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LABOR MOBILITY OF IMMIGRANTS: TRAINING, EXPERIENCE, LANGUAGE, AND OPPORTUNITIES*

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This article analyzes the labor mobility and human capital accumulation of male immigrants from the former Soviet Union to Israel. We estimate a dynamic choice model for employment and training in blue- and white-collar occupations, where the labor market randomly offered opportunities are affected by past choices. The estimated model accurately reproduces the patterns in the data. The estimated direct earning return to local training, local experience, and knowledge of Hebrew are very high, whereas imported skills have zero (conditional) return. The welfare gain from the impact of training on job offer probabilities is larger than its effect on wages.

1. INTRODUCTION

The transition pattern of highly skilled immigrants to a new labor market is characterized by high wage growth and a rapid decline in unemployment as immigrants first find blue-collar jobs and then gradually move into white-collar occupations. One of the factors in this process is the acquisition of local human capital in the form of a "new" language, experience, and skills gained from vocational training programs provided by the government.[2] In this article, we quantify the impact of the local accumulation of human capital and imported skills on labor mobility and wages (Weiss et al., 2003), with particular emphasis on the role of local training courses. In particular, we study the effect of training in white- and blue-collar occupations on wages, job offer probabilities, and individual utility. In addition, we estimate the predicted aggregate wage growth of immigrants and the individual welfare gain from the availability of training.[3]

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[2] Borjas (1994, 1999) and LaLonde and Topel (1994) provide comprehensive surveys on various topics in the economics of immigration.

[3] Heckman et al. (1999) provide a comprehensive survey of the methods and empirical findings regarding the gains from vocational training programs provided by the government. However, the econometric models they present are static.

To study these issues, we formulate a dynamic choice model, in which immigrants can be in one of the following states in each period: employed in a blue-collar occupation, employed in a white-collar occupation, attending a training course in either white- or blue-collar occupation, and not employed. Wages and job offers are random and are affected by the immigrant's endogenously accumulated experience and training, as well as his language fluency and imported skills.[4] We estimate the model using quarterly panel data from a sample of male immigrants who moved from the former Soviet Union (FSU) to Israel during the period 1990–1992. The data capture the labor market experience of immigrants during the first 20 quarters following their arrival in Israel.[5]

A unique feature of the sample is that almost all the immigrants in it had not expected the opportunity to move to a more developed economy that provides a significant initial support for immigrants. Hence, the prior labor market investments in the FSU can be viewed as independent of the immigration decision and therefore this sample can be thought of as an extreme example of discharged workers at the prime age (25–58) in the labor market. Therefore, studying the dynamics of these immigrants in the labor market, with emphasis on training programs and job offer rates, can help us quantify the effect of policies that attempt to promote employment among prime-aged nonemployed workers.

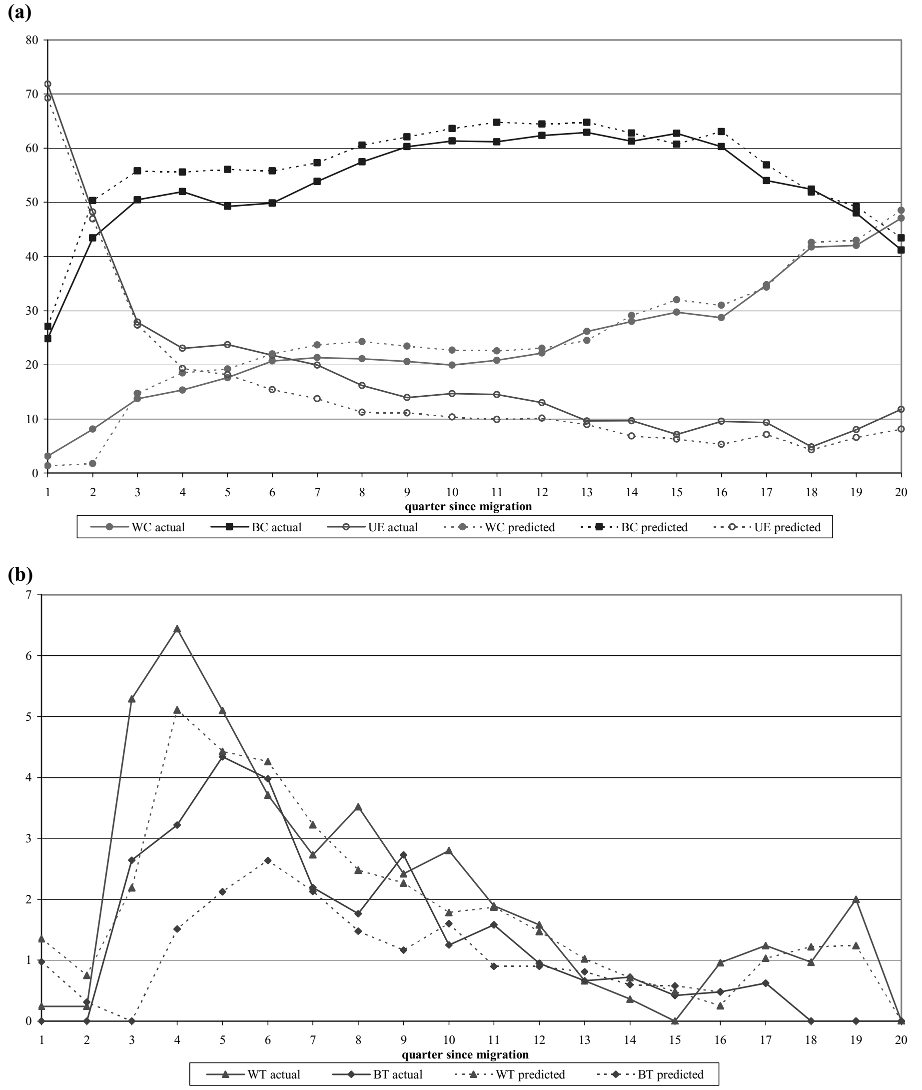
The existing labor economics literature on immigration focuses on immigrants' wage growth and its impact on natives' employment and wages. This vast empirical literature has documented high wage growth among immigrants during their first decade in the new country. The main issue examined is the effect of time since arrival and year of arrival on wages.[6] Our detailed and unique data on a cohort of immigrants include information on actual experience, language skills, occupational training participation, and pre-migration skills. The data enable us to further investigate alternative channels through which human capital and market opportunities determine the wage growth and labor mobility of immigrants within a dynamic stochastic choice model.

The estimated model is consistent with the main patterns of labor market mobility among immigrants as described above (see Figures 1a and 1b). The main reason for the slow transition to white-collar occupations is the very low offer probability of white-collar jobs. The predicted pattern of participation in training is consistent with the observed peak in training at the end of the 1st year in the new country and the decrease in participation over the following 2 years. The model also predicts the observed sharp decline in the share of those employed in

[4] The model is similar to that of Keane and Wolpin (1997) and Eckstein and Wolpin (1999). Card and Sullivan (1988), Ham and LaLonde (1996), and Heckman and Smith (1999) empirically analyze the interactions between training participation and (un)employment before and after the program.

[5] The mass migration from the Former Soviet Union to Israel started toward the end of 1989. For a more detailed description of this immigration wave, see Eckstein and Weiss (2002, 2004).

[6] Eckstein and Weiss (2004) extended this work using repeated cross-section samples for the same immigration wave that is investigated here. Their main finding is that the high wage growth during the first 5 years in the new country is characterized by a zero return to imported education during the 1st year after arrival. However, the return to education increases with time in the new country. Weiss et al. (2003) is an exception in the literature. They use a dynamic model to estimate the compatibility between the immigrant's job and his imported level of schooling.



*WC: white-collar jobs, BC, blue-collar jobs.
* WT: white-collar training, BT: blue-collar training

FIGURE 1

(A) ACTUAL AND PREDICTED PROPORTIONS IN UNEMPLOYMENT, BLUE-COLLAR JOBS, AND WHITE-COLLAR JOBS* AND (B) ACTUAL AND PREDICTED PROPORTIONS IN TRAINING*

blue-collar jobs and the increase in the share of those employed in white-collar jobs during the 5th year in Israel.[7]

The estimated potential earnings gain to white-collar training is 18–19% for about 73% of the immigrants and zero for the rest. Blue-collar training provides a

[7] Figure 1 demonstrates this clearly. It should be noted that the model allows for alternative explanations for this observation such as accumulated human capital and cohort effects.

potential earning gain of about 13% for 32% of the immigrants and zero for rest.[8] However, the predicted mean accepted wage is only 6% higher for participants in white-collar training and 9.8% higher for participants in blue-collar training. The difference between the estimated rate of return to training and the effect of training on mean accepted wages is due to the occupation-specific employment probability. The job offer probabilities and individual occupation selections dominate the estimated effects of training on potential wages. Knowledge of Hebrew has a large impact on earnings in both types of occupations, whereas knowledge of English affects potential wages in white-collar jobs only. Accumulated local experience is estimated to increase earnings by about 2% per quarter, whereas imported schooling and experience (age on arrival) have zero (conditional) return in the new country. It appears, therefore, that imported skills, except for English, do not contribute directly to wage growth, except through their effect on the accumulation of local skills. [9] However, we do find that imported human capital has a significant positive effect on white-collar (high-wage) job offer probability.

In addition to a high wage return, white-collar training doubles the white-collar job offer probability.[10] This effect is the main channel through which training affects the labor mobility of immigrants. However, the high return to local experience, the estimated negative utility from training, and the low availability of white-collar training are the main explanations for the predicted low participation rates in training.[11] Furthermore, the expected present value of the gain for an immigrant on arrival from the existence of training programs provided by the government is estimated to be 2.8–3.7%. Our findings support the claim that one should jointly model the multiple outcomes of training in a dynamic stochastic (search) model (Heckman et al., 1999).

In this article, we jointly estimate the impact of training on employment and wages. Thus, we are able to calculate the predicted aggregate wage growth that is due to the availability of the government vocational training programs. This wage growth increases with time since arrival reaching about 1% in the 3rd year following arrival and 1.6% in the 5th year. The large difference between the effect of training on the individual wage equations and on the predicted wage growth is due to the dynamic realized opportunities and selection decisions made by workers. As a result, the effect of training on observed employment and wages is a dynamic phenomenon that is only realized over a period of many years.

The rest of the article is organized as follows: Section 2 presents the quarterly panel data on the sample of male immigrants. Section 3 develops the discrete

[8] We allow for four unobserved types of immigrants in the population (Heckman and Singer, 1984). Our OLS estimates of the effect of training are large but insignificant, which is the most common result in the literature (LaLonde, 1995).

[9] Imported schooling affects the choice and the potential return to training. In this article, all our attempts to introduce interaction terms between imported skills and local accumulation of human capital failed since the relevant coefficients turned out to be very close to zero. It is possible that the small sample is the main reason for this result.

[10] Card and Sullivan (1988) and Ham and LaLonde (1996) found that participation in training has a significant positive effect on post-training employment probabilities.

[11] The negative utility from participation in training can be interpreted as a result of liquidity constraints on immigrants' investment in human capital.

choice human capital investment model. Section 4 presents the estimation results and the model's goodness of fit. Section 5 presents the policy implications of our results. Section 6 concludes.

2. DATA

The data for this study are based on a panel built from two surveys of the same sample. The first survey was conducted during the summer of 1992 on a random sample of 1,200 immigrants from the FSU who entered Israel between October 1989 and January 1992. The second survey was done in 1995 and only 901 of the immigrants were resampled.[12] The original sample consists of immigrants of working age (25–65) residing in 31 different locations in Israel at the time of the first survey. Both surveys contain a monthly history of employment and wages from the date of arrival in Israel until the time of the interview. The surveys also provide detailed information on participation in government-sponsored training programs, knowledge of Hebrew on arrival, participation in Hebrew classes, and Hebrew knowledge at the time of the surveys. In addition, the surveys contain information on demographic characteristics before and after migration. For our purposes, the monthly labor market data were converted into a quarterly (3 months) data set.

We consider only male immigrants who were 23–58 years old at the time of their arrival and use quarterly data on each from arrival until the last interview. As a result, the sample contains 419 immigrants of whom 316 were reinterviewed in the second survey, such that the total number of observations is 5,778. We restrict the sample to immigrants who did not become full-time students and were actively looking for a job in Israel.[13]

The immigrants' high level of imported skills is reflected in their average years of schooling (14.6) and the high proportion (68%) who worked in white-collar jobs (68%) in the FSU (see Table A1). White-collar jobs, such as researchers, managers, computer analysts, teachers, nurses, engineers, artists, and other highly skilled professionals generally require more than 12 years of schooling. The blue-collar occupations mostly require only basic skills.[14]

Language skills are measured by four questions relating to comprehension, speaking, reading, and writing. The immigrants were asked these questions both in Hebrew and in English. We use an index that attributes equal weight to each

[12] The surveys were conducted by the JDC - Brookdale Institute of Gerontology and Human Development, Jerusalem, Israel. The main reasons for the attrition in the second round are spoiled interviews in the first round, refusal to be interviewed again, and a few cases where the individual could not be found. Very few immigrants left Israel during the sample period, and, hence, a bias due to sample selection should not be an important issue here.

[13] A total of 5,778 observations are the sum of 419 initially sampled and 5,359 transitions (see Table 10). The main motivation for the restrictions is to make the data comparable to a model in which immigrants are seeking to integrate in the labor market. The quarterly aggregations are meant to reduce the size of the state space and to make the model dynamics more interesting.

[14] White-collar jobs correspond to codes 000–299 in the 1972 occupation classification of the Israeli Central Bureau of Statistics (CBS).

question and that takes a value of one for those who have no knowledge of the language and four for those who know the language fluently. Few immigrants had knowledge of English prior to migration and therefore, the average English index is only 1.76.[15]

The knowledge of Hebrew was measured in both interviews. Twelve percent of the immigrants were able to hold a simple conversation in Hebrew prior to their arrival. On arrival, all immigrants are assigned to a government-provided Hebrew course called an "Ulpan," which lasts two quarters.[16] Ninety-two percent of the immigrants attended Ulpan and 79% completed it. The knowledge of Hebrew increased by an average of 10% between the two surveys.

Each immigrant to Israel is eligible to participate in one government-sponsored vocational training program. These training programs are classified according to white-collar and blue-collar occupations. Training in white-collar occupations includes courses in computers, accounting, adaptation of engineering skills to local market requirements, etc. Training in blue-collar occupations includes courses in sales, cosmetics, diamond cutting, construction-related occupations, etc.[17] These training programs are open both to unemployed and displaced native Israelis, as well as to immigrants. A mandatory requirement for participation in training courses is to pass a test in the Hebrew language. Some of the programs can be considered as retraining, because their aim is to enable the participant to modify his skills to the needs of the Israeli labor market. For example, many immigrants worked in various fields of engineering prior to migration. Because some of these fields are not in demand in the Israeli labor market, various training programs were designed in order to adapt their skills.[18]

2.1. *Labor Market States.* We classified the labor market status of individuals according the classification used in our model. In each quarter, the immigrant can be in one of five labor market states: unemployed (UE), employed in a white-collar job (WC), employed in a blue-collar job (BC), attending a training course in a white-collar occupation (WT), or attending a training course in a blue-collar occupation (BT). Figures 1a and 1b describe the actual proportions of individuals in each state for the first 20 quarters since their arrival in Israel. Immigrants who attend Ulpan during the first two quarters are considered to be unemployed. The

[15] We assume that this level of English is constant over the life cycle. The interview was in Russian or/and Hebrew.

[16] It should be mentioned that each household of immigrants receives an absorption package of benefits during their 1st year in Israel. This package contains special allowances for rent and a mortgage, which can be partially extended for a longer period. Ulpan and training are also a part of the benefits.

[17] Although many government-sponsored training programs in the United States are offered to economically disadvantaged individuals with low skills level, Israeli classroom vocational training programs are designated mainly for high school and college graduates.

[18] The length of the training programs varies from one to three quarters. Based on discussions with public administrators, we learned that the duration of the courses depends on administrative constraints conditions and does not reflect differences in quantity or quality of the course material. In some occupations such as law and medicine, immigrants had to participate in special programs in order to obtain a license to practice in Israel. In our sample, there are no observations that belong to these occupations.

TABLE 1
TRANSITION RATES FROM OCCUPATION IN FSU TO TRAINING BY OCCUPATION IN ISRAEL (PERCENT)

Occupation in FSU	Training in White-Collar Occupation	Training in Blue-Collar Occupation	Percentage	Observations
White Collar	54.03	30.65	84.68	105
Blue Collar	4.84	10.48	15.32	19
Percentage	58.87	41.13	100.00	–
Observations	73	51	–	124

unemployment rate reaches 23% after a year in Israel and stabilizes at about 10% after 13 quarters. A substantial number of immigrants work in blue-collar jobs during their first 2 years in Israel. This proportion increases to more than 60% after two and a half years in Israel and remains at this level for almost two additional years (see Figure 1a). This pattern of slow dynamic transition is similar to what is believed to be typical immigrant behavior (Eckstein and Weiss, 2004).[19]

What might seem to be a substantial occupational downgrading during the first 4 years in the new country is reversed to a large extent later on. During the 5th year in Israel, the share of immigrants who work in BC jobs declines by almost 20% and the share of those employed in WC jobs increases by almost the same magnitude (see Figure 1a). Hence, the movement between occupations is an extended dynamic process.[20] Does the reversal in trend represent an occupational upgrading during the 5th year after migration or is it a result of the characteristics of the 1990 immigrants relative to the 1991/2 immigrants? To answer this question requires a structural model that can distinguish between the two hypotheses.

2.2. *Transitions.* The transitions between the five labor market states (Table A2) show high (80–97%) and increasing persistence in WC and BC jobs. The transitions from WC (BC) jobs to BC (WC) jobs are few and decrease over time. The rate of transition from work to unemployment after more than two and a half years in Israel is about 5%, which is substantially lower than the transition to unemployment from any other state.

Table 1 shows that 84% of the immigrants who attended a training course had worked in white-collar jobs in the FSU. Hence, immigrants who arrived with more skills are more likely to invest in training. On the other hand, a significant number of these immigrants were willing to downgrade their occupation as seen in the fact that 37% of the immigrants who had held a white-collar job in the FSU attended training in blue-collar occupations. This observation may reflect the way in which immigrants perceived their labor market opportunities in Israel. However, as can be seen in Table 2, this does not mean that they necessarily end up working in blue-collar jobs.

[19] Note that this pattern is similar to the transition to work among high school graduates, as described by Keane and Wolpin (1997).

[20] The low number of observations in the 5th year should be noted.

TABLE 2

FIRST JOB AFTER TRAINING IN ISRAEL BY OCCUPATION (PERCENT)

First Job After Training	Training in White-Collar Occupation	Training in Blue-Collar Occupation	Percentage	Observations
White Collar	34.26	9.26	43.52	47
Blue Collar	25.93	30.56	56.48	61
Percentage	60.19	39.81	100.00	–
Observations	65	43	–	108

NOTE: 16 immigrants hadn't found jobs after training (out of 124 who participated in training programs).

TABLE 3

MULTINOMIAL-LOGIT REGRESSION ON EMPLOYMENT BY OCCUPATION AND UNEMPLOYMENT

Variable	White Collar	Unemployed
Constant	−4.44	−0.48
	(0.5)	(0.48)
Hebrew	0.96	0.13
	(0.08)	(0.07)
English	0.66	0.15
	(0.04)	(0.05)
Age on arrival	0.01	0.02
	(0.01)	(0.01)
Years of schooling	0.03	0.03
	(0.02)	(0.02)
Training in WC	0.94	0.82
	(0.12)	(0.17)
Training in BC	−0.21	0.96
	(0.16)	(0.18)
Experience in Israel	0	−0.68
	(0.01)	(0.02)
Occup. in FSU WC	1.48	0.22
	(0.14)	(0.11)
No. of Obs.	5536	
Log Likelihood	−3558.40	

NOTE: The comparison group is employment in blue-collar jobs.

Table 2 shows that the occupation of the first job after training is not necessarily the same as the occupation trained for and that there is more downgrading than upgrading. However, the model developed in the next section shows that one cannot infer the long-term impact of training on the immigrant's occupational choice from the occupation of his first job.

To describe the role of training by occupation, we estimate a pooled multinomial logit regression for the immigrants' employment choices in different periods (Table 3). The dependent variable indicates whether the immigrant was working in a WC or a BC job or was unemployed at time t.[21] The variable WT (BT) equals 1 if the immigrant has completed training in WC (BC) before time t and equals zero otherwise. Training in white-collar occupations increases the probability of working in a white-collar job and being unemployed, whereas training in blue-collar occupations only affects (positively) the probability of being unemployed. Knowledge of Hebrew and English, age on arrival, and work in a white-collar occupation in the FSU increase the probability of both working in a white-collar job and being unemployed relative to working in a blue-collar job. Education (years of schooling) has no significant effect on these probabilities. Accumulated work experience in Israel reduces the probability of being unemployed. It is interesting to note that all the variables related to the level of human capital increase the probability of working in a white-collar job as well as being unemployed. In other words, skilled immigrants invest both in the accumulation of human capital and in job search.

2.3. *Wages.* There are only 574 wage observations: 132 in white-collar jobs and 442 in blue-collar jobs. This is significantly less than in standard cross-sectional data, and in order to check consistency with other data sets we report the growth rates of the variables. The quarterly growth in wages estimated by a simple regression of the mean wage on time since arrival is 2.2–3.0% per quarter. This represents an annual rate of about 9%, which is 2.6% higher than that found in a larger sample used by the Israeli Central Bureau of Statistics (CBS) Income Survey (see Eckstein and Weiss, 2004).

Following the standard specification of logged wages as a function of human capital indicators for each occupation, we first estimated simple pooled OLS regressions.[22] Obviously, we do not correct for the selection bias implied by the choices of the individual since this is a primary goal of the model. However, the OLS regressions provide benchmark correlations that describe the data in comparison to other studies.

Training enters as a dummy only for wages reported after the completion of the training program. The estimated coefficients have large standard errors indicating a small sample with high variance. However, the values of the coefficients indicate

[21] Note that each immigrant appears in this regression several times and that there is no individual fixed effect. Moreover, the regression does not control for the endogeneity of training and only provides a way to measure conditional transitions in the data. Standard errors allow clustering by individual.

[22] Results for the OLS wage regressions, which follow the specification of the model (SE in parentheses):

White-collar wage regression:

$$\begin{aligned}\ln w_{WC} = {} & \underset{(0.407)}{1.091} + \underset{(0.061)}{0.129}\, \textit{Hebrew} + \underset{(0.036)}{0.132}\, \textit{English} + \underset{(0.005)}{0.013}\, \textit{Age on arrival} + \underset{(0.022)}{0.021}\, \textit{Schooling} \\ & + \underset{(0.079)}{0.116}\, \textit{White Collar Training} - \underset{(0.129)}{0.045}\, \textit{Blue Collar Training} + \underset{(0.009)}{0.017}\, \textit{Experience}\end{aligned}$$

Blue-collar wage regression:

$$\begin{aligned}\ln w_{BC} = {} & \underset{(0.120)}{2.122} + \underset{(0.027)}{0.050}\, \textit{Hebrew} - \underset{(0.022)}{0.011}\, \textit{English} - \underset{(0.002)}{0.003}\, \textit{Age on arrival} + \underset{(0.006)}{0.008}\, \textit{Schooling} \\ & - \underset{(0.062)}{0.009}\, \textit{White Collar Training} + \underset{(0.055)}{0.056}\, \textit{Blue Collar Training} + \underset{(0.003)}{0.024}\, \textit{Experience}\end{aligned}$$

that the division of training and jobs according to the two occupational categories is justified. Furthermore, these results are similar to results obtained in many other studies that have attempted to assess the impact of training on wages (see Heckman et al., 1999).

The estimated coefficients for the knowledge of Hebrew and English are high.[23] The impact of the knowledge of Hebrew on wages in blue-collar jobs is smaller than that in white-collar jobs, but is still positive and significant, whereas the effect of English in BC jobs is negative and insignificant.[24] The correlation coefficients for imported human capital in the form of experience (age on arrival) and education are equal to zero in the BC wage equation.[25]

Based on the above observations, we now formulate a model that is consistent with the facts in the data and can provide consistent estimates for the parameters of the wage function.

3. THE MODEL

The model follows the dynamic programing approach to labor supply and schooling (see, for example, Keane and Wolpin, 1997; Eckstein and Wolpin, 1999), where in each period an individual chooses from a finite set of mutually exclusive alternatives over a finite horizon. Immigrants randomly receive job offers and training program offers in two occupations and choose one activity in each period. The model incorporates observed as well as unobserved heterogeneity (Heckman and Singer, 1984).

Formally, an immigrant i who arrives in Israel at age τ_i and is expected to live L periods faces a finite horizon planning period of duration $T_i = L - \tau_i$ quarters. In each period following arrival, $t = 1, 2 \ldots T_i$, he can choose one of five labor market alternatives $j = 0, 1, 2 \ldots, J, J = 4$. Let d^j_{itm} equals one if individual i of unobserved type m chooses alternative j at time t and zero otherwise. The index $j = 1$ corresponds to employment in a white-collar occupation (WC) and the index $j = 2$ corresponds to employment a blue-collar occupation (BC). When $d^j_{itm} = 1$ and $j = 3, 4$, the individual acquires training relevant to occupation $j - 2$. When

[23] The level of Hebrew in each quarter is the predicted index from the regression of index of Hebrew knowledge at the time of the first and second surveys on time since arrival, time square, length of Ulpan, and the indicator for Hebrew knowledge prior to migration:

$$\begin{aligned}\widehat{Heb} = \underset{(0.169)}{1.695} + \underset{(0.015)}{0.092}\, Ulpan\_length + \underset{(0.089)}{0.657}\, Hebrew\ before\ migration \\ + \underset{(0.031)}{0.071}\, time - \underset{(0.0013)}{0.0014}\, time^2.\end{aligned}$$

Given this format one can interpret the Hebrew index Heb as a given process of accumulation of local language and social norms.

[24] Berman et al. (2000) find similar results with respect to the knowledge of Hebrew. Chiswick and Miller (1999) find that the earnings return for English proficiency among legalized aliens in the United States is between 8 and 17%. Dustmann and van Soest (2001) find that the size of the gain from language fluency is sensitive to specification.

[25] Since we observe wages only during the first 5 years in Israel, we did not include a quadratic element for experience. Furthermore, the interaction terms for training and schooling and training and age on arrival turned out to be zero and had large standard errors.

$d^0_{itm} = 1$, the immigrant is searching for a job while unemployed. We denote by d_{itm} $\{d_{itm},\ j = 0, .., J\}$ the row vector.

We assume that for alternative j, $j = 1, 2, 3$, the immigrant either has or does not have the option to choose this alternative, whereas unemployment ($j = 0$) and training in a blue-collar occupation (BT), $j = 4$, are always available. However, we impose the constraint that both training programs are available only from the third quarter of residency in Israel for those immigrants who had no prior knowledge of Hebrew.[26] The immigrant can be admitted to a training program if he has not previously attended one and is allowed to participate in only one training program during his lifetime. Formally, given that an immigrant i of unobserved type m has chosen alternative r in period $t - 1$, the conditional probability that he can choose alternative j, $j = 1, 2, 3$, is given by

$$(1) \qquad P^{rj}_{itm} = P^{rj}(x_{itm}, d_{it-1m}, t),$$

where the matrix $\{P^{rj}_{itm} : r = 0, 1, 2 .., 4;\ j = 1, 2, 3\}$ is the periodic conditional offer probability matrix.[27] The vector x_{itm} represents individual characteristics. Specifically, the probabilities of receiving job offers in WC and BC have the following logistic form:

$$(2) \qquad P^{rj}_{itm} = \frac{\exp\{Q_{ijtm}\}}{1 + \exp\{Q_{ijtm}\}}, \ (j = 1, 2)$$

where the specification of Q_{ijtm} depends on j. During the first two quarters in Israel, immigrants who had no knowledge of Hebrew on arrival cannot receive a job offer in a WC occupation ($j = 1$). From the third quarter ($t \geq 3$), P^{r1}_{itm} is given by (2), such that

$$(3) \qquad \begin{aligned} Q_{i1tm} = {} & b_{011m} d^1_{it-1,m} + b_{021m} d^2_{it-1,m} + b_{031m} \left(d^0_{it-1,m} + d^3_{it-1,m} + d^4_{it-1,m} \right) \\ & + b_{111} I(1 \leq EX_{itm} \leq 4) + b_{121} I(EX_{itm} > 4) + b_{21} C^1_{itm} \\ & + b_{31} \tau_i + b_{41} L^H_{it} + b_5 L^F_i + + b_6 pwc_i, \end{aligned}$$

where $I(1 \leq EX_{itm} \leq 4)$ is an indicator that equals one if individual i of unobserved type m has accumulated $1 - 4$ quarters of work experience in Israel by time t and $I(EX_{itm} > 4)$ is an indicator that equals one if the individual has accumulated more than 4 quarters of work experience in Israel by time t. The law of motion of the endogenous general accumulated experience in the Israeli labor market, EX_{itm}, is $EX_{itm} = EX_{it-1m} + d^j_{it-1m}$, $j = 1, 2$ and upon arrival $EX_{i1m} = 0$. The indicator C^1_{itm} is equal to one if the worker has completed a training course in a white-collar

[26] Eligibility to participate in a training course typically expires after 18 quarters.

[27] As noted above, unemployment and BT are always available, implying $P^{r0}_{itm} = P^{r4}_{itm} = 1$.

occupation prior to period t.[28] As such, the probability of receiving a job offer in a white-collar occupation ($j = 1$) depends on the labor market state of the individual in the previous period (r), the unobserved type of the individual (indexed by m), accumulated experience in Israel, participation in a white-collar training course, age on arrival, knowledge of Hebrew, knowledge of English, and an indicator for WC job in the FSU. The effect of prior labor market state is allowed to vary across (unobserved) types.

The probability that an individual i receives a job offer in a blue-collar occupation ($j = 2$), P^{r2}_{itm}, is given by (2), such that Q_{i2tm} depends on which activity the individual engaged in during the previous period (r), which varies across types, accumulated experience in Israel, participation in a blue-collar training course, age on arrival and knowledge of Hebrew. Specifically,

(4)

$$\begin{aligned} Q_{i2tm} = {} & b_{012m} d^1_{it-1,m} + b_{022m} d^2_{it-1,m} + b_{032m}\left(d^0_{it-1,m} + d^3_{it-1,m} + d^4_{it-1,m}\right) \\ & + b_{112} I(1 \leq EX_{itm} \leq 4) + b_{042m}\left(d^0_{it-1,m} + d^3_{it-1,m} + d^4_{it-1,m}\right) I(t < 2) \\ & + b_{122} I(EX_{itm} > 4) + b_{22} C^2_{itm} + b_{32}\tau_i + b_{42} L^H_{it} + b_7 d^2_{it-1,m} I(t < 6) \end{aligned}$$

where $I(t < 2)$ is an indicator that equals one during the first quarter in Israel. The parameter b_7 is meant to capture the possibility that the persistence in BC jobs may differ during the first 18 months following arrival, during which immigrants change jobs more frequently than in later periods, which are characterized by greater stability.

The probabilities of receiving an offer to participate in white- or blue-collar training programs are zero during the first two quarters, unless the immigrant had prior knowledge of Hebrew. For $t > 2$, the probability of receiving a BT offer is assumed to be 1 and the estimated probability of receiving a WT offer does not change over time and we allow it to depend on schooling and to vary between types. Specifically WT offer takes the form

(5)
$$P^{rj}_{itm} = \frac{\exp\{\gamma_{0m} + \gamma_1 ed_i\}}{1 + \exp\{\gamma_{0m} + \gamma_1 ed_i\}}, \quad (j = 3).$$

Both training offer probabilities are independent of job offers. An immigrant who has already participated in a WT or BT program since his arrival does not receive another training offer. Once the training program is available, the immigrant is randomly assigned to a one-, two- or three-quarter training program. This allocation is determined by a random draw from a simple three-point discrete probability distribution where the proportions are equal to the actual ones. In other words, 33% are allocated to a one-quarter training program, 42% to a two-quarter program, and the other 25% to a three-quarter training program. The decision to

[28] The endogenous variables (EX_{itm}, C^j_{itm} $j = 1, 2$) are indexed by i and m, whereas the exogenous variables are only indexed by i because the evolution of these endogenous variables over time depends on the unobserved type of the individual (m).

participate in training (either WT or BT) is based on the expected present value of this choice conditional on these three alternative durations of each training course assuming the actual probabilities.[29]

The offered wage in occupation j, $j = 1, 2$, at period t is a standard log linear function of K^j_{itm}, the immigrant's occupation-specific human capital and a random *i.i.d* shock, z^j_{it}. That is,

$$\ln w^j_{itm} = K^j_{itm} + z^j_{it} \, . \tag{6}$$

The accumulation of human capital for each j, $j = 1, 2$, is determined by the following equation:

$$K^j_{itm} = \alpha_{0jm} + \alpha_{ej} EX_{itm} + \alpha_{cjm} C^j_{itm} + \alpha_{Hj} L^H_{it} + \alpha_{Fj} L^F_i + \alpha_{Aj} \tau_i + \alpha_{Sj} ed_i , \tag{7}$$

where EX_{itm} is general accumulated experience in the Israeli labor market and C^j_{itm} is an indicator that equals one if the worker has completed a training course in occupation j, $j = 1, 2$, prior to period t.[30] L^H_{it} indicates the level of Hebrew of individual i at time t in Israel, which we assume to be exogenous. Imported human capital is represented by the immigrant's education level (ed_i), age on arrival (τ_i), and the knowledge of English on arrival (L^F_i). Unobserved heterogeneity (m) is captured by the constant and by the return to training.

The current utility from labor market state j for individual i of unobserved type m at time t in Israel is denoted by U^j_{itm} and is given by

$$\begin{aligned} U^0_{itm} &= ue_m + \varepsilon^o_{it} \\ U^j_{itm} &= w^j_{itm}, \quad \text{for} \quad j = 1, 2 \\ U^j_{it} &= tr^j_m + \varepsilon^j_{it}, \quad \text{for} \quad j = 3, 4, \end{aligned} \tag{8}$$

where the random vector $\varepsilon_{it} = [\varepsilon^0_{it}, z^1_{it}, z^2_{it}, \varepsilon^3_{it}, \varepsilon^4_{it}]$ is normally distributed as $N(0, \Omega)$ where Ω is unrestricted, such that we allow for correlation in the errors of different labor market states within each period. The immigrant's utility in (8) is measured in monetary terms due to the linearity of utility in wages in the two employment states ($j = 1, 2$). The monetary value of the utility associated with a training program is denoted by tr^j_m, $j = 3, 4$, and that associated with unemployment ($j = 0$) by ue_m. The monetary units are determined by the wage definition, which is the hourly wage rate in NIS.[31]

[29] The calculations of the probabilities that enter the likelihood function are corrected according to this additional randomness in the model. This is done through the simulation of the joint probability for the observed outcomes.

[30] Note that experience in one occupation affects the human capital stock in the other occupation differently.

[31] We do not have data on actual government monetary transfers to the immigrants.

An immigrant i of unobserved type m is assumed to maximize the expected present value of his lifetime utility

$$E\left[\sum_{t=1}^{T_i} \beta^{t-1} \sum_{j\in J+1} U_{itm}^j d_{itm}^j | S_{i1m}\right] \tag{9}$$

through the choice of d_{itm}^j for all $t = 1, \dots, T_i$, where S_{i1m} is the vector of all the relevant state variables at the time of arrival. E denotes the expectation taken over the joint distribution of ε_{it} and the transition probabilities, P_{itm}^{rj}, and β is the discount factor, $0 < \beta < 1$. The state vector at time t in Israel is given by

$$S_{itm} = \left[EX_{itm}, C_{itm}^j, L_{it}^H, L_i^F, \tau_i, ed_i, pwc_i, d_{it-1m}^j, \varepsilon_{it}; \quad \text{for } j = 0, 1, 2, 3, 4\right],$$

where pwc_i is an indicator for having worked in a WC job prior to migration and ε_{it} is the realized value of the vector of shocks.

Let $V_{im}^r(S_{itm}, t)$ be the maximum expected lifetime utility of immigrant i of unobserved type m given by Equation (9) such that $d_{itm}^r = 1$. This value is defined recursively for $t = 1, \dots, T_i$ using the Bellman equation:

$$\begin{aligned} V_{im}^r(S_{itm}, t) = U_{itm}^r + \beta E \max \big\{ & V_{im}^j(S_{it+1m}, t+1), \\ & \text{for } j = 0, \dots, 4 \mid S_{itm}, t, d_{itm}^r = 1 \big\}. \end{aligned} \tag{10}$$

In order to simplify the model, we assume that the optimization period is divided into two subperiods. During the first 20 quarters, the model is solved explicitly. In the 21st quarter, the immigrant's utility is given by $V_{im}^j(S_{i21m}, t = 21)$, which is assumed to be a given linear function of S_{21m} for $j = 0, 1, \dots 4$ (see Eckstein and Wolpin, 1999) . Furthermore, we assume perfect foresight of the future behavior of the exogenous values of $L_{it}^H, t = 1, \dots, 21$. Given this simplification, we can solve the model by backwards induction from period $t = 21$.

3.1. *Solution Method.* The model does not admit an analytical solution. Using the end-point conditions and assuming a known distribution of ε_{it} and a functional form for the job offer probability functions, it is possible to numerically solve for the set of optimal decisions using backwards induction for any given values of the parameters. We solve the problem at each point of the state space. The E max expression in (10) is separated between the transition probabilities and the joint distribution of ε_{it}, since the two are independent. Let $g_{it+1m}^a(S_{it+1m}, t+1 \mid S_{itm}, t, d_{itm}^j = 1)$ be a vector that indicates the feasibility of each of the five possible choices where one indicates a feasible alternative and zero otherwise. This vector is defined for individual i of unobserved type m at time t for a potential outcome a at time $t+1$ given $(S_{itm}, t, d_{itm}^j = 1)$. For example, an unemployed immigrant with no restrictions on training participation can be unemployed or participate in BT, but the other three states are random. In this case, an example of a potential outcome, for $a = 1$, is $g_{it+1m}^1 = [1, 0, 0, 0, 1]'$, where 1 (0) in a given row indicates whether this choice is feasible (not feasible). Let $\tilde{V}^a_{it+1m}(S_{it+1m}, t+1 \mid S_{itm}, t, d^j_{itm} = 1)$ be the corresponding vector of the values of the feasible alternatives for individual i at time t for an outcome a at time $t+1$ given $(S_{itm}, t, d^j_{itm} = 1)$. At each zero in g^a_{it+1m} the corresponding $V^j_{im}(S_{it+1m}, t+1)$ is eliminated from $\tilde{V}^a_{it+1m}$ and at each one in $g^a{}_{it+1m}$ the value in $\tilde{V}^a_{it+1m}$ is equal to (10). The index of potential outcomes a has $A^j_{it+1m} = A(S_{it+1m}, t+1 \mid S_{itm}, t, d^j_{itm} = 1)$ total number of $t+1$ feasible choice sets. In our example, the vector $\tilde{V}^1_{it+1m}$ is given by

$$\begin{aligned}
&\tilde{V}^1_{it+1m}\left(S_{it+1m}, t+1 \mid S_{itm}, t, d^0_{itm} = 1\right) \\
&\quad = \left[V^1_{it+1m}\left(S_{it+1m}, t+1 \mid S_{itm}, t, d^0_{itm} = 1\right),\right. \\
&\qquad \left. V^4_{it+1m}\left(S_{it+1m}, t+1 \mid S_{itm}, t, d^0_{itm} = 1\right)\right]',
\end{aligned}$$

and there are eight potential outcomes that we denote by $A^0_{it+1m} = 8$. Let $P(g^s_{it+1m}(S_{it+1m}, t+1 \mid S_{itm}, t, d^j_{itm} = 1))$ be the conditional probability of $g^a_{it+1m}(S_{it+1m}, t+1 \mid S_{itm}, t, d^j_{itm} = 1)$. Now we can rewrite (10) as follows:

$$\begin{aligned}
(11) \qquad V^j_{im}(S_{itm}, t) = U^j_{itm} + \beta \sum_{a=1}^{A^j_{it+1m}} & P\left(g^a_{it+1m}\left(S_{it+1m}, t+1 \mid S_{itm}, t, d^j_{itm} = 1\right)\right) \\
& E\left(\max\left\{\tilde{V}^a_{it+1m}(S_{it+1m}, t+1 \mid S_{itm}, t, d^j_{itm} = 1)\right\}\right),
\end{aligned}$$

where E is the expectation operator taken only on the joint distribution of ε_{it}. The numerical complexity is due to the fact that the value function requires high-dimensional integrations for the computation of the "Emax function," which is denoted by the last term on the right-hand side of (11). We follow the procedure in Keane and Wolpin (1994), which uses Monte Carlo integrations to evaluate the integrals appearing in (11).

3.2. *Implications.* The model makes several predictions regarding the dynamic pattern of the proportion of immigrants in each labor market state (see Figures 1a and 1b). Participation in training related to a particular occupation is an investment in skills that are rewarded in that occupation by a higher wage, as well as increased job offer probability in that occupation. Human capital theory emphasizes the impact of human capital (schooling) on earnings (Ben-Porath, 1967). According to this theory, both the wage return and the job-offer reward to investment in training are realized over the entire future, and therefore, the implication of the model is that training should be started soon after arrival in Israel. However, in our model, training can also be viewed as an alternative to unemployment and, therefore, participation in training can be expected in later periods. Moreover, the availability of WT is random and, therefore, it is possible to observe participation in WT in later periods.

The accumulation of work experience and participation in a training program affect future wages faced by the individual as well as work possibilities that, in turn, affect future participation and wages in the labor market. Assuming that the availability of blue-collar jobs is higher than that of white-collar jobs (more blue-collar positions are available in the Israeli market than white-collar positions), the model predicts that workers who arrive with high potential human capital (i.e., schooling) initially invest by working in blue-collar jobs and obtain training and later find a job in a white-collar occupation. These predicted patterns of participation in training and occupational choice are consistent with those observed in the data (see Figures 1a and 1b).

3.3. *Simulated Maximum Likelihood Estimation.* Conditional on the values of the parameters and the observed state space for a given individual, the dynamic Bellman equation (10) looks like a standard indirect utility function in a multinomial choice model for panel data. The main complication in this case, in comparison to the multinomial probit (logit) model, stems from the solution to the dynamic programming model, which implies that the choices for each individual are correlated in each t. Furthermore, we need to allow for measurement error in observed wages. Specifically, we assume that $\ln w^{jo}_{itm}$, the log of the observed wage of individual i of unobserved type m at time t in occupation j, is of the form $\ln w^{jo}_{itm} = \ln w^{j}_{itm} + \eta^{j}_{it}$, where $\eta^{j}_{it} \sim N(0, \sigma^2_\eta)$ is the multiplicative measurement error.

The model is estimated using simulated maximum likelihood (SML) (McFadden, 1989; Keane and Wolpin, 1997). Let I be the number of individuals in the sample and denote by t_i the number of periods individual i is observed ($t_i \leq 20$). The vector of observed outcomes for individual i at date t, $t \leq t_i$ is given by $[d^{j}_{itm}, w^{jo}_{itm}]$. Note that the model's vector of parameters enters the likelihood through its effect on the choice probabilities and wages. Furthermore, an individual's wage is only observed when he is employed, and for each individual the sample is truncated at t_i.

Given the assumption of joint serial independence of the vector of errors, the simulated likelihood function is computed as a product of within-period conditional joint probabilities of the choices and the wage for each individual. The joint probabilities for each individual are computed using F ($F = 25$) simulations of the solution of the dynamic programming model for each observed outcome $[d^{j}_{itm}, w^{jo}_{itm}]$ conditional on the observed state S_{it-1m}. In other words, we use the simulated outcomes to compute $\Pr(d^{j}_{itm}, w^{jo}_{itm} \mid S_{it-1m}) = \Pr(d^{j}_{itm} \mid w^{jo}_{itm}, S_{it-1m})\phi(w^{jo}_{itm})$, where ϕ is the density of the observed wage.

To calculate the simulated value for $\Pr(d^{j}_{itm} \mid w^{jo}_{itm}, S_{it-1m})$ consider, for example, the case of $j = 1$, in which we calculate $\Pr(d^{1}_{itm} = 1 \mid w^{jo}_{itm}, S_{it-1m})$.[32] As noted above, there are various unobserved potential alternatives at t and, therefore, we must integrate them out in order to calculate the probability of the observed choice. The probabilities of the unobserved alternative choices, given that $d^{1}_{itm} = 1$ and S_{it-1m}, are computed using (1). The conditional probability of $d^{1}_{itm} = 1$ for each of

[32] For the states in which the wage is not observed, we compute the conditional probability using the simulated wage. In the same way, we compute the conditional probability for the states in which no wage outcome exists (e.g., unemployment).

these unobserved alternatives is computed using smooth simulated probabilities as suggested by Keane and Wolpin (1997).[33]

Due to the unobserved heterogeneity in the model, we solved the model for each type independently and the likelihood function is a weighted average of the likelihood of each type. Assuming that there are M unobserved types of individual ($m = 1, .., M$) and that the type probabilities depend on the individual's initial conditions (and therefore vary across individuals), the likelihood function can be written as

$$(12)\quad L(\theta) = \prod_{i=1}^{I} \sum_{m=1}^{M} \Pr\left(d^j_{i1m}, w^{jo}_{i1m}, d^j_{i2m}, w^{jo}_{i2m}, \ldots, d^j_{it_im}, w^{jo}_{it_im} \mid S_{i1m}, type = m\right) \times \pi_{im}(S_{i1m}),$$

where θ is the vector of parameters to be estimated and $\pi_{im}(S_{i1m})$ is the probability of inidividual i being of type m, which depends only on education and age on arrival and is given by

$$(13)\quad \pi_{im} = \frac{\exp\{\pi_{0m} + \pi_{1m}ed_i + \pi_{2m}\tau_i\}}{\sum_{m=1}^{M} \exp\{\pi_{0m} + \pi_{1m}ed_i + \pi_{2m}\tau_i\}}.$$

As explained above, we simplify the solution of the dynamic model by assuming a parameterized analytical format for the value function in the 21st quarter after migration. In particular, the present value of the utility of individual i of type m in the 21st quarter is the following linear function of the state variables in that period:

$$(14)\quad V^j_{im}(S_{i21m}, t = 21) = \delta_{1m} + \delta_2 EX_{i21m} + \delta_{3m} C^1_{i21m} + \delta_4 ed_i + \delta_5 \tau_i + \delta_6 L^H_{i21} + \delta_7 L^F_i + \delta_8 d^1_{i20m} + \delta_9 d^0_{i20m} + \delta_{10m} C^2_{i21m}.$$

3.4. *Identification.* The fact that we have (relatively) few wage observations limits the precision (i.e., results in large standard errors) of the estimated parameters of the earning function and limits the possibility of estimating interaction terms between imported human capital (age on arrival and schooling) and local accumulated human capital indicators in this equation. On the other hand, the data include a large number of observations on the transitions between the five individual state variables. These rich transitions moments are the main source of the identification of the job and training offer probabilities, as well as the utility parameters of training and unemployment outcomes.

[33] For example, for the probability that $d^1_{itm} = 1$, we use the Kernel smoothing function: $\exp(\frac{(V^1_{im}(S_{itm},t) - \max(V^f_{im}(S_{itm},t))}{\tau}) / \sum_{k=0}^{4} \exp(\frac{(V^k_{im}(S_{itm},t) - \max(V^f_{im}(S_{itm},t))}{\tau})$, where f is the simulation index and we use $F = 25$ simulations for calculating the smoothed probabilities. $V^f_{im}(S_{itm}, t)$ is the vector of all potential values for the particular case of potential alternative choice that is used for the calculation of the probability. τ is the Kernel smoothing parameter that we set to 500. The probability is calculated as the average over the F draws.

4. RESULTS

The model was estimated using simulated maximum likelihood (Equation (12)), based on the full solution of the dynamic model and the particular functional form specifications described above.[34] The model was estimated both with two types ($M = 2$) and with four types ($M = 4$). The likelihood ratio test rejects the restricted two types model at a marginal significance level of 0.003 with 48 restrictions (the test statistic is equal to 79.36). In this section, we report the results from the four-type estimated model and discuss the fit of the model to the aggregate labor states, the transitions between these states and wages, as well as the estimated parameters and their economic interpretation.[35]

4.1. *Model Fit*

4.1.1. *Labor market states.* Given the estimated parameters of the model, we calculate the predicted proportion of immigrants in each of the five labor market states (see Figures 1a and 1b).[36] The predicted proportions of immigrants closely matches the main dynamic patterns of the aggregate outcomes of unemployment, employment, and training. Specifically, the model accurately predicts the rapid decrease in unemployment during the 1st year of residency in Israel and the movements in unemployment during the last 2 years of the sample period. However, it underpredicts unemployment during the 2nd and 3rd years. Most of the underprediction of unemployment is a result of the overprediction of employment in BC jobs.

The predicted rise in the share of immigrants who are employed in WC closely matches the observed patterns, whereas the predicted pattern of participation in training is roughly consistent with the data. The estimated model predicts a peak in participation in WT (BT) in the fourth (sixth) quarter (5% in WT and 2.6% in BT), whereas the actual peak in WT (6.4%) occurs in the fourth quarter and that in BT (4.3%) occurs in the fifth quarter.

Based on a simple χ^2 Newman-Pearson fit test for the first 20 quarters, we reject the hypothesis that there is no difference between the actual and predicted proportions in unemployment, WC, WT, and BT, each taken separately. We do not reject this hypothesis with respect to employment in BC. The fit test for the model

[34] The program is written in FORTRAN90 code and iterates between the solution of the Dynamic Programming (DP) and the calculation of the likelihood function. For each of the 419 immigrants in our sample, we calculate the *Emax* at 2,070 points in the state space that may arise during the 20 period planning horizon (which implies 2,070 combinations of EX, C^1, C^2, d_1, d_2, d_3 and d_4). At each of these points, we use 150 simulated draws of the vector ε to calculate the E max. The state space increases linearly with the number of unobserved types. In this version of the model, we assume four unobserved types, implying that for each person we calculate the value functions in ($4 \times 2{,}070$) points in the state space. We use parallel processing (super-computers) on 8 or 16 or 32 processors on an IBM and Silicon Graphics (Origin2000) super-computer at Tel-Aviv University and on a Silicon Graphics super-computer at Boston University.

[35] For the estimated model with two types, see Cohen and Eckstein (2002).

[36] These predictions are based on 50 one-step-ahead simulations of the choices of each of the 419 individuals in our sample aggregated over the estimated types.

as a whole shows a rejection at the 1% level. In addition, we find a significant difference between the predicted and actual choice distributions for all of the choices during the first 11 quarters and during the 16th quarter.[37]

The model accurately reproduces the observed 20% decline in the share of those employed in BC and the increase in the share of those employed in WC during the 5th year in Israel (see Figure 1a).[38] This is a surprising and important result and there are potentially three sources for this change in occupational choices: (i) the endogenous accumulated human capital, in the form of experience, training, and knowledge of Hebrew, which affects job offer probabilities and wages; (ii) the actual dynamic change in the stocks (proportions) of immigrants in each labor market state;[39] and (iii) the differences between the exogenous characteristics of the cohort of 1989–90 and the cohort of 1991–92 ("cohort effects").

Using unconditional predictions for the entire 20 quarters in Israel, the model predicts a higher share for BC and substantially fewer immigrants in training than is found in the data or predicted by the one step ahead (conditional) predictions. In this case, the reduction in the proportion of BC starts as UE reaches bottom toward the end of the 3rd year in Israel and BC proportions are predicted to decrease by 6% during the 4th and the 5th year. Simulations based on a sample of identical immigrants (with the same schooling level and age on arrival as those of the 1989–90 cohort) also predict a reduction of about 6% in the share of BC during the 5th year in Israel. Hence, we can conclude that the cohort explanation (point (iii) above) is not an important factor in explaining net transition into WC during the 5th year in Israel. That is, the 18% net increase in WC employment is divided between 6% that is due to (i) above, with the rest due to the actual reduction in the stock of BC workers that led to a net move to WC directly and indirectly through UE (source (ii) above).

The simulated mean wages and reservation values consistently show substantial gain following the acceptance of WC job offers. Hence, the only reason for the low increase in the proportion of immigrants working in WC throughout the sample period is the relatively low WC offer rates conditional on not having worked previously in a WC job.

4.1.2. *Transitions.* Table 4 presents the actual and predicted mean transitions based on the same simulations and data presented in Figures 1a and 1b. The model accurately predicts the persistence in WC jobs, BT, and WT. However, it produces too little persistence in unemployment and correspondingly too much transition from UE to BC jobs, as shown in Figures 1a and 1b. The predicted transitions

[37] We also estimated the model ($M = 2$) by minimizing the sum of squared differences between the actual and the predicted aggregated labor market choices which are presented in Figures 1a and 1b. Obviously, the fit of the estimated model to aggregate choices improved; however, this estimation did not provide a good fit to the individual's choices.

[38] Note that the one period ahead prediction for the sample adjusts the state (S_{itm}) each period for each individual in the sample according to the outcome in the data. Unconditional prediction is based on simulations in which the state for each individual (S_{itm}) is based on the predicted outcome.

[39] Source (ii) is measured by the difference between the unconditional and conditional predictions of the model. The latter is affected by the attrition of the sample at the end of the period.

TABLE 4

ACTUAL AND PREDICTED TRANSITION RATES (PERCENT)*

To / From	UE Actual	UE Model	WC Actual	WC Model	BC Actual	BC Model	WT Actual	WT Model	BT Actual	BT Model	Obs.
UE	66.85	56.37	7.07	8.15	21.86	33.12	2.70	2.10	1.51	0.26	1,258
WC	1.53	1.00	95.51	98.46	1.43	0.05	1.15	0.40	0.38	0.09	1,046
BC	3.89	2.04	0.64	1.44	93.56	95.92	0.92	0.45	0.99	0.14	2,828
WT	18.38	22.23	17.65	9.90	12.50	11.11	51.47	56.77	0.00	0.00	136
BT	23.08	26.39	4.40	3.27	20.88	12.82	0.00	0.00	51.65	57.52	91
Total											5,359

*Each row totals 100%.

TABLE 5

ACTUAL AND PREDICTED ACCEPTED WAGES BY SENIORITY AND TRAINING*

	WC Occupation Actual	WC Occupation Model	WC Occupation Obs.	BC Occupation Actual	BC Occupation Model	BC Occupation Obs.
By quarters in Israel						
1–4	21.77	13.86	4	10.47	10.98	64
5–8	15.06	14.96	46	10.97	11.68	139
9–12	18.86	16.64	29	11.87	12.63	73
13–16	20.45	17.86	25	12.50	13.66	97
17–20	21.52	19.08	28	15.23	14.72	69
By training						
No training	17.93	16.14	96	11.99	12.18	402
After training	19.98	17.18	36	12.66	13.39	40

*Wage per hour in July 1995 prices (NIS).

from training to the two employment states and to unemployment correspond fairly accurately to the observed transitions. The transitions to training originate mainly from unemployment.

4.1.3. *Accepted wages.* Table 5 shows that the average annual compounded predicted wage growth of 6% for BC and 7% for WC during the first 5 years in Israel are consistent with the observed wage growth.[40] This fact is also consistent with the average wage growth observed in cross-sectional data and the estimation results reported by Eckstein and Weiss (2004). The data show that wages are increased by 11.1% for immigrants who participated in training for WC occupations and by 6% for participants in training for BC occupations. The model, however, predicts that mean accepted wages are 6.4% higher for WT participants and 9.9% higher for BT participants. Given the estimated wage parameters, which are reported below, this result indicates that the model's selection process of individuals to employment by occupation dominates the estimated predicted return to training.

[40] Note that the poor fit in quarters 1–4 for WC wages is a result of having only four observations with one large outlier.

4.2. *Estimated Parameters*

4.2.1. *Wage parameters.* The four types of immigrants face substantially different estimated rates of return to training in the two occupations (see Table 6).[41] The rate of return to WT in WC jobs is 19% for type 1, 18% for type 3, and zero for types 2 and 4. The predicted weighted return across types for the average immigrant is 13.6%, which is higher than the OLS estimate of 11.6%.[42] Similarly, the rate of return on BT in BC jobs is 12.7% for type 1, 3.6% for type 3, and zero for types 2 and 4.[43] Hence, most of the immigrants (types 1 and 3) gain substantially from any training program. The unobserved heterogeneity in the estimated return to training that we find here can explain the large variance of the estimated training coefficients that are reported in the literature (Heckman et al., 1999). The dynamic programming model provides a complicated control for the selection of individuals to training and work by occupation and implies a higher estimate for the impact of training on wages than does the OLS regression. These estimated returns to training are large relative to those reported in the existing literature.[44]

Accumulated experience in Israel has a positive and significant impact on wages. An additional quarter of experience increases the wage in WC by 2% and in BC by 1.9%. These coefficients show that the actual experience effect is similar across occupations and is very close to the estimated coefficient from the OLS regressions. Knowledge of Hebrew has a significant and positive impact on wages in both occupations, whereas knowledge of English has a positive effect on wages in WC jobs, but a negative effect on wages in BC jobs.[45] The Hebrew coefficient implies that the wage rate of return to average knowledge of Hebrew (compared to no knowledge of Hebrew) is 15–19%, which is close to the OLS estimates.

The estimated parameters of the wage equation imply that the value of imported human capital in the form of schooling and experience abroad (age on arrival), conditional on local accumulated human capital, is zero. The only imported human capital that is rewarded in Israel is the knowledge of English and Hebrew at arrival.

[41] We encountered several technical difficulties in estimating the SE with four types as reported here. The SE are larger overall than we find in the estimation of the model with only two types reported in Cohen and Eckstein (2002).

[42] For the average immigrant (by schooling and age at arrival), the probability of each type is reported in Table 6.

[43] In the estimation, we imposed the constraint that the return to BT (WT) in WC (BC) jobs is equal to zero. This restriction followed the OLS wage regression results (see footnote 22) and the estimation results obtained with two types.

[44] It should be noted that all the training parameters in Table 6 are not significantly different from zero. However, for the specification with two types the WT (BT) impact for type 1 on wages in WC(BC) was significant (see Cohen and Eckstein, 2002). In this case, we also conducted several Wald tests for the various outcomes of training. For example, we reject the hypothesis that training does not affect wages (four zero-restrictions) at a marginal probability level of 10%. Other joint restrictions on training are also rejected. Given the small number of wage observations, the four types increased the number of parameters and the estimated standard errors of the coefficients in the wage regression.

[45] Note that the knowledge of English and Hebrew indices vary between 1 to 4, where a person with no language skills has an index of 1. The mean index is 1.76 for English and 2.7 for Hebrew.

TABLE 6

ESTIMATED WAGE FUNCTION PARAMETERS

Wage Parameters	BC Wage		WC Wage
α_{01} - type1	1.88*		1.63*
	(0.08)		(0.28)
α_{02} - deviation of type2 from type1	0.23*		−0.18
	(0.08)		(0.47)
α_{03} - deviation of type3 from type1	0.03		0
	(0.1)		(0.23)
α_{04} - deviation of type4 from type1	0.14		−0.36
	(0.09)		(4.26)
α_H - Hebrew	0.11*		0.1
	(0.03)		(0.07)
α_F - English	−0.04*		0.14*
	(0.02)		(0.04)
α_A - age on arrival	0		0.01
	(0)		(0.01)
α_S - years of schooling	0.01		0.01
	(0.01)		(0.02)
α_e - experience	0.02*		0.02
	(0)		(0.01)
α_{c11} - WC training, type1			0.19
			(0.55)
α_{c12} - WC training, type2			0
			(0.42)
α_{c13} - WC training, type3			0.18
			(0.13)
α_{c14} - WC training, type4			0
			(4.47)
α_{c21} - BC training, type1	0.13		
	(0.18)		
α_{c22} - BC training, type2	0		
	(4.22)		
α_{c23} - BC training, type3	0.04		
	(0.12)		
α_{c24} - BC training, type4	0		
	(0.26)		
Proportion of type1		0.32	
Proportion of type2		0.12	
Proportion of type3		0.41	
Proportion of type4		0.14	

NOTES: Standard deviations appear in parentheses. Significant parameters at the 5% level are marked with an asterisk. Type proportions are for the average immigrant, who has 14.6 years of schooling and is 38 years old on arrival.

Our estimates suggest that the return to local Israeli human capital is a result of accumulated local experience, knowledge of Hebrew, and training. The results with respect to imported human capital are roughly equivalent to the OLS estimates, although this might be the result of the short period since arrival.

Eckstein and Weiss (2004), who used cross-sectional data that included FSU immigrants from earlier waves, find that the return to imported human capital is zero on arrival but significantly increases with time since arrival. However, the cross-sectional data do not include data on actual experience, knowledge of Hebrew and English, and training. In this article, we use actual data on accumulated human capital in the host country and, therefore, can better measure the sources for wage growth in the new country.[46] According to our specification, locally accumulated human capital depends on imported skills through the effect of education and age on arrival on the type probabilities, which in turn affect the return to training and the availability of job offers and WT offers.

4.2.2. *Job offer and white-collar training offer parameters.* The estimated parameters of the logistic job offer probabilities (Equations (3) and (4)) are presented in Table 7 and the implied offer probabilities conditional on previous choice and weighted by types (for the average immigrant) are reported in Table 8. These probabilities are based on the average exogenous attributes in our sample and on the levels of the endogenous human capital variables.[47] Due to institutional restrictions, we assume that WC job offers are not available in the first quarter for immigrants who attend Ulpan and have no prior knowledge of Hebrew.

The large coefficients of employment in the previous period in the same occupation for all types and in both occupations imply that the individual almost always retains his job regardless of his other characteristics ($P^{11} = 1$ and $P^{22} > 0.98$). Immigrants who did not work in the previous quarter, either because they were unemployed or were enrolled in one of the training programs, face a *higher* probability of receiving a job offer than immigrants who worked in the other occupation. The difference is from three- to sixfold. For example, the offer rate from unemployment to WC is between 11% and 26% per quarter in the 1st year (see Table 8) and from BC to WC is between 3.4% and 9.4%. Hence, job arrival rates from the other occupation are significantly lower for working individuals for all types (see also Table 9).[48] We also find that the BC job offer probability in the first quarter is significantly lower than in later periods (see Table 9).

Accumulated general work experience in Israel has a negative effect on the probability of receiving job offers in WC and BC occupations. In order to understand this result, one must keep in mind that these marginal effects are conditional on the last period's state. Conditional on the fact that the immigrant is working, the estimated job offer rate for the same occupation is one, independent of the level of experience (see Table 8). However, an unemployed immigrant with some local experience has a lower job offer rate. These results indicate that the job offer probabilities are sensitive to the individual's employment history, which is intuitively very reasonable.

[46] The result in Eckstein and Weiss (2004) is based on a nonlinear interaction between schooling, age on arrival, and time in the host country.

[47] The average attributes are: age on arrival, 38, English skill index, 1.76, and Hebrew skill index, 2.7. For the WC job offer calculation, we consider an immigrant who worked in a WC job in the FSU.

[48] This result is consistent with the standard assumption regarding the rates of arrival of offers in search models, where on-the-job search is allowed (see the survey by Eckstein and van den Berg, 2008).

TABLE 7

ESTIMATED JOB OFFER PROBABILITY PARAMETERS

Job Offer Parameters	WC Offer ($j = 1$)	BC Offer ($j = 2$)
b_{01j1} - worked in WC at $t-1$, type1	16*	−2.13*
	(4.47)	(0.46)
b_{01j2} - worked in WC at $t-1$, deviation of type2 from type1	−0.01	0.77
	(4.47)	(1.07)
b_{01j3} - worked in WC at $t-1$, deviation of type3 from type1	0.1	−6.92
	(4.47)	(4.47)
b_{01j4} - worked in WC at $t-1$, deviation of type4 from type1	0.1	−1.4
	(4.47)	(4.47)
b_{02j1} - worked in BC at $t-1$, type1	−2.65*	6.15*
	(0.5)	(1.24)
b_{02j2} - worked in BC at $t-1$, deviation of type2 from type1	−2.19	1.92
	(2.82)	(3.72)
b_{02j3} - worked in BC at $t-1$, deviation of type3 from type1	−1.05	−1.55
	(1.03)	(1.35)
b_{02j4} - worked in BC at $t-1$, deviation of type4 from type1	−5.19	−0.22
	(4.45)	(1.37)
b_{03j1} - didn't work at $t-1$, type1	−1.75*	−0.49*
	(0.21)	(0.13)
b_{03j2} - didn't work at $t-1$, deviation of type2 from type1	0.6	1.03*
	(0.63)	(0.32)
b_{03j3} - didn't work at $t-1$, deviation of type3 from type1	−0.75*	−0.91*
	(0.34)	(0.2)
b_{03j4} - didn't work at $t-1$, deviation of type4 from type1	−5.23	2.24*
	(4.47)	(0.37)
b_{11j} - work experience in Israel 1–4	−0.35	−0.14
	(0.22)	(0.11)
b_{12j} - work experience in Israel > 5	−1.01*	−0.65*
	(0.28)	(0.18)
b_{2j} - training in occupation j	1.12*	0.02
	(0.24)	(0.12)
b_{3j} - age on arrival	−0.03*	0
	(0.01)	(0)
b_{4j} - Hebrew	0	0
	(0.09)	(0.06)
b_5 - English	0.24*	–
	(0.09)	
b_6 - WC = 1 in Soviet Union	0.62*	–
	(0.27)	
b_{04} - first period dummy from UE	–	−0.66*
		(0.16)
b_7 - first 5 periods dummy from BC	–	−2.27*
		(0.27)

NOTES: Standard deviations appear in parentheses. Significant parameters at the 5% level are marked with an asterisk.

Participation in training related to a certain occupation has a large positive effect on job offers in the same occupation. Table 8 demonstrates that participation in WT almost triples the WC job offer probability from both UE and BC states. In particular, if the average immigrant has no experience in Israel, he would receive

TABLE 8

JOB AND TRAINING OFFER PROBABILITIES (WEIGHTED BY TYPES)*

From		To WC			BC			WT		
Experience		0	1–4	5+	0	1–4	5+	0	1–4	5+
WC	After training	1.00	1.00	1.00	0.06	0.05	0.03		0.00	
	No training	1.00	1.00	1.00	0.06	0.05	0.03		0.04	
BC	After training	0.09	0.07	0.04	0.99	0.99	0.99		0.00	
	No training	0.03	0.02	0.01	0.99	0.99	0.99		0.04	
UE	After training	0.26	0.21	0.12	0.38	0.36	0.27		0.00	
	No training	0.11	0.08	0.05	0.38	0.36	0.27		0.04	

NOTES: The BT offer is assumed to be one if the state is "no training." The average immigrant's characteristics are: Age on arrival is 38, Hebrew skill index is 2.7, English skill index is 1.76, years of schooling is 14.6, and the immigrant worked in a WC job in the FSU.

TABLE 9

ESTIMATED WC AND BC JOB OFFER PROBABILITIES FROM UNEMPLOYMENT BY TYPES

	WC Job-Offer Probability							
	No Training				After Training			
Experience	Type 1	Type 2	Type 3	Type 4	Type 1	Type 2	Type 3	Type 4
0 first period	–	–	–	–	–	–	–	–
0 other periods	0.15	0.25	0.08	0.00	0.36	0.50	0.21	0.00
1–4	0.11	0.19	0.06	0.00	0.28	0.42	0.16	0.00
5+	0.06	0.11	0.03	0.00	0.17	0.27	0.09	0.00
	BC Job-Offer Probability							
	No Training				After Training			
Experience	Type 1	Type 2	Type 3	Type 4	Type 1	Type 2	Type 3	Type 4
0 first period	0.22	0.44	0.10	0.73	0.22	0.45	0.10	0.73
0 other periods	0.35	0.60	0.18	0.84	0.36	0.61	0.18	0.84
1–4	0.32	0.57	0.16	0.82	0.33	0.57	0.16	0.82
5+	0.22	0.44	0.10	0.73	0.23	0.45	0.10	0.73

NOTES: The average immigrant's characteristics are : Age on arrival is 38, Hebrew skill index is 2.7, English skill index is 1.76, and the immigrant worked in a WC job in the FSU.

a WC job offer each quarter with probability of 0.11 and participation in WT increases this offer probability by 136% to 0.26. The same immigrant with no training but with five or more quarters of work experience in Israel will receive a WC job offer with a probability of 0.05. Participation in WC training (WT) increases this probability to 0.12, whereas participation in BT increases the BC job offer from unemployment only slightly.

Knowledge of Hebrew does not affect the WC and BC job offer probabilities, though it does affect wages in both occupations (see Table 7). This is a surprising result that may indicate that although individuals who spend more time learning the new language put more search effort into finding a job, they are also more selective, such that these effects tend to offset each other.

We find that holding a WC job in the FSU and arriving with English skills (i.e., imported human capital) have a significant positive effect on the rate of WC job offers. However, the fact that the individual worked in a WC occupation has a much lower impact on job offer probabilities than does training.

We assume that BT is always available, but find that the quarterly probability of receiving a WT offer is negatively affected by schooling and differs among the four types. For the average immigrant, the quarterly probability of receiving a WT offer equals 0.027 for type 1, 0.084 for type 2, 0.05 for type 3, and almost zero for type 4 (see Table 9 and Table A3). These are relatively low rates that are the outcome of the observed low rate of transition to the white-collar training programs.

4.2.3. *Net utility from unemployment and training.* The utility while unemployed and in training (either BT or WT) is negative (see Table A3) and varies significantly across types. This can be interpreted as a result of high search costs or other investment costs associated with the state of nonemployment. Type 1 prefers unemployment to both WT and BT, whereas type 2 prefers WT to UE and UE to BT. Since the utility of type 2 while attending WT is higher than the utility of being unemployed, his participation in WT might be motivated by the current utility gain rather than by expected future returns.

The government-provided income is the same for UE and training. Hence, the estimated lower value of utility in training indicates that there is additional disutility from training relative to UE. The very low utility in both UE and training may be influenced by the fact that immigrants have no access to formal or informal loans and, therefore, their consumption while not working is very low. Note that the negative utility while in training is an important reason for the observed low participation in training and, therefore, the interpretation of the parameters has interesting policy implications.

4.2.4. *Terminal value.* This is the most ad hoc component of the model. Nevertheless, Table A3 shows that all the estimated parameters have the expected a priori signs. Thus, all the human capital variables have positive coefficients. Age and being unemployed in the previous period reduce the terminal value of the immigrant's utility after 21 quarters in Israel. Since utility is measured in terms of per hour wage in NIS, the parameters can be interpreted accordingly. For example, training in WC increments the terminal value by 2,156 NIS for types 1 and 3 and by 1,398 (1,650) NIS for type 2 (4), whereas training in BC increments the terminal value by 528 NIS for types 1 and 3 and by 222 (114) NIS for type 2 (4).[49]

4.2.5. *The interpretation of types.* The estimated proportion of types (Table 6) depends on the two main imported characteristics: age on arrival and education

[49] The consistency of the estimated terminal value is a complicated problem that is not dealt with here.

TABLE 10
PREDICTED TRANSITION RATES BY TYPE (PERCENT)*

From	To												
	UE				WC				BC				
Type	1	2	3	4	1	2	3	4	1	2	3	4	Total
UE	57.67	32.02	75.20	17.21	11.16	17.88	6.04	0.07	29.07	47.63	15.58	82.12	1258
WC	0.97	0.87	1.05	1.03	98.21	98.58	98.58	98.58	0.09	0.18	0.00	0.02	1046
BC	0.89	0.13	3.97	1.18	3.03	0.36	1.11	0.01	95.18	99.27	94.28	98.57	2828
WT	20.40	11.19	29.78	8.43	13.79	19.21	7.84	0.25	9.04	12.82	5.62	34.56	136
BT	26.09	16.31	33.91	8.95	4.68	7.52	2.29	0.02	11.71	18.66	6.29	33.52	91
Total													5359

From	To								
	WT				BT				
Type	1	2	3	4	1	2	3	4	Total
UE	1.84	2.21	2.93	0.33	0.26	0.26	0.26	0.26	1258
WC	0.66	0.29	0.29	0.29	0.09	0.09	0.09	0.09	1046
BC	0.75	0.10	0.49	0.09	0.14	0.14	0.14	0.14	2828
WT	56.76	56.78	56.76	56.76	0.00	0.00	0.00	0.00	136
BT	0.00	0.00	0.00	0.00	57.52	57.52	57.52	57.52	91
Total									5359

NOTE: Each row totals 100%.

(Table A3). As noted, the estimated wage function (Table 6) indicates that types 1 and 3, which together account for 73% of the population, receive a high wage return to training in both occupations, whereas for types 2 and 4 the wage return to training is zero. Table 9 indicates that WC job-offer probability from unemployment is the highest for type 2 and is almost zero for type 4. However, the BC job-offer probability from unemployment is highest for type 4 and lowest for type 3. Type 1's conditional probability of moving from a BC to a WC job is significantly higher than that of the other types, and type 2's conditional probability of moving from a WC to a BC job is significantly higher than that of the other types (Table 9).

Table 10 presents the mean predicted quarter-to-quarter transitions between the five alternative labor market states for all immigrants conditional on the unobserved type.[50] The main result is that types 2 and 4 experience less persistent unemployment. Although type 2 moves from unemployment to both WC and BC jobs, type 4 moves only to BC jobs and has zero transitions to WC jobs. In addition, type 4 has the most direct movements from training (either WT or BT) to BC jobs, whereas type 2 has the most direct movements from training to WC jobs. It is interesting to note that the two types who stay the longest in unemployment (types 1 and 3) also have higher transitions from training to unemployment.

[50] The transitions here are based on the same simulations that were used to form the weighted transitions in Table 4.

These results indicate that only a small group of immigrants (types 2 and 4) are suited to market demand. Type 2 is better suited in both occupations, whereas type 4 is suited only to BC jobs, and neither gain anything from vocational training programs. However, the largest proportion of the immigrants (type 3, 41%) require a comprehensive retraining in order to adjust their skills to the demand of the Israeli labor market. In other words, conditional on observed human capital, these immigrants face low job-offer rates, but gain substantially by investing in government-provided training programs. These training programs are costly in time but provide a large wage compensation in later periods. Another large group of immigrants (type 1, 32%) are similar to type 3 but have higher job offer rates. They must also invest in training in order to improve their skills in WC jobs and therefore have a high wage return to training in these jobs.

5. POLICY IMPLICATIONS

Training programs are the main government instrument for intervention in the labor market. In this section, we analyze the impact of policy experiments that change the availability of training programs relative to the existing estimated policy. In order to do this, we compare the outcomes of the simulation of the estimated model (existing policy or benchmark) to the outcomes of the simulation of the following four alternative training policies:

Case 1: No training is offered.[51]
Case 2: Only training related to blue-collar occupations (BT) is offered.
Case 3: Only training related to white-collar occupations (WT) is offered.
Case 4: The WT offer probability is doubled.[52]

The simulation outcomes are all conditional on each individual's state on arrival, but not on the actual subsequent outcomes. First, we measure the effect of the policy experiments on wages and unemployment for an average immigrant (Table 11). Then, we measure the aggregate predicted wage growth that is due to the policy experiments (Table 12), and, finally, we measure the effect of the policies on the immigrant's welfare (Tables 13 and 14).

5.1. *Wages and Unemployment in the 4th and 5th Years.* Table 11 reports the predicted difference in mean accepted wages and mean unemployment rate during the 4th and 5th years in the new country between the benchmark and the simulated alternative policy. We find that the policy experiments have a small impact on the predicted long-term unemployment rate among immigrants. In the benchmark economy, the unemployment rate after 3 years is predicted to be less than 4%

[51] A related and potentially interesting policy would be the termination or extension of Ulpan (Hebrew language course) on the immigrants' training, employment, and welfare. Unfortunately, the available data are not detailed enough to allow a serious analysis of this important question.

[52] The probability of BT is assumed to be one in the model. The WT offer probability, which depends on schooling and unobserved type, is doubled for each immigrant according to his WT offer probability in the benchmark economy.

TABLE 11

PREDICTED POLICY EFFECT ON MEAN ACCEPTED WAGES AND UNEMPLOYMENT DURING THE 4TH AND 5TH YEARS*

	Policy Change					
	Case 1: No Training			Case 4: Double WT Offer		
	Percent Change		Change	Percent Change		Change
Immigrant	WC Wage	BC Wage	UE Rate	WC Wage	BC Wage	UE Rate
BC in FSU, schooling = 12	−3.4	−0.4	0.4	1.6	0.4	−0.2
WC in FSU, schooling = 15	−3.1	−0.3	0.4	1.7	0.2	−0.4

*Percentage change in wages and unemployment relative to the benchmark. The average immigrant's age on arrival is 30.

TABLE 12

PREDICTED ANNUAL EFFECT OF TRAINING AVAILABILITY ON MEAN ACCEPTED WAGES*

	Total	White Collar	Blue Collar
Year 1	0.09	0.18	0.06
Year 2	0.67	1.40	0.23
Year 3	1.12	2.12	0.23
Year 4	1.40	2.40	0.29
Year 5	1.61	2.46	0.43
All Years	1.16	2.35	0.19

*Percentage change in the estimated model relative to the economy without training (case 1).

TABLE 13

PREDICTED POLICY EFFECT ON HOURLY PRESENT VALUE (PV)*

	Immigrant			
	BC in FSU, Schooling = 12		WC in FSU, Schooling = 15	
Policy Change	Age on Arrival 30	Age on Arrival 45	Age on Arrival 30	Age on Arrival 45
Upon Arrival	3243.02	3008.79	3258.55	3000.33
Case 1: No Training	3152.55	2912.66	3156.19	2889.36
	(−2.79)	(−3.19)	(−3.14)	(−3.7)
Case 2: No WT	3152.55	2912.66	3156.19	2889.36
	(−2.79)	(−3.19)	(−3.14)	(−3.7)
Case 3: No BT	3243.02	3008.79	3258.55	3000.33
	(0)	(0)	(0)	(0)
Case 4: Double WT	3309.91	3079.05	3338.2	3085.94
Offer	(2.06)	(2.34)	(2.44)	(2.85)

*PV utility - NIS per hour in June 1995 prices. Percentage change relative to the benchmark in parentheses.

and remains close to that level after that. Earnings are affected in the predicted direction, such that mean earnings in WC jobs decrease due to the nonavailability of training programs and increase as the availability of WT increases. The impact of the availability of WT programs on wages in BC jobs is small. There is almost no

TABLE 14

PARTITION OF THE GAIN FROM TRAINING BY SOURCE - PERCENT OF TOTAL GAIN

Experiment	Immigrant			
	BC in FSU, Schooling = 12		WC in FSU, Schooling = 15	
	Age on Arrival 30	Age on Arrival 45	Age on Arrival 30	Age on Arrival 45
No training	(3152.55)	(2912.66)	(3156.19)	(2889.36)
Return in utility only	1.11	1.55	0.59	0.83
	(3153.55)	(2914.15)	(3156.79)	(2890.28)
Return in utility and terminal value	64.68 (3211.07)	69.88 (2979.83)	56.23 (3213.74)	60.59 (2956.6)
Return in utility, terminal value, and job offer	98.19 (3241.38)	99.02 (3007.84)	97.37 (3255.86)	98 (2998.1)

NOTES: PV utility - NIS per hour in June 1995 prices appears in parentheses.

difference in the effect of these policies on immigrants with different backgrounds (i.e., education and occupation in the source country).

The most interesting result is that increasing the availability of WT (case 4) has a large impact on accepted wages and affects the predicted mean accepted wages in both white-collar and blue-collar occupations at about the same rate. The increase in the BC mean accepted wage is a result of the selection of different types of immigrants to WT programs and, subsequently, to WC jobs.

We do not report the results of cases 2 and 3 here since the availability of BT has zero impact on mean accepted wages and unemployment. The main result is that the *only* gain is from white-collar training programs. The availability of these training programs has a very large impact on participation and predicted wage growth, but only a minor predicted impact on unemployment. An important point to remember is that the endogeneity of all these outcomes is very important in generating the main results.

5.2. *Aggregate Wage Growth Due to Training.* It is common to view the predicted aggregate change in wages as the gross economy rate of return to the training policy that was implemented.[53] In Table 12, we report the predicted annual effect (according to year since arrival) of training availability on the mean accepted wage as a percentage change relative to an economy without training (case 1). We use our sample of 419 males as a representative sample of male immigrants in order to calculate the effect of the policy on all male immigrants in the economy. The calculation of the aggregate rate of wage growth due to training differs from the estimated coefficient of training in the wage equations since it includes dynamic selection by workers themselves, in addition to the impact of training on wages and the random opportunities.

[53] The implicit assumption is that the mean wage measures mean productivity (the wage measures marginal productivity). The net economy return should account for the costs and benefits, both private and social, of the programs, which are not taken into account here. These wage changes are used in the government decision process to compare the outcome of the training program to other public investments.

The predicted average aggregate wage growth due to training over the first 5 years following arrival is about 1.16% (Table 12). The most important result is that the total rate of return increases over time. In the 1st year, the effect is almost zero since only a small number of immigrants are predicted to participate in training. Most of the participation in training occurs between the end of the 1st and the 3rd year following arrival in Israel. Therefore, it is not surprising to observe that the return to training increases during this period. The large increase in return in the 5th year is due to the large shift of workers from BC to WC as discussed above. The main gain from training is due to the accumulation of training among type 1 immigrants who eventually find WC jobs. Finally, since the predicted 1.12–1.61% growth in wages occurs between the 3rd and the 5th year following arrival, it is safe to conclude that the present value increase in wages due to training is more than 1%.

5.3. *Immigrants Welfare Gain from Training.* We consider the impact of each of the four experiments on the hourly present value (PV) of utility for four representative immigrants that differ only in their imported human capital: age on arrival, years of schooling, and occupation in the FSU. Knowledge of Hebrew and English are set at their sample means. The results of the experiments are presented in Table 13 in the form of PV level of utility for each case and percentage difference from the estimated model.

If no training is available, then the utility of a male immigrant is reduced by 2.8–3.7% and if the availability of WT is doubled, the PV utility increases by less (2–2.85%). These are very reasonable estimates for the overall individual welfare gain from the availability of training and reflect all costs and benefits that are associated with participation in training programs. An interesting result is that the gain for older immigrants from the existence of WT is higher than the gain for younger immigrants with the same education level. On the other hand, the policy that eliminates BT programs has no impact at all on immigrants welfare. This implies that training in high-skill occupations is an important investment for older immigrants at all skill (education) levels.

In order to further investigate the welfare gains from training, we partition the total gain from the existence of training in both occupations by restricting the potential sources of the gain (Table 14). Specifically, we use as a benchmark the PV of the estimated model under the "no training" policy (case 1). Then, we allow for training to be available as in the benchmark estimated probabilities (that is, WT available according to the immigrant's education and unobserved type and BT available with probability one). The gains from training are allowed to change in a particular sequential order. First, if the gain from training is only due to the utility from the participation in training, then the PV gain is 0.6–1.55% of the total percentage gain reported in Table 14.

Most of the gain (56–70%) is derived from the effect of training on the terminal value. The estimated terminal value component of the gain from training approximates all the future returns from training, which include job offer rates and wage returns. Hence, it is not surprising that this component captures most of the individual gain. The effect of training on job offer probabilities accounts for about 30–41% of the gain. Hence, the wage return during the first 5 years accounts for about 1–2% of the immigrant's PV utility gain from training. This result is due to the fact that the high return to training in wages is reduced by the low offer probability of WT, the loss in utility, and the loss of potential experience while attending training.[54]

6. CONCLUSIONS

In this article, we estimated a dynamic choice model for the employment of immigrants in blue- and white-collar occupations and training, where the randomly offered opportunities in the labor market are affected by past choices. Participation in training programs affects mean wage offers and job-offer probabilities by occupation and provides direct utility. Furthermore, the knowledge of the new country's language changes over time and imported human capital affect both mean wage offers and job-offer probabilities by occupation.

The estimated model accurately captures the pattern of observed labor market choices by immigrants during their first 5 years following arrival. The estimated coefficients of the wage function show that the conditional estimated rates of return to white-collar training are very high for 73% of immigrants. These rates are lower for blue-collar training but still significant for 32% of the immigrants. However, they are zero for the rest. The return to knowledge of Hebrew in both occupations is high, whereas the knowledge of English affects only wages in white-collar jobs. Accumulated experience in the new country has about a 2% return per quarter, whereas imported schooling and experience (age) have zero return conditional on the local accumulated human capital. The high return to local experience, the large estimated disutility from training, and the low offer probability of training in white-collar occupations are the main reasons for the observed low number of male immigrants who participate in training. As a result, the total individual ex ante welfare gain from the existence of training programs is estimated to be 2.8–3.7%. Furthermore, the increase in wages during the first 5 years, which is due to the availability of government-provided vocational training programs, is estimated to be about 1.16%. However, the wage growth due to training increases over time and reaches 1.6% by the 5th year following arrival to the new country.

Several implications emerge from these findings. First, the individual and overall gain to the economy from training in white-collar occupations is much higher than from training in blue-collar occupations. Second, the realization of the return to training may take a long time due to low job offers. Third, the impact of training on outcomes through job offer probability is larger than the direct effect on the mean of the offered wage distribution. The similarity between immigrants and displaced workers suggests that the above model can be used to evaluate the effect of alternative active labor market policies that are aimed at enhancing the transition from unemployment to work.

[54] In order to check for the robustness of the calculations, we changed the order of the return components in Table 14. The results were very close to those in Table 14 with a somewhat higher proportion of the gain due to the terminal value.

TABLE A1
SUMMARY STATISTICS

	Observations	Percent	Mean	SD
Schooling	419	–	14.58	2.74
Age on arrival	419	–	38.05	9.15
White collar in FSU	284	67.78	–	–
Blue collar in FSU	127	30.31	–	–
Did not work in FSU	8	1.91	–	–
Married	363	86.63	–	–
English	419	–	1.76	0.94
Hebrew before migration	50	11.93	–	–
Ulpan attendance	386	92.12	–	–
Ulpan completion	332	79.24	–	–
Ulpan length (months)	387	–	5.61	1.34
Hebrew1 (first survey)	419	–	2.71	0.82
Hebrew2 (second survey)	316	–	2.98	0.83

TABLE A2
TRANSITIONS BETWEEN THE LABOR MARKET STATES*

	Quarters 8 & 9					
Quarters 3 & 4	WC	BC	WT	BT	UE	Obs.
WC	79.57	10.75	3.23	2.15	4.30	93
BC	2.58	80.80	1.72	2.87	12.03	349
WT	51.28	28.21	0.00	0.00	20.51	39
BT	23.81	52.38	0.00	0.00	23.81	21
UE	18.93	47.93	6.51	1.78	24.85	169
	Quarters 14 & 15					
Quarters 8 & 9	WC	BC	WT	BT	UE	Obs.
WC	90.52	6.90	0.00	0.86	1.72	116
BC	4.56	90.88	0.35	0.70	3.51	285
WT	41.18	41.18	0.00	0.00	17.65	17
BT	25.00	66.67	0.00	0.00	8.33	12
UE	23.86	44.32	0.00	0.00	31.82	88
	Quarters 18 & 19					
Quarters 14 & 15	WC	BC	WT	BT	UE	Obs.
WC	96.72	3.28	0.00	–	0.00	61
BC	2.47	90.12	2.47	–	4.94	81
WT	–	–	–	–	–	–
BT	0.00	100.00	0.00	–	0.00	1
UE	30.00	20.00	0.00	–	50.00	10

*The upper left box in the first matrix was created by calculating the number of people who worked in "white collar" occupations in the 3rd (4th) quarter and were still working there in the 8th (9th) quarter and averaging the two numbers by the number of observations of those working in "white collar" occupations in the 3rd and 4th quarters.

TABLE A3

ESTIMATED PARAMETERS - TRAINING OFFER, UTILITY, AND TERMINAL VALUE

WC Training Offer Parameters	
γ_{01} - type1	−2.63* (1.04)
γ_{02} - type2	−1.43 (1.01)
γ_{03} - type3	−2 (1.02)
γ_{04} - type4	−6.72 (4.47)
γ_1 - years of schooling	−0.07 (0.06)
Utility Parameters	
ue_1 - unemployment benefit, type1	−252.91* (4.37)
ue_2 - unemployment benefit, deviation of type2 from type1	−1249.25* (4.47)
ue_3 - unemployment benefit, deviation of type3 from type1	−14.62* (4.45)
ue_4 - unemployment benefit, deviation of type4 from type1	−1235.79* (4.47)
tr_1^3 - WT benefit, type1	−559.72* (4.46)
tr_2^3 - WT benefit, deviation of type2 from type1	218.5* (4.47)
tr_3^3 - WT benefit, deviation of type3 from type1	17.9* (4.47)
tr_4^3 - WT benefit, deviation of type4 from type1	−499.75* (4.47)
tr_1^4 - BT benefit, type1	−1116.48* (4.44)
tr_2^4 - BT benefit, deviation of type2 from type1	−725.11* (4.47)
tr_3^4 - BT benefit, deviation of type3 from type1	−22.41* (4.47)
tr_4^4 - BT benefit, deviation of type4 from type1	97.77* (4.47)
Terminal Value Parameters	
δ_{11} - type1	1000.03* (4.47)
δ_{12} - deviation of type2 from type1	0 (4.47)
δ_{13} - deviation of type3 from type1	0.1 (4.47)
δ_{14} - deviation of type4 from type1	−0.1 (4.47)
δ_2 - experience	208.41* (4.36)
δ_{31} - WC training, type1	2156.47* (4.47)
δ_{32} - WC training, deviation of type2 from type1	−758.81* (4.47)
δ_{33} - WC training, deviation of type3 from type1	2.04 (4.47)
δ_{34} - WC training, deviation of type4 from type1	−499.89* (4.47)
δ_4 - years of schooling	10.28* (4.47)
δ_5 - age on arrival	−8.7 (4.47)
δ_6 - Hebrew	60.07* (4.47)
δ_7 – English	60.02* (4.47)
δ_8 – worked in WC last period	116.01* (4.47)
δ_9 - unemployed last period	−649.15* (4.47)
δ_{101} -BC training, type1	528.49* (4.47)
δ_{102} -BC training, deviation of type2 from type1	−306.59* (4.47)
δ_{103} -BC training, deviation of type3 from type1	−2.33 (4.47)
δ_{104} -BC training, deviation of type4 from type1	−404.92* (4.47)
Type Proportion Parameters	
π_{01} - type1	−0.22 (0.24)
π_{02} - type2	−0.97 (2.08)
π_{03} - type3	−1.76 (1.66)
π_{04} - type4	2.41 (1.53)
π_{11} - years of schooling, type1	−0.71* (0.1)
π_{12} - years of schooling, type2	−0.75* (0.14)
π_{13} - years of schooling, type3	−0.57* (0.09)
π_{14} - years of schooling, type4	−0.89* (0.13)
π_{21} - age on arrival, type1	0 (0.88)

TABLE A3
CONTINUED

π_{22} - age on arrival, type2	0.01 (0.87)
π_{23} - age on arrival, type3	−0.01 (0.87)
π_{24} - age on arrival, type4	−0.02 (0.88)
Cholesky Decomposition	
ε^0 - variance of error UE	11.43
z^1 - variance of error WC	0.16
covariance (BC, WC)	−0.06
z^2 - variance of error BC	0.11
covariance (WT, UE)	−0.78
ε^1 - variance of error WT	1.73
covariance (BT, UE)	−1.08
ε^2 - variance of error BT	9.45

NOTES: Standard deviations appear in parentheses. Significant parameters at the 5% level are marked with an asterisk.

REFERENCES

BEN-PORATH, Y., "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy* 15(1967), 352–65.

BERMAN, E., K. LANG, AND E. SINIVER, "Language Skill Complementarity: Returns to Immigrant Language Acquisition," NBER working paper no. W7737, 2000.

BORJAS, G. J., "The Economics of Immigration," *Journal of Economic Literature* 32 (1994), 1667–717.

——, "The Economic Analysis of Immigration," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Volume 3A (New York: North-Holland, 1999), 1697–760.

CARD, D., AND D. SULLIVAN, "Measuring the Effects of CETA Participation on Movements In and Out of Employment," *Econometrica* 56 (1988), 497–530.

CHISWICK, B., AND P. MILLER, "Language Skills and Earnings Among Legalized Aliens," *Journal of Population Economics* 12.1 (1999), 63–89.

COHEN, S., AND Z. ECKSTEIN, "Labor Mobility of Immigrants: Training, Experience, Language and Opportunities," CEPR-DP-1544, 2002.

DUSTMANN, C., AND A. VAN SOEST, "Language Fluency and Earnings: Estimation with Misclasified Language Indicators," *The Review of Economics and Statistics* Vol.LXXIII-4 (2001), 663–74.

ECKSTEIN, Z., AND G. J. VAN DEN BERG, "Empirical Labor Search: A Survey," *Journal of Econometrics* (2008, forthcoming).

——, AND Y. WEISS, "The Integration of Immigrants from the Former Soviet Union in the Israeli Labor Market," in Ben-Bassat Avi, ed., *The Israeli Economy, 1985–1998: From Government Intervention to Market Economics*, Essays in Memory of Prof. Michael Bruno (Cambridge, MA: MIT Press, 2002), 349–78.

——, AND ——, "On the Wage Growth of Immigrants: Israel 1990–2000," *Journal of European Economic Association* 2(4) (2004), 665–95.

——, AND K. I. WOLPIN, "Why Youth Drop Out of High School: The Impact of Preferences, Opportunities and Abilities," *Econometrica* 67(6) (1999), 1295–339.

HAM, J. C., AND R. J. LALONDE, "The Effect of Sample Selection and Initial Conditions in Duration Models: Evidence from Experimental Data on Training," *Econometrica* 64(1) (1996), 175–205.

HECKMAN, J., AND B. SINGER, "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data" *Econometrica* 52(2) (1984), 271–320.

——, AND J. A. SMITH, "The Pre-Program Earnings Dip and the Determinants of Participation in a Social Program: Implications for Simple Program Evaluation Strategies," NBER Working Paper No.W6983, 1999.

——, R. J. LALONDE, AND J. A. SMITH, "The Economics and Econometrics of Active Labor Market Programs," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Volume 3A (New York: North-Holland, 1999), 1865–2097.

KEANE, M. P., AND K. I. WOLPIN, "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence," *Review of Economics and Statistics* 76 (1994), 648–72.

——, AND ——, "The Career Decision of Young Men," *Journal of Political Economy* 105 (1997), 473–522.

LALONDE, R. J., "The Promise of Public Sector-Sponsored Training Programs," *Journal of Economic Perspectives* 9(2) (1995), 149–68.

——, AND R. H. TOPEL, "Economic Impact of International Migration and the Economic Performance of Migrants," mimeo, University of Chicago, 1994.

MCFADDEN, D., "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration," *Econometrica* 57(5) (1989), 995–1026.

WEISS, Y., R. M. SAUER, AND M. GOTLIBOVSKI, "Immigration, Search and Loss of Skill," *Journal of Labor Economics* 21(3) (2003), 557–92.