similar for both the full model and restricted model) and for the sample of women and the sample of men.

5.2 Implications of the Parameter Estimates

A very important difference in the results for men and women is that the type-probability parameters for women in the full and restricted models depend crucially on the husband's level of education. The main reason for allowing for such dependence is because we do not directly observe the decision of the husband. Hence, it raises concerns that the husband and wife may not be making decisions jointly, but rather are following the husband, or, at the very least, make decisions that favor the husband characteristics. However, one might argue that this dependency is merely a reflection of the underlying sorting process of men and women in the marriage market. Under this scenario, the significance of the estimated coefficients is only an artifact of the correlation in unobservable factors between husbands and wives.

To be able to determine which of the two explanations is supported by the data, we also re-estimated the model of BGL for men, allowing for exactly the same specification as in the model for women discussed above. That is, we allow the type-probability parameters to depend on the education of the wife.

The results for that model indicate that all the relevant coefficients statistically and economically insignificant. That is, there is a very pronounced asymmetry between the dependence of the wife on the husband education and the independence of the husband on the wife's education. This asymmetry indicates that the apparent significance of the coefficients of the husband's education in the full model for women may not be due to the correlation in unobserved factors between the husband and wife, but rather due to other factors. The most likely reason for that is that the families concentrate first on finding a job for the husband and choose the residential location for the family accordingly. It is only then that the women concentrate their effort on finding a job. While the results provided above strongly suggest that this is indeed the process that the families in our sample follow, it is hard, if not impossible, to unequivocally establish this fact statistically. However, the available evidence does help support this hypothesis.

A somewhat puzzling result at first glance is the fact that the husband's education is also significant in the restricted model for women, where the type probabilities are computed conditional on the residential location choices. But this can be explained by the fact that, in general, any decision taken by one spouse impacts what the other spouse can do. Thus, the fact that the husband's education has a significant impact on the type probabilities for women, but the converse is not true, indicates further that the family makes decisions that are more suited to the husbands needs rather than the needs of his wife. For example, a choice of the husband to commute to work outside his residential region has direct implications on the types and locations of jobs that the wife can take. This appears to clearly be the case for women in our samples, but not for men. This, in turn, explains the significance of the husband's education on the wife's type probabilities and the lack of significance of the wife's education on the husband's type probabilities.

As indicated above, there are strong evidences that help support the hypothesis posed above regarding the hierarchy in decision making in the family. First, the evidence provided in Section 1 clearly shows that women lagged men in acquiring jobs. It also demonstrates that women obtained lower paid jobs than for men in both the white and blue-collar sectors. This seems to indicate that women exert less effort in pursuing labor market opportunities, at least initially, than the men. Moreover, their labor market activities are concentrated closer to their place of residence. For example, fewer women travel outside their place of residence (see Table 9 below). This is consistent with the notion that women are engaged more in internal aspects of the family, a fact that is consistent with the general findings in the literature provided in Section 1. That is, women do not put their career as high on the family priority list as their husbands, at least at the beginning of a new period in a new country. This also provides a strong rationalization for women to accept lower wages, as is clearly evident in the data. The convenience of being closer to home, simply outweighs the desire to have higher salaries in places that require significant traveling time.

All this evidence suggests that the model for women is very different from that for men. In fact, it suggests that while men maximize their utility by endogenously choosing their job and place of residence, women maximize their utility by choosing their jobs, and whether or not to commute, after the residential location has already been established by the family, that is, they take the place of residence as given. Hence, we find that the restricted model is appropriate for modeling the behavior of women. Indeed, this is our preferred model and thus most of the discussion provided below is with respect to that model.

While there is overwhelming support for the restricted model, the ultimate reason for the underlying process that led to the observed sequential choices of the husbands and wives cannot be uniquely identified. In fact, the apparent pattern may stem from the structure and action of the Israeli labor market, which the families take as given. Alternatively, it may simply originate from the family's preferences that chooses the husband to pursue his career first.

In principle, it may be the case that the Israeli labor market favors men, and thus they are more likely to get better job opportunities and more often than women. Therefore, the patterns we observe whereby men get a job and settle with their families closer to where their jobs are located, are merely reflections of the opportunities provided by the market rather than a self-conscious decision of the family. In what follows we conduct a number of alternative counterfactual simulations that are aimed at better understanding the contributions of the alternative factors to the observed phenomena in the data.

5.3 Restricted Model Predictions

In Tables 6 through 9 below we report the predictions of the restricted model along with the actual data for a few key variables. In Table 6 we report the actual and predicted employment statuses, by semester. We also depict this in Figures 2a-d. The model captures the exact curvature of the employment alternatives. It predicts the non-employment rate and the pattern of change in the non-employment rate extremely well. The model also predicts quite well the employment in the blue-collar occupations, for both the full-time and part-time jobs in that sector, but somewhat under-predict the growth in the employment in the white-collar sector. It is worthwhile noting that the fraction of women working in the white-collar sector is rather small, reaching less than 20% by the end of the sample period, despite the fact that all the women in the sample are highly educated (engineers) in their prime working age. For men, almost 35% were working in the white-collar sector by the end of the sample period.

The fact that very few women work in the white-collar sector is also the main reason why it is harder for the model to predict the employment share in the white-collar sector by regions, as is transparent from Table 7. Nevertheless, on average, the predictions of the model are quite accurate in that it correctly predicts the average employment shares in the white-collar occupations across the regions country, except for Haifa and Shfela. The number of women employed in the white-collar sector is too small to allow us to have precise predictions.

In complete contrast, the model's predictions regarding the employment shares of blue-collar workers in the the seven regions of the country is quite good. As has already been shown above, the larger share of employment was in the blue-collar sector despite the fact that larger fraction of the female sample obtained engineering diplomas in the FSU. Well over 70% of the women in the sample worked in the blue-collar sector by the end of the sample period. Table 8 clearly shows that the model accurately captures very well the employment shares in each of the regions as well as the turning points in the employment shares over the sample period. Over the entire sample period, the means of the employment shares by region deviate only marginally from those predicted by the model. Recall that for those working in the blue-collar sector we assume that they work and reside in the same place. Women, in general, have more responsibilities in the household, which limit their ability to travel. This is clearly evident for the women who are employed in the blue-collar sector, in which the wages are much lower than in the white-collar sector, and especially for those who work in part-time jobs of this sector, as the low wages make commuting virtually impossible.

In Table 9 we present the joint work-residential location for women in the white-collar occupations. The data shows that on average about 60% of the women who work in the white-collar sector also reside in the same area where they work. The model predicts that a larger percentage of the population of women would work where they live, namely 76%. This apparent difference is not as alarming as one might conclude at first glance. The women who do commute to work do so to adjacent regions to where they live. As such, a large share of the employment in the white-collar sector is in the regions around Tel Aviv, namely Sharon and Shfela. Consequently, the model does very well in predicting the overall share employed in these regions, but is less accurate in predicting the exact location within these three regions. As for the other regions, the model does quite well in predicting the larger employment shares in the Negev and the Galilee, as well as predicting the fact that very few commute into these two regions from elsewhere.

5.4 Decomposing the Differences in Labor Market Outcomes for Women and Men

We have already observed significant differences in the observed data and in the models' predictions of labor market outcomes for women and men. In order to be able to detect the sources of these huge differences we first conduct a sequence of decompositions. Specifically, we conduct four alternative counterfactual simulations in which we use different sets of parameters estimates from the various models described above. We then compare the employment and wage outcomes across these alternative counterfactuals. We generally consider four sets of parameters in the model: (1) wage function related parameters in both the white-collar and blue-collar sectors in all regions—the *labor market - wage* parameters; (2) parameters that are related to the job offers and job loss probabilities —the *labor market - offer & loss* parameters; (3) parameters in taste function for residential choices—the *taste* parameters; and (4) parameters from the housing costs function—the *housing costs* parameters.

In the counterfactual simulations whose results are reported below we use different combinations of these sets of parameters estimated from the full model for men and from the restricted model for women. We also use each combination of the parameters with both the women's data discussed above and the men's data from BGL. This allows us to provide an Oaxaca-like decomposition, which, in turn, allows us to provide a clear diagnosis about the sources for the observed differences between men and women.

We present the results in Tables 10 and 11 for the employment and wage outcomes, respectively. In both tables, we report the predictions for the base model for men (i.e., M-Full) using men data and the base model for women (i.e., W-Rest.) using women data. The results for these two simulations are reported in columns 2 and 4 of the tables, respectively. We then simulate the full model for men with data for women and the restricted model for women with the data for men. We report the results for these two simulations in columns 3 and 5 of the tables, respectively.

In columns 6 and 7 we report the results for the final two simulations. In the results reported in column 6, we use the men's full model parameters under the restrictions implied by the women's restricted model (so there are no taste and housing cost), with the women's data. We do so in order to decompose the effects of the labor markets from other factors that affect the individual's decision. In the last simulation we also eliminate the impact of tastes and housing costs but we use the labor market - wage parameters - for women, instead of those of men, as in the previous simulation. The labor market offer and loss parameters remain the same as in the previous simulation, namely, we use the parameters for men. We do so, in order to be able to decompose the labor market effects into its two possible components. In principle, it may be that women are not discriminated against in the labor market when they get jobs, but they might be discriminated against in the labor market as far as job opportunities are concerned.

As has already been indicated above, we see significant differences in the respective models' predictions for women and men, as reported in columns 2 and 4 of Tables 10 and 11. In particular, there are huge differences in the employment patterns and in the wages earned in the blue-collar sector, and even more so in the white-collar sector. With the results of this set of simulations, we can decompose the overall observed differences between men and women into several important components.

The first interesting comparison is between the results provided in columns 2 and 5. This is an Oaxaca-type decomposition in the sense that we use the model for men with women's data and conversely. We note that when the full model for men is applied to women's data, the women are doing better than the men in all aspects. In particular, there is a smaller fraction of non-employed women than men, and a larger fraction of women than men who are employed in the white-collar sector. Moreover, the average (and median) wages for women in both the blue-collar and white-collar sectors are predicted to be higher than those for men, with very similar variation as is clear from the reported standard deviations and inter-quartile ranges. That is, based solely on their observables, if women had behaved in the same fashion as men (i.e., according to the full model for men), had been treated in the same fashion as men by the Israeli labor market, and had the same tastes for residential choices, commuting costs, and housing costs, then their outcomes would have been better than those for men. In other words, based on their observables, the women seem to be better suited to the Israeli labor market requirements than their male counterparts.

If women were treated in the same fashion as men by the Israeli labor market, but were still not making the decision regarding the residential location of the family (see column 6), as in the case of the restricted model, then their situation would not have been as good as in the counterfactual simulation considered in column 5. Nevertheless, they still would have been better off than under the true model. In fact, they would have done just as well as their male counterparts in term of their occupational choices, and even better as far as wage outcomes are concerned, especially in the blue-collar sector. Naturally, under the same labor market conditions, women are better off when they can choose their residential location (as in column 5) than when they cannot make this choice (column 6). Thus, the differences in the labor market outcomes for women in the scenarios of columns 5 and 6 could be largely explained by the inability to choose the residential location.

So far, it is clear from the counterfactual simulations that the Israeli labor market does not "treat" women and men in a similar fashion. In fact, it is quite clear that women are at a severe disadvantage relative to their male counterparts. To better understand the exact source, we can compare the results in columns 6 and 7. The only difference between these two counterfactual simulations is that in column 6 we use only the parameter estimates for men with women's data. In contrast, in column 7 we use the wage parameter estimates for women, while for the remaining labor market parameters we use those for men. The results in these two counterfactual simulations clearly demonstrate that women's wages are worse than the wages of their male counterparts. That is, the results indicate that not only it is more difficult for women to obtain offers in both the blue-collar and white-collar sectors, but the wages that they obtain are lower than those for their male counterpart. It is worthwhile noting that based on the data we have, one cannot rule out other explanations for the apparent "discrimination" of women. One needs to be cautious about the conclusions because other explanations are possible too. It may be the case that women simply avoid looking for a job until the husband gets one and only then pursue their career (see the literature review for this explanation). Nevertheless, the results clearly indicate that if women had the men's model, they would have done better than the men.

5.5 Implications of Model Choices - Random Allocation Simulation

In order to identify which of the two models examined for each gender (full model and restricted model) is the "true" model for the gender, we conduct a set of counterfactual simulations that we term as the *random allocation* simulations. Under this scenario, we assign an individual randomly to a place of residence in the first period of the model. We then simulate the model according to the parameter of the originally estimated model, holding the place of residence assigned in the first period unchanged. We focus our attention on two important outcomes of the model: (1) employment choices; and (2) the distribution of wages. We report the results in Tables 12 through 14. In the two panels of Table 12 we provide the results for the employment choices, under the full model (top panel) and the restricted model (bottom panel). In each panel we provide the predictions of the relevant base model and then the random allocation simulation for that model, that is, the random simulation allocation that uses the parameter estimates for that model.

Restricting attention to the full model results for the women first, we see that under random allocation the fraction of non-employed women rises from and average of 39% under the base model to an average of over 50% for the random allocation simulation. The increase in the fraction of non-employed women comes largely from the reduction in the fraction of women who are employed as full-time in the blue-collar sector (reduction from 39% to 31%). For men, the directions of the changes are generally similar, but much smaller in magnitude. Overall, there is an increase of about 4 percentage points in the fraction of non-employed, which comes largely from a similar decrease in the blue-collar sector.

Why are the changes for women and men so different? Given the evidence provided above, it is quite clear that the full model does not seem to be the correct model for women. Hence, the parameter estimates from this model would not correspond to a correct behavioral model for the women. Thus, any counterfactual simulation that would be based on these parameters would lead to erroneous results, which, in our case, are quite dramatic. Indeed, a careful examination of the simulation results based on the *restricted model* show that if anything, the random allocation provide results that are more advantageous for women relative to those obtained for the restricted model. The fraction in the non-employed category decreases from almost 40% to less than 37%, and more women work in the white-collar sector instead of working as full-time employees in the blue-collar sector. This provides some additional support for the validity of the restricted model. That is, when women are randomly allocated to a residential location, they are better off, on average, than under the restricted model, under which they simply follow their husband.

In contrast, we see that for men the directions of the employment choices are completely reversed. That is, if the restricted model was the true model for men, then the fraction of non-employment under the random allocation is worse than that under the restricted model. The latter results for men and women imply that the choices of the families' residential locations favor the husbands. In turn, this suggests that the reported residential location in the data (in both the men and women samples) reflects the decisions that were taken largely based on the men's characteristics. Consequently, it indicates that the true model for men is the one used in BGL, namely the full model. The implications of the results for women and men are consistent with what the literature has already found, namely, that families optimize with respect to the husbands activity first. It would have been especially puzzling if we found the the true model for both men and women is the full model. This would be logically, as well as empirically, inconsistent.

It is worth noting that the results above demonstrate the importance of an appropriate model choice. Within the samples, the predictions of both the full model and restricted model are quite similar. But the underlying parameter estimates obtained for the two models are different enough to provide entirely different results when we consider counterfactual simulations. So, as in many other cases, the within sample goodness of fit cannot be by itself the determining factor of model choice.

To further establish the implications of the model choice we now restrict attention to the results for wages reported in Tables 13 and 14. Table 13 presents the same statistics on predicted wages under each of the four cases as described above for Table 12. We note that the predictions of both models are quite similar, and very close to the observed data. Overall, the changes in the observed wages due to the random allocation under the counterfactual experiments do not lead to overwhelmingly different results for either model. Nevertheless, some differences are noticeable. For example, the average wage for women in the white-collar sector increases when moving from the predictions of the full model to the random allocation under the full model. But, even in these cases it is hard to pinpoint the exact reasons leading to these observed results, because the composition of individuals in the employment categories are very different. To overcome this, we present a detailed breakdown of the results for people who may have experienced different choices under the base case and the random allocation simulation.

In the two panels of Table 14, we present the results for women and men. In each of the panels we provide the wage statistics for all the possible cross tabulation of the employment choices under the specific model of interest and the employment choices under its random allocation counterpart. We provide this cross tabulation for both the full model (in the top part of each panel) and the restricted model (in the bottom part of each panel).

For example, in line 6 of Panel A we see the women who chose to work in the white-collar sector under the restricted model. The average wage for these women who also choose the white-collar sector under the random allocation is 3,233, under the base restricted model and 3,371, under the random allocation simulation of that model, respectively. This represent an increase of 4.6% in the average wage for this group of women. For the women who chose to work in a full-time job in the blue-collar sector under both models, the increase in the average wage is 3.3% (from 2,171 to 2,243). The results for the men are in complete contrast for both the restricted and the full models. In fact, for men the average wage in the two scenarios discussed above actually declined. This indicates that women are not maximizing their utility relative to what they could have had in the absence of having a husband. This provides more evidence that families maximize their utility with respect to the husband's characteristics first, and only then the women make their optimal (constrained) choice.

5.6 Outcomes under Wage Maximization

Under this simulation we use the parameters that were previously estimated for the full and restricted models assuming now that women are only interested in maximizing the present value of their stream of income for the remainder of their life. We specifically assume that women do not take into account any expenses and/or their preferences for residing in a particular region. We conduct the same exercise for men. It is the comparison between the results for men and women, using both the parameters of the full and restricted models, that shed new additional light on the importance of the labor market in the family allocation decisions in Israel.

The results are presented in Tables 15 through 17. In Table 15 we report the results for the employment choices. Obviously, when one can choose to work anywhere, without having to take into consideration any form of costs, the non-employment fraction decreases dramatically under both the parameters of the full and restricted models, and for both men and women. Nevertheless, we clearly see that the changes between the base model and its corresponding simulation results are much stronger for women than for men. Consider the two leading models for men and women, namely the full model for men and the restricted model for women. The changes for women are a lot more dramatic than for men. This results seems straightforward, if indeed a woman is restricted to live where her husband chose to live. There is a huge decrease in the fraction of non-employed women, from about 40% under the base model to less than 9% under the wage maximization simulation. Even with the parameters of the full model the decrease in non-employment is more than 15 percentage points. A much smaller decrease is observed for men under the parameters of both models, and especially under the parameters of the full model; a decrease of about 5 percentage points.

To provide an overall measure of the effect of the implied constrained optimization for women, namely the loss due to the inability to choose the place residence, we compute the difference in the differences between the average wages under the of maximization of the wages and the maximization of the utility for women and for men, under the preferred models. The average wage for married women according to the restricted model (including 0 for non-working women) over the entire sample period is 1,204 NIS. According to the wage maximization counterfactual, the average wage for married women is 2,416 NIS. That is, we observe a 100% increase in wages. The average wage for married men according to the full model is 2,586 NIS, while the average wage for married men according to wage maximization counterfactual is 3,666 NIS, that is, an increase of 41.8%. This implies that the loss for women, due to the fact that they do not choose the residential location, is 100-41.8=58.2% of their current average wage over that of men.

The reason for these apparent results is very simple if we believe that the full model is the true model for men and the restricted model is true for women. Under the former model, the family is optimizing following the preference of the husband. Hence, to a large extent, the husband is already maximizing his present value of the stream of future income under the base (full) model. This process within the family seems to impose huge restrictions on women. So, when they are free to optimize, with the goal of maximizing income, there is a lot to be gained for them.

In terms of the actual wage statistics under the base model and the simulation, we see in Table 16 that the average (or median) wages at the time the samples were collected change very little, and sometime in the wrong directions, meaning that the average wages under the wage maximization simulation are lower than those under the base model. This is simply a reflection of the fact that more people choose to work, and their wages can be lower than the wages for those who chose to work under the base model. It is important to note though that the individual expectation about the future stream of wages certainly increases, as many more of them are working with fewer periods of non-employment. This is what is demonstrated in Table 17 for the entire population of women and men.

Here we only look at the statistics of the overall wage distribution (including observation with the values zeros) at the time the samples were collected, specifically because we want to account for all those who do not work and thus have zero wages. We see that the wage increase for women under the restricted model is huge, almost twice as large as under the base model. While the increases for men are also transparent, they are much smaller in magnitude. The differences stem not because the predictions of the wage by the original (full) model are wrong, but rather because of the fact that, among other things, we abstract from the other costs that are associated with accepting a job.

6 Summary and Conclusions

In this study we expand on BGL. We augment the DP model developed in BGL with the necessary features that are essential for examining the role of the women in the family decisions regarding the residential choice. In BGL we focus on the male portion of the group of immigrants who came to Israel from the FSU during the period 1989 to 1995. Here we focus on their female counterparts. We do so for two reasons. One reason is simply in order to examine whether or not any of the conclusions were different if one uses data for only the female population. The second, and even more important reason, is to identify the sources for the vast disparities between the outcomes of women and men in the labor market.

Several facts are quite clear from the data. First, the advancement of women in the labor market lagged considerably than for men both in terms of employment opportunities and in terms of wages. Also, there is a significant number of women in part-time jobs only in the blue-collar sector, but there are virtually no men employed in part-time jobs in either sector. The employment patterns for the men and women in the immigrant population parallels that for the highly educated native population. Generally, there seems to be clear asymmetry in the data between the effect of husbands on their wives and the effect of wives on their husbands, which might reflect different behavior.

Thus, for each gender we estimate two alternative models and then examine which of them is the appropriate model for explaining the behavior of married male and female immigrants in Israel: (a) full model; and (b) restricted model. The former is similar to the one estimated in BGL, with the necessary changes made to accommodate the specifics features the are transparent from the data for the female population. The latter model removes the residential decision from the choice. Under the restricted model, a person is assumed to take the residential decision as given, while making decisions regarding employment and commuting.

For both the full and restricted models, the estimated type probabilities for women crucially depend on their husbands' levels of education. This is not the case for men. The parameter estimates in the type probability that correspond to the wife's education in the men's models are statistically and economically insignificant. This illustrates the important dependence of the wife on the husbands' choices, suggesting that the male in the family moves first, and thus has the first mover advantage, that is, his decisions are less constrained than his female counterpart. It is obvious why that might be the case in the full model for women where the residential location is taken as a choice, but it is also true for the restricted model. In general, any decision taken by one spouse has implications on what the other spouse can do. The fact that the husbands education has significant impact on the type probabilities for the women, but the converse is not true, further indicates that the family makes decisions that are more suited to the husbands needs rather than to his wife's. For example, if the husband does not work where the family resides then it may put some restrictions on the kind of job that the wife can take. It appears that this is indeed the case for women in our samples, but not for men.

Using these models, we conduct a number of counterfactual simulations which assist us in examining which of the two models (i.e., full and restricted) is the appropriate model to explain the behavior of married male and female immigrants in Israel.

The first is the *random allocation* simulation. Under this counterfactual simulation we randomly assign each family to a specific place of residence in the first period of the model and hold it unchanged for the remaining periods. The results of this set of simulations provide further support to the relevancy of the restricted model for women and the full model for men. Under the full model, the random allocation generates a significant wage loss for men, but a huge wage gain for women. This gain is somewhat less pronounced under the restricted model. The results of this simulation also indicate that the differences in wage between men and women cannot be explained by the fact that women and men have different specialization areas in engineering. Indeed the results here indicate that under the random simulation the mean wage for women increases, while that for men decreases. This indicate that the difference in wage are in large part due to the restrictive choices for women.

In the second counterfactual simulation, entitled wage maximization, we consider the outcomes if the only consideration for both men and women were wage maximization, disregarding all other expenses, such as housing and commuting costs. Again, we see huge effects for women but only mild effects for men. This is yet another indication that women are engaged with what can be termed as constrained optimization. If the main goal for them was to maximize their wage, they could have gotten much better jobs and have had higher employment, especially in the white-collar sector, by choosing different residential locations. The magnitude of the effects of wage maximization for men are not as large, because to a large extent, this is what the families are already doing (although in the residential location decisions the family also considers factors other than maximizing the wage of the husband, such as networks and amenities).

Thus, the results indicate that the most appropriate model for women is the restricted model, while for men it is the full model. That is, the family maximizes its utility by endogenously choosing the job and place of residence according the opportunities of the husband, while women make their employment choices after the residential location has already been established by the family. This clear difference is in part the result of the huge differences in labor market conditions, particularly wages, for men and women in Israel, which induces the family to concentrate mainly in utilizing first the human capital of the husband.

Based on the appropriate model for men and women (i.e. full model for men and restricted model for women), the results for wages of women are dramatically different from those obtained for men. There is a lot less variation in the region specific parameters for women than for men in the white-collar sector. There is almost no variation in the regional specific wages for women in the blue-collar sector, while there are significant differences for men across regions. Also, the estimates reflect a huge difference between female and male wages. In general, wages for women are 30%-50% lower than those for men across all regions and in both the white and blue-collar sectors. An interesting result consistent for both men and women, is that there is no return to the experience previously obtained in the FSU, but strong returns to the experience acquired in Israel.

In order to assess the magnitude of the labor market losses that women suffer due the strategy of the families to adapt the residential locations mainly to the husbands' characteristics, we propose an index that isolated this effect. According to this index, we find that the female losses are on average about 60% of their current wages, namely, if the women were to choose the residential locations of the family their wages would increase by about 60% on average.

In order to decompose the overall disparities between women and men in the labor market into their specific components, we conduct other counterfactual simulations using different combinations of the model's parameters and data source. The main finding from these simulations is that if the women were to behave and were treated in the marketplace like men, their labor market outcomes would have been better than those for men.

It is also found in these simulations that it is more difficult for women to obtain offers in both the blue-collar and white-collar sectors and the jobs that women obtain are with much lower wages relative to the wages of their male counterparts. Nevertheless, the results may simply reflect the fact that women do not pursue their career as vigorously as their male counterparts. It is only after their husbands get settled in a job that they pursue their own career. It is quite likely that the clear results presented above demonstrate a situation in which both alternatives are playing major roles in the observed patterns of employment among female and male immigrants in Israel.

7 References

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Table 1: Descriptive Statistics

Variable	Mean	St. Dev.	Obs.
Employed	.77	-	529
Months in Israel	45.65	(17.20)	529
Age	43.19	(8.02)	529
Years of education	15.94	(1.29)	529
Previous experience as engineers	14.7	(8,06)	
Married	.78	-	529
Children under 21 living at home	1.08	(.80)	529
Years of education of spouse	15.73	(2.30)	412
From Ukraine	.29	-	529
From Belarus	.11	-	529
From Russia	.37	-	529
Year of Arrival:			
1989	.01	-	
1990	.31	-	
1991	.24	-	
1992	.15	-	
1993	.16	-	
1994	.13	-	
Monthly earnings:			
Semester 2	1,896	(906)	13
Semester 5	1,836	(664)	29
Semester 8	2,246	(1,314)	35
Semester 10-12	2,716	(1,078)	151
Monthly housing costs:			
Semester 2	1,149	(380)	29
Semester 5	996	(431)	43
Semester 8	915	(429)	51
Semester 10-12	1,003	(545)	177

Note: The first three variables Married and Children under 21 are 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

Husband's Education	**14**	**15,16**	**17**
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

Wife's Education	**14**	**15,16**	**17**
Non-employment	22.44	20.91	22.19
White-collar	16.97	24.72	18.03
Blue-collar	60.60	54.37	59.78

Table 3: Occupational Statistics in Israel

Gender	Occupation	Natives		Immigrants	
		%	Wage	%	Wage
Male	0	5.4	—	18.8	—
	1	65.9	10,018	26.9	6,244
	2	22.7	7,598	54.3	3,597
Female	0	12.0	—	31.1	—
	1	40.4	5,306	11.1	3,825
	2	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)
Husband employed in:						
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	-.0073	.0007	.0001
	(.02808)	(.0086)	(.0254)	(.0094)	(.0320)	(.0058)
Wife employed in:						
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	877 (65.69)	58 (4.34)	301 (22.55)	99 (7.42)	1,335 (100.0)
White-collar	9 (2.56)	337 (96.01)	5 (1.42)	0 (0.00)	351 (100.0)
Blue-collar, FT	89 (6.13)	9 (0.62)	1,337 (92.14)	16 (1.10)	1,451 (100.0)
Blue-collar, PT	28 (7.80)	8 (2.23)	36 (10.03)	287 (79.94)	359 (100.0)

b. Men's Employment Transitions

Occupation at t	Occupation at $t+1$			
	Non-Empl.	White Collar	Blue Collar	Total
Non-employment	574 (47.63)	118 (9,79)	513 (42.57)	1.,205 (100.0)
White-collar	17 (1.71)	971 (97.78)	5 (0.50)	993 (100.0)
Blue-collar	168 (5.94)	62 (2.19)	2,599 (91.87)	2,829 (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	.854	.529	.378	.322	.268	.231	.197	.175	.120	.097
White-collar	.011	.044	.064	.088	.121	.137	.148	.176	.187	.194
Blue-collar - FT	.091	.321	.440	.470	.487	.508	.542	.533	.582	.602
Blue-collar - PT	.044	.106	.118	.120	.124	.124	.113	.116	.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	.132	.110
White-collar	.014	.035	.059	.078	.096	.108	.129	.150	.168	.182
Blue-collar - FT	.098	.315	.422	.484	.526	.559	.566	.575	.582	.592
Blue-collar - PT	.031	.088	.109	.118	.126	.129	.126	.123	.118	.117

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	.250	.276	.342	.333	.360	.327	.327	.283	.343	.284
Sharon	.000	.150	.069	.079	.083	.080	.082	.096	.152	.057	.085
Shfela	.200	.100	.207	.132	.104	.100	.102	.096	.065	.057	.116
Haifa	.200	.500	.069	.053	.084	.101	.163	.154	.174	.228	.173
Galilee	.400	.150	.172	.158	.125	.100	.082	.116	.130	.143	.158
Negev	.200	.300	.207	.210	.229	.200	.224	.192	.174	.143	.208
Jerusalem	.000	.000	.000	.026	.042	.060	.020	.019	.022	.029	.022

b. Predicted

Region	Semester										Mean
	1	2	3	4	5	6	7	8	9	10	
Tel Aviv	.091	.351	.359	.348	.329	.279	.262	.226	.160	.160	.257
Sharon	.006	.055	.090	.096	.096	.102	.096	.100	.104	.096	.084
Shfela	.625	.261	.186	.165	.151	.130	.131	.138	.154	.187	.213
Haifa	.009	.050	.057	.065	.068	.083	.092	.100	.091	.112	.073
Galilee	.239	.139	.129	.130	.146	.154	.164	.175	.202	.243	.172
Negev	.026	.125	.157	.176	.187	.222	.225	.232	.252	.168	.177
Jerusalem	.004	.020	.022	.021	.024	.030	.030	.030	.037	.034	.025

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	.197	.116	.130	.132	.116	.095	.066	.061	.058	.061	.103
Sharon	.127	.125	.130	.110	.089	.091	.097	.107	.103	.091	.107
Shfela	.267	.323	.323	.331	.344	.331	.363	.357	.379	.417	.344
Haifa	.056	.099	.091	.110	.100	.116	.124	.107	.098	.099	.100
Galilee	.127	.148	.120	.118	.143	.140	.146	.153	.150	.152	.140
Negev	.127	.090	.101	.092	.096	.128	.111	.118	.126	.106	.110
Jerusalem	.099	.099	.105	.107	.112	.099	.093	.097	.086	.076	.097

b. Predicted

Region	Semester										Mean
	1	2	3	4	5	6	7	8	9	10	
Tel Aviv	.095	.092	.103	.101	.093	.083	.065	.051	.040	.038	.076
Sharon	.112	.117	.108	.105	.098	.106	.103	.115	.116	.107	.109
Shfela	.303	.316	.331	.333	.332	.330	.354	.350	.370	.377	.340
Haifa	.135	.131	.121	.125	.124	.128	.128	.121	.109	.119	.124
Galilee	.184	.170	.156	.151	.154	.144	.153	.170	.165	.171	.162
Negev	.094	.095	.093	.104	.114	.122	.118	.121	.129	.119	.111
Jerusalem	.077	.079	.087	.081	.085	.087	.079	.072	.072	.070	.079

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	6.35	1.52	1.52	0.00	0.00	0.00	0.00	9.39
Sharon	2.79	6.09	0.00	0.00	0.00	0.00	0.00	8.88
Shfela	23.10	1.27	8.38	0.51	1.52	0.00	0.00	34.78
Haifa	0.00	0.25	0.00	6.35	2.03	0.00	0.00	8.63
Galilee	0.00	0.00	0.00	5.84	9.14	0.00	0.00	14.97
Negev	0.00	0.00	0.51	0.00	0.00	20.30	0.00	20.81
Jerusalem	0.00	0.00	0.00	0.00	0.00	0.00	2.54	2.54
Total	32.23	9.14	10.41	12.69	2.69	20.30	2.54	100.00

b. Predicted

Place of Residence	Work Location							
	Tel Aviv	Sharon	Shfela	Haifa	Galilee	Negev	Jerus.	Total
Tel Aviv	13.94	4.66	1.01	0.00	0.00	0.00	0.00	19.61
Sharon	2.20	2.52	0.30	0.00	0.00	0.00	0.00	5.02
Shfela	7.22	0.45	12.18	0.00	0.00	1.27	0.00	0.00
Haifa	0.00	0.00	0.00	5.05	3.24	0.00	0.00	8.29
Galilee	0.00	0.00	0.35	1.10	16.95	0.00	0.10	18.50
Negev	0.00	0.00	0.20	0.00	0.00	25.42	0.00	25.62
Jerusalem	0.00	0.00	0.03	0.00	0.00	0.28	1.49	1.81
Total	23.36	7.63	14.07	6.15	20.11	26.97	1.59	100.00

Table 10: Decomposition of Labor Market Outcomes for Women and Men

Occupational Choices

Group Predictions	**Simulation Specification**					
	Men		**Women**			
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Labor Mkt, Wage	M-Full	W-Rest.	W-Rest.	M-Full	M-Full	W-Rest.
Labor Mkt, Jobs	M-Full	W-Rest.	W-Rest.	M-Full	M-Full	M-Full
Tastes	M-Full	—	—	M-Full		
Housing costs	M-Full	—	—	M-Full		
	Occupational Choices					
Non-employed	22.84	35.55	39.93	21.32	25.07	22.05
White-collar	20.94	8.14	10.24	26.55	21.14	23.19
Blue-collar	56.21	56.31	49.83	52.13	53.79	54.76

Table 11: Decomposition of Labor Market Outcomes for Women and Men

Wage Statistics

Group Predictions	**Simulation Specification**					
	Men		**Women**			
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Labor Mkt, Wage	M-Full	W-Rest.	W-Rest.	M-Full	M-Full	W-Rest.
Labor Mkt, Jobs	M-Full	W-Rest.	W-Rest.	M-Full	M-Full	M-Full
Tastes	M-Full	—	—	M-Full		
Housing costs	M-Full	—	—	M-Full		
	Wage Statistics					
White-Collar Occupations:						
Mean	4,914	3,003	3,184	5,121	4,696	3,286
Median	4,471	2,766	2,934	4,690	4,273	3,028
St. deviation	2,228	1,293	1,343	2,294	2,143	1,392
IQ range	2,683	1,557	1,610	2,770	1,957	1,961
Blue-Collar Occupations:						
Mean	3,096	2,041	1,973	3,248	3,297	2,240
Median	2,809	1,892	1,826	2,957	3,027	2,079
St. deviation	1,402	942	918	1,469	1,392	906
IQ range	1,692	1,203	1,169	1,808	1,687	1,142

Table 12: Counterfactual Simulation - Random Allocation Occupational Choices

Occupation	Data	Full Model		Restricted Model	
		Base	Random	Base	Random
A. Women					
Non-employed	35.04	39.36	50.52	39.93	36.64
White-collar	11.78	11.71	10.21	10.24	15.26
Blue-collar, FT	43.13	39.05	31.07	40.17	38.39
Blue-collar, PT	10.04	9.88	8.20	9.66	9.70
B. Men					
Non-employed	22.25	22.84	26.47	23.66	25.93
White-collar	20.91	20.94	20.54	19.61	13.64
Blue-collar	56.83	56.21	53.00	56.73	60.44

Table 13: Counterfactual Simulation - Random Allocation, Wage Statistics

Wage Statistics	Data		Full Model				Restricted Model			
			Base		Random		Base		Random	
	White	Blue	White	Blue	White	Blue	White	Blue	White	Blue
A. Women										
Mean	3,113	2,032	3,156	1,924	3,627	1,926	3,184	1,973	3,268	1,991
Median	3,000	2,000	2,908	1,784	3,326	1,783	2,934	1,826	2,989	1,827
St. deviation	1,353	859	1,335	891	1,571	893	1,343	918	1,420	947
Inter-quartile	1,850	1,000	1,592	1,137	1,877	1,117	1,610	1,169	1,704	1,185
B. Men										
Mean	4,778	3,204	4,914	3,096	4,723	2,996	4,816	3,134	4,899	3,034
Median	4,459	3,037	4,471	2,809	4,294	2,720	4,408	2,852	4,500	2,776
St. deviation	2,028	1,204	2,228	1,402	2,129	1,332	2,110	1,407	2,113	1,314
Inter-quartile	2,199	1,206	2,683	1,692	2,562	1,612	2,548	1,710	2,548	1,596

Table 14: Random Allocation Counterfactual Simulation - Wage Statistics

A. Women

Choice under Original Model		Choice under Random Allocation							
		Non-Employed		White-Collar		Blue-Collar FT		Blue-Collar PT	
		Original Model	Random	Original Model	Random	Original Model	Random	Original Model	Random
Full Model:									
1.	Non-Employed	-	-	-	3,497	-	1,984	-	957
2.	White	3,047	-	3,264	3,757	3,189	2,194	3,251	1.061
3.	Blue, FT	2,036	-	2,138	3,608	2,189	2,163	2,234	1,044
4.	Blue, PT	966	-	1,019	3,749	1,019	2,237	1,054	1,070
Restricted Model:									
5.	Non-Employed	-	-	-	3,162	-	2,020	-	991
6.	White	2,970	-	3,233	3,371	3,170	2,279	3,222	1,088
7.	Blue, FT	1,959	-	2,151	3,262	2,171	2,243	2,236	1,070
8.	Blue, PT	939	-	1,008	3,341	1,018	2,285	1,042	1,102

B. Men

Choice under Original Model		Choice under Random Allocation					
		Non-Employed		White-Collar		Blue-Collar	
		Original Model	Random	Original Model	Random	Original Model	Random
Full Model:							
1.	Non-Employed	-	-	-	4,569	-	2,883
2.	White-collar	4,778	-	5,114	4,917	4,816	3,150
3.	Blue-collar	2,994	-	3,226	4,625	3,054	2,944
Restricted Model:							
4.	Non-Employed	-	-	-	4,853	-	3,066
5.	White-collar	4,697	-	5,231	5,111	4,826	3,167
6.	Blue-collar	3,066	-	3,279	4,799	3,056	2,994

Table 15: Wage maximization Counterfactual - Occupational Choices

Occupation	Data	Full Model		Restricted Model	
		Base	Wage Max	Base	Wage Max
A. Women					
Non-employed	35.04	39.36	25.19	39.93	8.79
White-collar	11.78	11.71	6.81	10.24	32.86
Blue-collar, FT	43.13	39.05	53.53	40.17	54.81
Blue-collar, PT	10.04	9.88	4.47	9.66	3.543
B. Men					
Non-employed	22.25	22.84	17.40	23.66	11.72
White-collar	20.91	20.94	40.00	19.61	41.08
Blue-collar	56.83	56.21	42.59	56.73	47.20

Table 16: Wage maximization Counterfactual - Wage Statistics

Wage Statistics	Data		Full Model				Restricted Model			
			Base		Wage Max		Base		Wage Max	
	White	Blue	White	Blue	White	Blue	White	Blue	White	Blue
A. Women										
Mean	3,113	2,032	3,156	1,924	3,131	2,593	3,184	1,973	2,973	3,028
Median	3,000	2,000	2,908	1,784	2,905	2,510	2,934	1,826	2,749	2,947
St. deviation	1,353	859	1,335	891	1,247	1,103	1,343	918	1,199	1,206
Inter-quartile	1,850	1,000	1,592	1,137	1,494	1,468	1,610	1,169	1,436	1,629
B. Men										
Mean	4,778	3,204	4,914	3,096	5,340	4,715	4,816	3,134	5,605	4,916
Median	4,459	3,037	4,471	2,809	4,931	4,583	4,408	2,852	5,200	4,799
St. deviation	2,028	1,204	2,228	1,402	2,195	1,773	2,110	1,407	2.269	1,853
Inter-quartile	2,199	1,206	2,683	1,692	2,707	2,395	2,548	1,710	2,846	2,515

Table 17: Wage maximization Counterfactual - Wage Statistics

Wage Statistics	Data	Full Model		Restricted Model	
		Base	Wage Max	Base	Wage Max
A. Women					
Mean	1,612	1,587	2,355	1,692	2,967
Median	1,700	1,541	2,402	1,644	2,837
St. deviation	1,326	1,369	1,443	1,352	1,241
Inter-quartile	2,500	2,408	1,740	1,824	1,568
B. Men					
Mean	2,960	3,212	4,576	3,161	4,791
Median	3,000	2,969	4,525	2,969	4,756
St. deviation	1,992	2,188	2,432	2,140	2,558
Inter-quartile	1,897	2,396	2,769	2,380	2,921

Figure 1: Occupational Choices for Men and Women

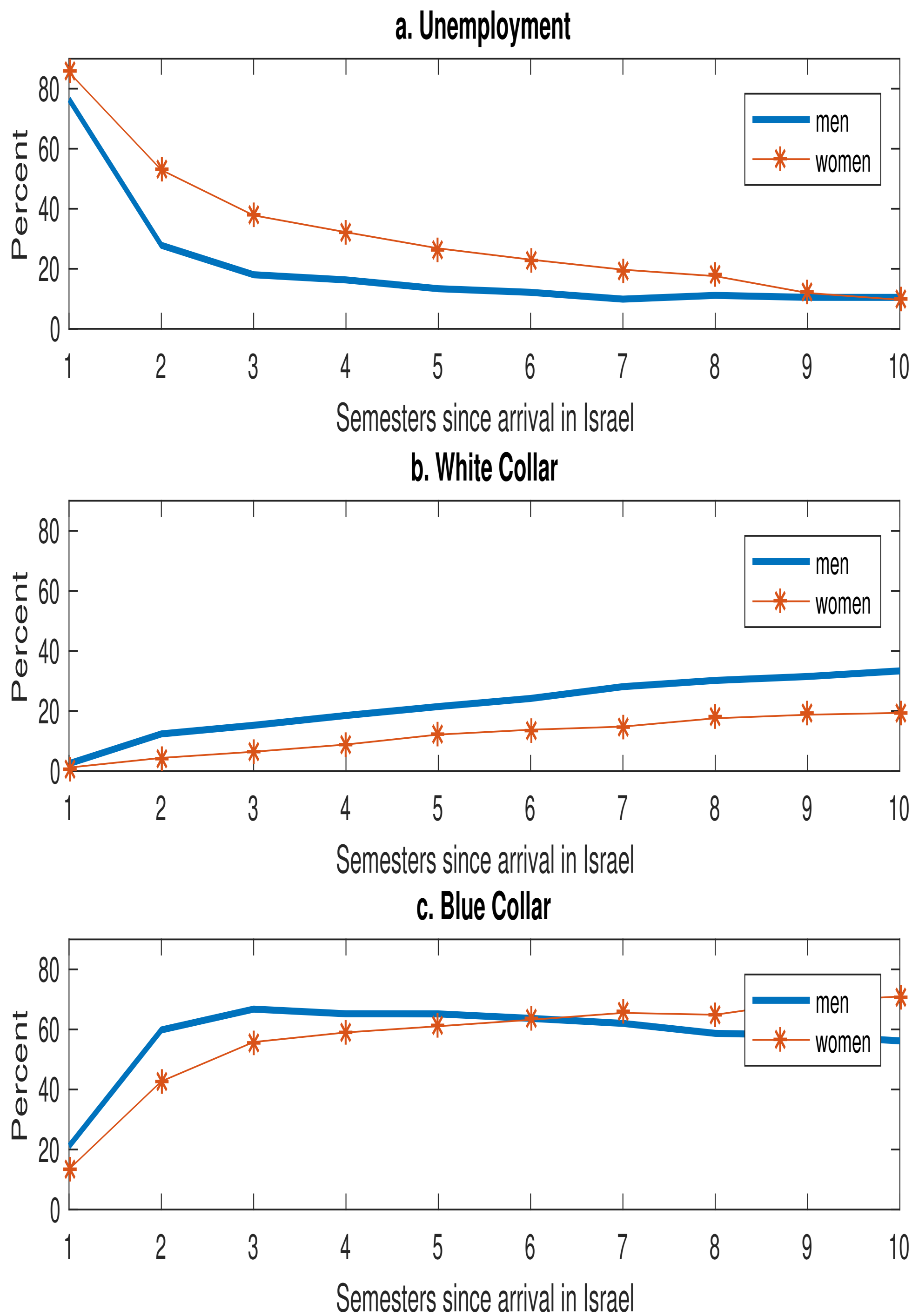
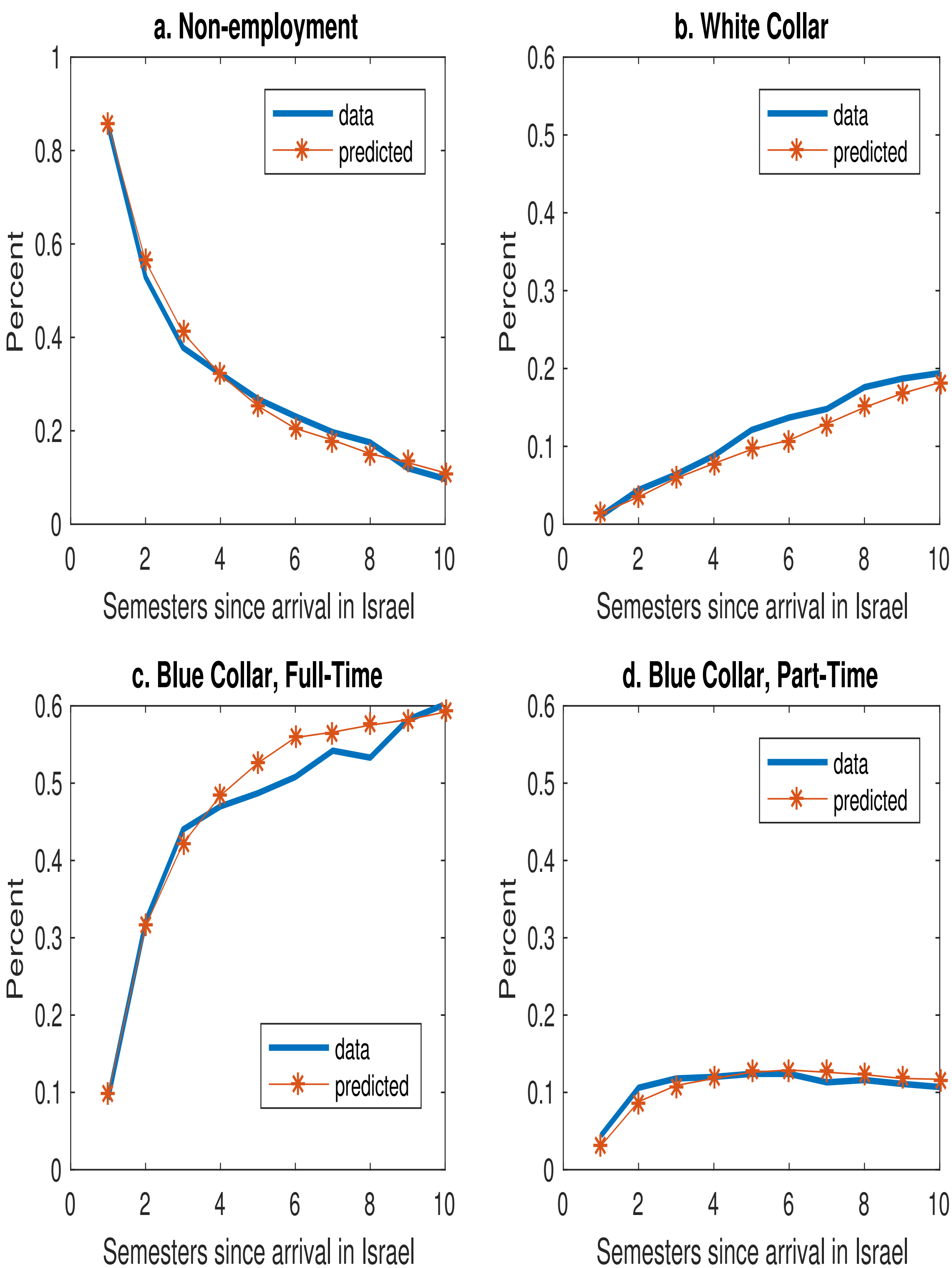


Figure 2: Distribution of Empoyment Status, By Semester



Appendix A-Results for the Full Model for Women

Table A.1: Utility of Non-Employment

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Value of non-employment, $b_{1rt}(\varepsilon_{i1rt})$:									
		α (for t=1)							
1	Tel Aviv	2,269	7.3						
2	Sharon	455	0.8						
3	Shpela	2,496	5.0						
4	Haifa	1,836	4.8						
5	Galilee	1,079	3.0						
6	Negev	1,090	1.8						
7	Jerusalem	8,215	1.5						
Taste For Residental location, $\tau_r(x_{it}, \mu_{it})$:									
		τ_0		τ_1		τ_2		τ_3	
8	Tel Aviv	0	-	0	-	0	-	0	-
9	Sharon	775	.4	-325	.7	-659	22.2	528	.6
10	Shpela	2,308	1.8	589	1.5	1,254	26.0	-2,111	5.9
11	Haifa	392	1.3	874	4.5	2	13.5	-1,259	1.7
12	Galilee	-615	1.1	1,259	2.9	2,947	51.9	-3,260	1.4
13	Negev	-1,396	1.5	-1,026	1.9	-698	18.1	1,251	.6
14	Jerusalem	0	-	0	-	0	-	0	-
Housing cost, $hc_{trj}(x_{it})$:									
		γ_0		rp					
15	Tel Aviv	6.94	.002	.096	.0003				
16	Sharon	6.68	.001	.051	.0007				
17	Shpela	6.89	.001	.046	.00002				
18	Haifa	6.58	.002	.066	.0006				
19	Galilee	6.35	.002	.028	.0009				
20	Negev	6.31	.001	.023	.0024				
21	Jerusalem	6.89	.001	.054	.0001				
		γ_1		γ_2		γ_3		γ_4	
22	All Regions	.003	.00002	.033	.00003	.166	.0003	.356	.0003
		$\sigma^2_{\epsilon_1}$							
23	All regions	6.4	.001						

$u_{i1rt} = b_{1rt}(\varepsilon_{i1rt}) + \tau_r(x_{it}, \mu_{it}) - hc_{trj}(x_{it}) - \gamma_j I(r_t \neq r_{t-1})$,
$b(\varepsilon_{i1rt}) = \alpha_r I(t = 1) + exp(\varepsilon_{i1rt})$,
$\tau_r(x_{it}, \mu_{it}) = \tau_r^1(\mu_{it}) + \tau_r^2(x_{it})$, $\quad \tau(\mu_{it}) = \gamma_{0r} + \gamma_{1r}R_{1i} + \gamma_{2r}R_{2i} + \gamma_{3r}R_{3i}$,
$hc_{trj}(x_{it}) = 6 * exp(\gamma_{0r} + \gamma_1 M_{it} + \gamma_2 NK_{it} + \gamma_3 TP_{1i} + \gamma_4 TP_{2i})/(1 + rp_r)^{T-t}$.
For brevity, we do not report the estimates for $\tau_{4r}, ..., \tau_{7r}$ from $\tau_r^2(x_{it})$ in (7).

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, $ln\, w_{jkrit}(x_i, x_t)$:									
		β_{02r}							
1	Tel Aviv	7.823	.002						
2	Sharon	7.733	.002						
3	Shpela	7.868	.002						
4	Haifa	7.823	.001						
5	Galilee	7.639	.003						
6	Negev	As in 2	-						
7	Jerusalem	As in 2	-						
		$\beta_{12}(for\ S{=}\,15,16)$		$\beta_{22}(for\ S{>}\,16)$		β_{32}			
8	All regions	.044	.0001	.128	.0001	-.003	.000006		
		β_{42}		β_{52}		β_{62}		β_{72}	
9	All regions	.036	.0000002	-.166	.0002	.147	.0001	-.238	.0004
Traveling costs $tc(r, r')$:									
		tc_1		tc_2		tc_3		tc_4	
10	All regions	4,721	10.1	21,837	1.0	15,360	3.6	1,993	1.3
Error structure:									
		ρ_2		$\sigma^2_{v_2}$					
11	All regions	.616	.027	.327	.00007				

$\tau_r(x_{it}, \mu_{it})$: As in Table A.1, $hc_{trj}(x_{it})$: as in Table A.1,
$u_{ikrt} = 6{*}(w_{krt}(x_i{,}x_{kt})e^{\epsilon_{krt}} + \tau_r(x_{it}, \mu_{it}){-}hc_{trj}(x_{it}){-}\gamma_j I(r_t \neq r_{t-1}) - tc(r, r')$ for $k = 2$.
$\ln\ w_{2rit}(x_i, x_1) = \beta_{02r} + \beta_{12} I(S_i = 15, 16) + \beta_{22} I(S_i > 16) + \beta_{32} x_{0i} + \beta_{42} x_{\mathrm{kt}}$
$+\beta_{52} I(age_i \geq 40) + \beta_{62} TP_{1i} + \beta_{72} TP_{2i} + \epsilon_{2rit}$,
$\epsilon_{2rit} = \rho_2 \epsilon_{2rit-1} + \nu_{2rti}$,
$TC_1{=}TC_{1,2}, TC_{1,3}$, $TC_2{=}TC_{1,4} = TC_{1,5}, TC_{1,6}, TC_{1,7}, TC_{2,5}, TC_{2,6}, TC_{2,7},$
$, TC_{3,4}, TC_{3,5}, TC_{3,6}, TC_{3,7}, TC_{4,6}, TC_{4,7}, TC_{5,6}, TC_{5,7}, TC_{6,7},$
$TC_3 =$
$TC_{2,3}, TC_{2,4}$, $TC_4 =$
$TC_{4,5}$.

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

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Log wage, $ln\, w_{jkrit}(x_i, x_t)$:							
	β_{03}						
1	Tel Aviv	7.447	.0001				
2	Sharon	7.507	.013				
3	Shpela	7.478	.002				
4	Haifa	7.467	.001				
5	Galilee	7.439	.002				
6	Negev	7.486	.002				
7	Jerusalem	7.466	.002				
		$\beta_{13}(for S = 15, 16)$		$\beta_{23}(for\ S > 16)$		β_{33}	
8	All regions	.012	.0002	.025	.0002	.039	.00003
		β_{43}		β_{53}			
9	All regions	-.153	.0002	.301	.0001		
		ψ					
10	Part-time fraction	.751	.0006				
Error structure:							
		ρ_3		$\sigma^2_{V_3}$			
11	All regions	.599	.001	.259	.0006		

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

$$\ln\ w_{3rit}(x_i, x_1) = \beta_{03r} + \beta_{13} I(S = 15, 16) + \beta_{23} I(S > 16) + \beta_{33} x_{kt} + \beta_{43} TP_{1i} + \beta_{53} TP_{2i} + \epsilon_{3rit}.$$

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

No.	Occupation	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
		η_k of Type 0		η_k of Type 1		η_k of Type 2	
1	White-collar	-5.915	.004	-8.635	.005	-5.159	.005
	Implied Prob.	.0027		.0002		.0057	
2	Blue-collar	-5.867	.736	Same as above		Same as above	
	Implied Prob.	.0028		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, γ_{02r}		Blue-Collar, γ_{03r}			
1	Tel Aviv	-2.690	.679	.414	.001		
2	Sharon	-4.404	.041	.716	.135		
3	Shpela	-3.859	.251	1.099	.004		
4	Haifa	-3.963	.002	.401	.00002		
5	Galilee	-3.616	.003	1.176	.001		
6	Negev	-2.717	.001	.545	.001		
7	Jerusalem	-4.352	.004	.430	.001		
		λ_1		λ_2		λ_3	
8	White-Collar	.013	.0002	.014	.0001	-.028	.005
9	Blue-Collar	-	-	-	-	-	-
		λ_4		λ_5		λ_6	
10	White-Collar	-.0370	.000002	.079	.0004	.063	.005
11	Blue-Collar - FT	-.0372	.00219	-	-	.068	.001
12	Blue-Collar - PT	-.0681	.00004	-	-	-.001	.130
		λ_7		λ_8			
13	White-Collar	1.021	.00005	-2.845	.002		
14	Blue-Collar	-1.926	.001	.409	.001		
		White-Collar ψ		Blue-Collar ψ			
15	ψ(from ψP_{krit}) for t=1	.096	.00002	.094	.002		

$P_{kirt} = \psi_k exp(A_{kirt})/(1 + exp(A_{kirt}))$, if t=1
$P_{kirt} = exp(A_{kirt})/(1 + exp(A_{kirt}))$, otherwize.
$A_{k^{;}rit} = \lambda_{0kr} + \lambda_{1k=2} I(S = 15, 16) + \lambda_{2k=2} I(S > 16) + \lambda_{3k=2} I(Non - empat_{t-1})$
$+\lambda_{4k}(\text{age at arrival}) + \lambda_{5k=2}(\text{Exp. as eng. in FSU}) + \lambda_{6k} t + \lambda_{7k} TP_{1i} + \lambda_{8k} TP_{2i}$

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	φ_o	0	-	-1.305	.001	1.411	.00002
2	φ_1	0	-	1.213	.0004	-2.012	.00003
3	φ_2	0	-	3.728	.002	-.507	.250
4	Moving costs-all regions (except from Tel-Aviv)	122,026	33.1	33,404	7.1	38,343	10.1
5	Difference in moving costs from Tel-Aviv	-11,788	1,837.9	Same as for Type 0		Same as for Type 0	

$\pi_j = Pr(Type\ j) = exp(B_j)/(1 + exp(B_1) + exp(B_2)), \quad j = 1, 2, 3,$

$B_j = \varphi_{0j} + \varphi_{1j} I(H_S = 15, 16) + \varphi_{2j} I(H_S > 16).$

	Type 0	Type 1	Type 2
Less than 15	.186	.050	.763
15 or 16	.406	.371	.223
17 or more	.068	.765	.167

Table A.7: Other Parameters

		Estimate	St. Err.
Standard deviation of measurement errors:			
1	Wages	.375	.00009
2	Cost of housing (κ)	.186	.00004
	Base classification error rate:		
3	Parameter, ϑ	.749	.00005
	Implied probability	.679	

$c = exp(\vartheta)/(1 + exp(\vartheta))$=.679=1-classification error.
The wage punishment parameter estimate is zero.

Appendix B-Results for the Restricted Model for Women

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, $b_{1rt}(\varepsilon_{i1rt})$:									
		α (for t=1)							
1	Tel Aviv	2,247	366.7						
2	Sharon	477	81.3						
3	Shpela	2,750	44.3						
4	Haifa	1,771	373.7						
5	Galilee	1,088	196.4						
6	Negev	1,123	18.2						
7	Jerusalem	8.093	525.5						

Table B.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, $ln\, w_{jkrit}(x_i, x_t)$:									
		β_{02r}							
1	Tel Aviv	7.750	.020						
2	Sharon	7.637	.002						
3	Shpela	7.778	.010						
4	Haifa	7.721	.001						
5	Galilee	7.469	.010						
6	Negev	As in 2	-						
7	Jerusalem	As in 2	-						
		$\beta_{12}(for\ S{=}\ 15,16)$		$\beta_{22}(for\ S{>}\ 16)$		β_{32}			
8	All regions	.044	.026	.128	.003	-.003	.0002		
		β_{42}		β_{52}		β_{62}		β_{72}	
9	All regions	.036	.0002	-.168	.003	.144	.007	-.238	.056
Traveling costs $tc(r, r')$:									
		tc_1		tc_2		tc_3		tc_4	
10	All regions	5,403	670.5	52,472	419.5	21,705	738.5	2,085	162.1
Error structure:									
		ρ_2		$\sigma^2_{v_2}$					
11	All regions	.640	.030	.327	.020				

$$\ln\ w_{2rit}(x_i, x_1) = \beta_{02r} + \beta_{12} I(S_i = 15, 16) + \beta_{22} I(S_i > 16) + \beta_{32} x_{0i} + \beta_{42} x_{\text{kt}}$$
$$+ \beta_{52} I(age_i \geq 40) + \beta_{62} TP_{1i} + \beta_{72} TP_{2i} + \epsilon_{2rit},$$

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

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

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

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

No.	Variable	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
Log wage, $ln\, w_{jkrit}(x_i, x_t)$:							
	β_{03}						
1	Tel Aviv	7.341	.083				
2	Sharon	7.545	.006				
3	Shpela	7.475	.017				
4	Haifa	7.526	.001				
5	Galilee	7.450	.010				
6	Negev	7.432	.001				
7	Jerusalem	7.558	.165				
		$\beta_{13}(for S = 15, 16)$		$\beta_{23}(for\ S > 16)$		β_{33}	
8	All regions	.013	.015	.024	.007	.039	.001
		β_{43}		β_{53}			
9	All regions	-.156	.014	.301	.061		
		ψ					
10	Part-time fraction	.719	.227				
Error structure:							
		ρ_3		$\sigma^2_{V_3}$			
101	All regions	.626	.021	.256	.022		

$\tau_r(x_{it}, \mu_{it})$: As in table B.1, $hc_{trj}(x_{it})$: as in table B.1,

$$\ln\ w_{3rit}(x_i, x_1) = \beta_{03r} + \beta_{13} I(S = 15, 16) + \beta_{23} I(S > 16) + \beta_{33} x_{kt} + \beta_{43} TP_{1i} + \beta_{53} TP_{2i} + \epsilon_{3rit}.$$

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

No.	Occupation	Estimate	St. Err.	Estimate	St. Err.	Estimate	St. Err.
		η_k of Type 0		η_k of Type 1		η_k of Type 2	
1	White-collar	-5.895	.212	-8.646	.248	-5.132	.526
	Implied Prob.	.0027		.0002		.0059	
2	Blue-collar	-5.818	1.692	Same as above		Same as above	
	Implied Prob.	.0030		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, γ_{02r}		Blue-Collar, γ_{03r}			
1	Tel Aviv	-2.150	.022	.402	.012		
2	Sharon	-4.373	.218	.704	.027		
3	Shpela	-4.381	.012	.874	.0003		
4	Haifa	-4.020	.082	.394	.008		
5	Galilee	-3.595	.148	1.184	.030		
6	Negev	-2.578	.038	.508	.021		
7	Jerusalem	-4.437	.296	.397	.025		
		λ_1		λ_2		λ_3	
8	White-Collar	.014	.0002	.015	.0006	-.018	.002
9	Blue-Collar	-	-	-	-	-	-
		λ_4		λ_5		λ_6	
10	White-Collar	-.0370	.0001	.084	.004	.099	.001
11	Blue-Collar - FT	-.0 376	.001	-	-	.085	.001
12	Blue-Collar - PT	-.0684	.052	-	-	-.051	.004
		λ_7		λ_8			
13	White-Collar	1.703	.0002	-2.994	.036		
14	Blue-Collar	-1.470	.004	1.062	.007		
		White-Collar ψ		Blue-Collar ψ			
15	ψ(from ψP_{krit}) for t=1	.083	.147	.377	.003		

$P_{kirt} = \psi_k exp(A_{kirt})/(1 + exp(A_{kirt}))$, if t=1
$P_{kirt} = exp(A_{kirt})/(1 + exp(A_{kirt}))$, otherwize.
$A_{k^{\cdot}rit} = \lambda_{0kr} + \lambda_{1k=2} I(S = 15, 16) + \lambda_{2k=2} I(S > 16) + \lambda_{3k=2} I(Non - empat_{t-1})$
$+\lambda_{4k}(\text{age at arrival}) + \lambda_{5k=2}(\text{Exp. as eng. in FSU}) + \lambda_{6k} t + \lambda_{7k} TP_{1i} + \lambda_{8k} TP_{2i}$

Table B.6: Type-specific parameters

		Type 0		Type 1		Type 2	
		Estimate	St. Error	Estimate	St. Error	Estimate	St. Error
1	φ_o	0	-	-1.305	.0002	1.438	.097
2	φ_1	0	-	1.329	.006	-1.993	.006
3	φ_2	0	-	3.876	.019	-.528	.026

$\pi_j = Pr(Type\ j) = exp(B_j)/(1 + exp(B_1) + exp(B_2)), \qquad j = 1, 2, 3,$
$B_j = \varphi_{0j} + \varphi_{1j} I(H_S = 15, 16) + \varphi_{2j} I(H_S > 16).$

	Type 0	Type 1	Type 2
Husband education:			
Less than 15	.182	.050	.768
15 or 16	.385	.394	.221
17 or more	.060	.790	.150

Table B.7: Other Parameters

		Estimate	St. Err.
Standard deviation of measurement errors:			
1	Wages	.379	.024
	Base classification error rate:		
2	Parameter, ϑ	.754	.030
	Implied probability	.679	

$c = exp(\vartheta)/(1 + exp(\vartheta))$=.680=1-classification error.
The wage punishment parameter estimate is zero.