Training and Occupational Choice of Highly Skilled Immigrants[*]

Preliminary draft of work in progress.

Sarit Cohen and Zvi Eckstein,[†]

April 19, 2000

Abstract

[*] We thank Mike Keane, Yoram Weiss and Ken Wolpin for dicussions related to this paper. Osnat Lifshitz provided excellent reasearch assistance. We are also grateful for financial support from NIH grant 1 R01 HD34716-01.

[†] Tel Aviv University (saritc@post.tau.ac.il), Tel Aviv University and Boston University (eckstein@post.tau.ac.il).

1 Introduction

The transition pattern of post schooling individuals, displaced workers and immigrants to the labor market has similar characteristics. Unemployment falls quickly as workers first find blue-collar jobs, followed by a gradual movement to white-collar occupations. For immigrants, the transition includes the learning of the new country's language as well as the skills demanded by the new labor market.[1] This paper focuses on male immigrants who moved from the former Soviet Union to Israel and are characterized by their high levels of skills, education and age (see table 1)[2]. We study the impact of participation in training programs, job search, occupational choice and language acquisition of immigrants on their integration to the new labor market. In particular, we formulate a dynamic choice model for employment in blue and white collar occupations and training, where the labor market randomly offered opportunities are affected by the immigrant's past choices.[3] The model provides a labor supply pattern that is consistent with the observed choices and enables us to estimate the rate of return for training.

Government sponsored training programs are commonly viewed as the best method for subsidizing human capital investment for displaced workers and immigrants. The vast literature on the return to government sponsored training programs has been heavily occupied by the sample selection problem and the empirical result that the estimated return for training is not significantly different from zero.[4] While that literature is mainly based on data regarding low skilled disadvantaged workers, this paper considers a sample of highly skilled immigrants who unexpectedly moved to a completely different labor market. Using our data, the standard regression analysis indicates a large but insignificant estimates for the rates of return to the different type

[1] Borjas (1994) and LaLonde and Topel (1994) provide comprehensive surveys on the economics of immigration.

[2] The mass migration from the Former Soviet-Union to Israel started towards the end of 1989. For a more detailed description of this immigration wave see Eckstein and Weiss (1999). Several studies suggest that the return to various human capital variables depends on the national origin of these stocks. Eckstein and Weiss (1998) find that upon arrival, immigrant men receive no return for their imported skills. Friedberg (2000) finds variation in the return to foreign schooling across origin countries and an insignificant return to foreign experience.

[3] White collar cccupations include engineers, physicians, professors, other professionals with an academic degree, managers, teachers, technicians, nurses, artists and other professionals; blue collar occupation includes unskilled workers.

[4] See the recent survey by Heckman, LaLond and Smith (1999).

of training.[5] In order to further investigate the role of training in the labor market transition of workers, we formulate a model that jointly considers alternative motives for the participation in training programs. In particular, participation in training, which we separate by the broadly defined blue and white-collar occupations, affects the wage and the job offer probabilities differently in each occupation. Furthermore, the individual may have direct utility from participating in training and we allow for each of these elements to be different for two unobserved types of individuals (Heckman and Singer (1984)).

We follow a sample of about 400 male immigrants, who arrived in Israel between 1989-1992, for most of their first 20 quarters (five years) in Israel. Most of them studied Hebrew extensively during their first two quarters in Israel and then searched for work. Depending on availability, they could attend one government sponsored training program that is supposed to adjust or transform their imported skills. Participation in training started in the third quarter, peaked at the fourth and ended after 3 years in Israel. Only about 30 percent attained any training. Most immigrants left unemployment to blue-collar occupations, although about 70 percent of them were working previously in white-collar jobs in the former USSR. After more than three years the unemployment rate, which was initially about 28%, was stabilized at about 10% (above national average) and the transition to white-collar jobs continued throughout the fifth year after migration. The mean wage per hour growth rate is about 9% annually, which is 2.6% higher than the rate we find in a larger sample given by the income survey of the CBS (See Eckstein and Weiss (1998)).

Weiss, Sauer and Gotlibovski (1999) use a dynamic model framework in order to study the occupational choice of male immigrants who arrived in Israel during the recent wave. The data they use is similar to the data we use in this study. Their work focuses on the compatibility between the immigrant's work and his imported level of schooling and its effect on the immigrant's wage and welfare. They find that male immigrants experience a wage loss because they are partially unemployed and also because they are employed in jobs that require less schooling than their actual schooling that they accumulated in the fromer Soviet Union. The growth of earinings in their model is affected directly by the accumulated time in Israel (not experience) and the

[5] This is the common result in the literature (see a survey by Lalonde(1995)).

actual occupational upgrade. In the model of this paper we focus on wage growth that is due to participation in training, the accumulation of work experience and on the occupational upgrade.

Our estimation results show that the rate of return to white-collar training is 12% for white-collar work and lower for blue-collar training, but these rates are not signi…cant statistically. Moreover, the white (blue) collar type of training has almost zero returns for wages in blue (white) collar jobs. However, the impact of training on the o¤er probabilities while the individual is working is large and signi…cant. For an average immigrant, taking a white-collar type training would increase the probability to receive a white collar-job o¤er by about 135%. Taking a blue-collar training program would increase the probability to receive a blue-collar job-o¤er by about 67%. Given the large number of immigrants who arrived in Israel during the recent wave, the e¤ect of training on job availability in both white and blue-collar occupations is substantial:

The estimated model well …ts the main characteristics of the labor market assimilation of the immigrants: the fast reduction in unemployment and the sharp increase in the share of workers employed in blue collar jobs, followed by a gradual movement to white-collar occupations. The model tends to overpredict the proportion of immigrants in unemployment and to underpredict the employment in white collar and blue collar occupations, mainly during the …rst eight quarters in Israel. With respect to participation in training, the predicted pattern is roughly consistent with the observed data: Participation in training programs peaks during the …rst year in Israel, and subsequently decreases, though not monotonically.

Structural estimation of the model allows us to quantify the impact of alternative government intervention policies that a¤ect the availabiltiy training programs and on the individual welfare. We …nd that if no training program would have been o¤eres, the expected loss, in terms of the present value of utility, ranges between 6 to 8.3 percent, depending on the immigrant's age on arrival and years of schooling. These rates are about the same as the standard estimated rate of return on a year of schooling.

The rest of the paper is organized as follows. Section 2 presents the main labor supply facts regarding the …rst …ve years of male immigrants in a new country based on quarterly data. Section 3 develops the dynamic discrete-choice model of labor supply and human capital investment as well as the speci…cation for estimation. Section 4 summarizes the estimation results and model …t and section 5 presents few implications of our results.

2 Labor Supply Description: Data

Data

The data for this study is based on a survey conducted by the JDC - Brookdale Institute of Gerontology and Human Development. The first survey was conducted during the summer of 1992 on a random sample of 1,200 immigrants from the former USSR who entered Israel between October 1989 and January 1992. The second survey was done in 1995 and only 901 of these immigrants were re-sampled. The original sample consists of immigrants at working-ages (25-65) residing in 31 different locations in Israel at the time of the first survey. These immigrants reported their residence, occupation, schooling and some other demographic characteristics in the former USSR. Both surveys contain a complete history of jobs held from the date of arrival in Israel until the interview. They also provide information on wages in each job and detailed information on participation in government sponsored training programs. Furthermore, the data contains detailed information on their knowledge of Hebrew on arrival, participation in Hebrew studies (ULPAN in Hebrew) and their knowledge of Hebrew at the date of the surveys.

Our study is restricted to 419 male immigrants that on their arrival in Israel were 23-58 years old. None of the individuals returned to be full time students and they were actively looking for a job in Israel. The survey labor market history is based on a monthly report which we converted into a quarterly (three months) data set. For 316 of the immigrants we have data from both surveys.

Skills on Arrival

Table 1 provides the descriptive information on the characteristics of the sample on their arrival in Israel. The average schooling level is 14.6 years and it is high relative to Israeli males (12.5 years of schooling). We divide jobs into two broad occupations, white and blue collar. White-collar jobs are related to work that requires more than 12 years of schooling such as managers, teachers, nurses, engineers, artist and other high-skilled professionals. The blue-collar occupations consist of all jobs which require mainly basic knowledge of reading and writing. 68% of males that previously worked in the former USSR in jobs related to white-collar occupations, while after four years in Israel only about 30% of working males have white-collar jobs.

The knowledge of language is measured by four questions on the ability to understand, to speak, to read and to write the language. The immigrants were asked these questions both in Hebrew and in English. We use an index that gives equal weights for all questions. Hence, no knowledge of the language get the value of one and the number four is given to those individuals that are ‡uent in using the language. In table 1 we report the mean value of knowledge of English that is collected at the …rst survey. We assume that this level of English is the same as the knowledge the immigrants had when they arrived in Israel.

Table 1. Summary Statistics at Arrival

	Observations	Percent	Mean	SD
Schooling	419	–	14.58	2.74
Age on arrival	419	–	38.05	9.15
White collar USSR	284	67.78	–	–
Blue collar USSR	127	30.31	–	–
Did not work in USSR	8	1.91		
Married	363	86.63	–	–
English	419	–	1.76	0.94

Hebrew

As explained above, the knowledge of Hebrew is measured at the two interviews. In table 2 we provide the data related to the knowledge of Hebrew. 12% of the immigrants were able to have a simple conversation in Hebrew before their arrival. 92% learned Hebrew in a special program called "ulpan" which was completed by 79%. The indices of the knowledgehe of Hebrew at the two surveys, which are approximately two years apart, show a 10% increase for the average individual. It should be noted that the standard length at the basic Hebrew training (Ulpan) is two quarters and almost all immigrants attend it immediately after their arrival.[6]

[6] Also note that the immigrants arrived on di¤erent dates and therefore have di¤erent tenure in Israel at the time of the survey.

Table 2. Hebrew Knowledge

	Observations	Percent	Mean	SD
Hebrew before migration	50	11.9	–	–
Ulpan Attendance	386	92.3	–	–
Ulpan completion	332	79.2	–	–
Length of Ulpan (months)	387	–	4.6	1.34
Hebrew1 (first survey)	419	–	2.71	0.82
Hebrew2 (second survey)	316	–	2.98	0.83

In Table 3 we present results from the pooled regression where the dependent variable is the index of the knowledge of Hebrew at the time of the first and second surveys (thus the number of observations is 419+316=735). As seen in the table, time since arrival is a significant indicator of the knowledge of Hebrew. Using the regression in table 3 we form a predicted Hebrew index for each individual in the sample based on the estimated regression. The main impact on the predicted index is the time in Israel plus the individual individual fixed effect which we assume to be equal to the residual.

Table 3: Hebrew regression

Variable	Estimate
b_{cons}	$\underset{0.1690}{1.6954}$
b_{Ulpan_length}	$\underset{0.0145}{0.0915}$
$b_{Hebrew\ before\ migration}$	$\underset{0.0886}{0.6574}$
$b_{time\ in\ Israel}$	$\underset{0.0307}{0.0714}$
$b_{time\ in\ Israel\_square}$	$\underset{0.0013}{-0.0014}$
Number of Observations	735
R^2	0.1680

Labor Market Choices

We organized the data such that the labor market state in the data fit the state in the model. In each quarter the immigrant could be in one out of five labor market states: Unemployed (UE), working in a white-collar job (WC), working 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). Training in white collar jobs include courses in computers, adjusting knowledge of engineers in a certain area and technicians in certain …elds. Training in blue collar jobs include courses in sales, cosmetics, diamond cutters, electricians, travel agents, etc.. Table 4 presents the actual proportion of individuals in each state at each quarter since the date of arrival in Israel for a maximum of …ve years (20 quarters). Figures 1a and 1b describe the actual and estimated proportions.

Table 4. Proportion of Immigrants by Labor Market Activity.

Quarter Since arrival	UE	WC	BC	WT	BT	Observations
1	71.84	3.10	24.82	0.24	0.00	419
2	48.21	8.11	43.44	0.24	0.00	419
3	27.88	13.70	50.48	5.29	2.64	416
4	23.02	15.35	51.98	6.44	3.22	404
5	23.72	17.60	49.23	5.10	4.34	392
6	21.75	20.69	49.87	3.71	3.98	377
7	19.95	21.31	53.83	2.73	2.19	366
8	16.13	21.11	57.48	3.52	1.76	341
9	13.94	20.61	60.30	2.42	2.73	330
10	14.64	19.94	61.37	2.80	1.25	321
11	14.51	20.82	61.20	1.89	1.58	317
12	12.97	22.15	62.34	1.58	0.95	316
13	9.60	26.16	62.91	0.66	0.66	302
14	9.68	27.96	61.29	0.36	0.72	279
15	7.11	29.71	62.76	0.00	0.42	239
16	9.57	28.71	60.29	0.96	0.48	209
17	9.32	34.78	54.04	1.24	0.62	161
18	4.85	41.75	52.43	0.97	0.00	103
19	8.00	42.00	46.00	2.00	2.00	50
20	11.76	47.06	41.18	0.00	0.00	17
Total:						5778

The unemployment rate reaches 23% after a year and stabilizes at about 10% after 13 quarters (more than 3 years) in Israel. A substantial number of immigrants join the labor force and work in blue collar jobs during the …rst two years in Israel. The proportion of these individuals reach more than 60 percent after two and a half years in Israel and stay at this level for almost two additional years. However, we observe that during the …fth year in Israel the proportion of those working in blue-collar jobs is reduced by almost 20% and the proportion of white-collar jobs increases in almost the same proportion. Hence, the movement between occupations is a long process. This pattern of slow dynamic transition is similar to what is believed to be typical of immigrants' behavior (Chiswick, (1992), Eckstein and Weiss (1998)). Moreover, it is similar to the transition to work of high school graduates as described by Keane and Wolpin (1997).

What might seem as a substantial reduction in job quality after 4 years in the new country, bears a signi…cant change after four years in the new country.[7] What causes this to happen? Note that participation in training programs peak between the fourth to the sixth quarter after arrival and then the proportion goes down to almost no participation after more than three and a half years in Israel (see …g.1b). What role does training take in a¤ecting the increase in working in white-collar jobs? Alternatively, it is possible that the availability of jobs or the accumulated experience and knowledge of the local labor market cause the late move to white-collar jobs. The early peak in training is consistent with the human capital theory which clearly shows that if you wish to study, then it is better to do it as soon as possible.

The transitions between the …ve labor market states are summarized in table 5.

[7] It should be noted that the number of observations at the …fth year is low.

Table 5: Transitions among the Labor Market States

Quarters 3 and 4	WC	BC	WT	BT	UE	Obs.
	Quarters 8 and 9					
WC	79.57	10.76	3.22	2.15	4.30	93
BC	2.57	80.86	1.72	2.85	12.00	350
WT	51.28	28.20	0.00	0.00	20.51	39
BT	25.00	50.00	0.00	0.00	25.00	20
UE	18.94	47.93	6.51	1.77	24.85	169

Quarters 8 and 9	WC	BC	WT	BT	UE	Obs.
	Quarters 14 and 15					
WC	90.52	6.90	0.00	0.86	1.72	116
BC	4.57	91.87	0.035	0.007	3.51	285
WT	41.20	41.20	0.00	0.00	17.60	17
BT	25.00	66.66	0.00	0.00	8.34	12
UE	23.86	44.33	0.00	0.00	31.81	88

Quarters 14 and 15	WC	BC	WT	BT	UE	Obs.
	Quarters 18 and 19					
WC	96.72	3.27	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

[8]

[8] The upper right hand box in the …rst matrix was created by calculating the number of people who worked in white-collar occupation in the 3rd(4th) quarter and also worked in the same occupation in the 8th(9th) quarter and averaging the two numbers by numbers of observations working in white-collar in the 3rd and 4th quarter.

The main observation is that there is high persistence in occupational distribution. The rate of those remaining in white-collar occupations (blue-collar occupations) starts at 80% (81%), increases to 91% (92%) and further increases to 97% (drops to 90%). This increased persistence in white-collar occupation account for much of the later increase in the proportion of workers in this occupation. The transition from white-collar jobs to blue-collar jobs substantially decreases over time. The rate of transition from blue-collar 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. A job in a white-collar occupation shows more stability than a blue-collar job. The transition from blue-collar to white-collar jobs starts at a low rate, then increases to 4.6% and then declines to about 2.5%. These transition probabilities show that for an immigrant who does not …nd a white-collar job, frequent transitions between di¤erent labor market locations are we observed.

Training

A key aspect of this paper is the role of training in the life time career decision of the high skilled immigrants. The length of the training programs is distributed between one to three quarters whereas training in blue-collar jobs is shorter (see table 6). We assume that the value of the program is the same, regardless of the length. We assume that the actual length is a function of an institutional setting that is exogenously determined.

Table 6. Distribution of Length in Training
(in quarters)

Num: of Quaters	Training in White ¡ Collar	Training in Blue ¡ Collar	Observations
1	16:9	14:5	39
2	27:4	15:3	53
3	14:6	11:3	32
Total	58:9	41:6	124

Table 7 shows that 37% of immigrants who were working before migration in white-collar jobs and participated in training, trained in blue-collar jobs. This observation indicates the non-trivial way in which the immigrants perceived their labor market opportunities in Israel. 84% of the immigrants who went to training had previously worked in white-collar jobs in the former USSR. Hence, immigrants who arrived with more skills have a higher tendency to get into training. Yet a signi…cant number of immigrants are willing to downgrade their occupation. But, as can be seen in table 8, this does not mean that they will necessarily end up working in blue-collar jobs.

Table 7. Transition Matrix from Occupation in Former USSR to Training in Israel.

Occupation in Former USSR	Training in White Collar	Training in Blue Collar	Proportions	Observations
White Collar	54.03	30.65	84.68	105
Blue Collar	4.84	10.48	15.32	19
Proportions	58.87	41.13	100.00	–
Observations	73	51	–	124

Table 8 shows that the …rst job after training is not in the same occupation as the occupation of the training program. There is more downgrading than upgrading. However, this does not mean that long term impact of training on the transition to working in an occupation related to the same type of training is insigni…cant.

Table 8. First Job After Training in Israel According to the Training Sector*

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

*16 immigrants hadn't found a job after training (out of 124 who participated in training programs).

In Table 9A we present the pooled multinomial logit regression for the immigrants' choices in di¤erent periods. The dependent variable indicates whether the immigrant was working in WC, BC or was unemployed at time t. Note that each immigrant in this regression appears several times and there is no individual …xed e¤ect.

The knowledge of Hebrew and English, age on arrival and working in white-collar occupation in the USSR increase the probability of both working in white-collar job and being unemployed relative to working in blue-collar jobs. Education (years of schooling) has no signi…cant e¤ect on these probabilities. The variable training in WC (BC) occupation is a dummy variable that equals 1 if the immigrant has graduated in WT (BT) before time t and equals zero otherwise. Training in white-collar occupations increases the probability of working in white-collar jobs and being unemployed, while training in blue-collar jobs only a¤ects positively the probability of being unemployed. Work experience in Israel reduces the probability of being unemployed. It is interesting to note that all variables that are related to the level of human capital increase the probability of working in white-collar jobs as well as being unemployed. This observation indicates that the skilled immigrants invest more in search assuming that searchduring unemployment is more intensive. However, this aspect will be investigated by the structural model.

Table 9: Multinomial-logit on employment and unemployment

Variable	White collar Occupation	Unemployed
b_{cons}	¡ 4:4424 (0:5034)	¡ 0:4753 (0:4804)
b_{Hebrew}	0:9612 (0:0761)	0:1342 (0:0701)
$b_{english}$	0:6563 (0:0428)	0:1529 (0:0497)
$b_{age\ at\ arrival}$	0:0135 (0:0055)	0:0205 (0:0052)
$b_{years\ of\ schooling}$	0:0331 (0:0212)	0:0332 (0:0190)
$b_{training\ in\ WC}$	0:9421 (0:1153)	0:8183 (0:1658)
$b_{training\ in\ BC}$	¡ 0:2101 (0:1594)	0:9586 (0:1815)
$b_{accumulated\ experience}$	¡ 0:0046 (0:0100)	¡ 0:6807 (0:0233)
$b_{occupation\ in\ USSR}$	1:4837 (0:1417)	0:2156 (0:1137)
Num. of Obs.	5536	
Log likelihood	-3558.40	

* The comparison group is employment in blue-collar jobs.

Wages

Figure 2 displays the average wage in each quarter for both occupations. The wages in white collar jobs are more volatile than those in blue collar jobs, and it is clear that the wage increases in both occupations. The mean wage in both occupations is about 11 IS per hour during the …rst 4 quarters in Israel and 17 IS per hour during the 5'th year in Israel. The quarterly wage growth estimated by a simple regression of the means on time is 2.2-3% per quarter. This growth rate is about 9% annually, which is 2.6% higher than the rate we …nd in a larger sample given by the income survey of the CBS (see Eckstein and Weiss (1998)). A simple pooled log wage regression is given in Table 10. It is obvious that we do not correct for all the selections biases implied by the choices made by the individual. Training enters as dummy only for wages reported after the graduation of the course. It is interesting to note that this regression shows that training has no impact on wages. This result is consistent with the …nding in the literature (see, e.g., Heckman et.al.). An additional year of experience in Israel has a one percent wage return which is much lower than the experience coe¢cient for native Israelis (see Eckstein and Weiss (1998)). The rates of return on Hebrew and English are substantial. The highest level of the Hebrew index is four which implies a return of 6% above that of an average knowledge of Hebrew, which is the level of 2.8. The premium for working in white collar jobs rather than blue collar jobs, is 30% , but the return to education and experience (age) on arrival in Israel, is zero.

Table 10: Ln Wage Regression

Variable	ln hourly wage dummy occupations	ln hourly wage in white collar occupations	ln hourly wage in blue collar occupations
b_{cons}	2:0029 (0:1215)	1:0475 (0:4261)	2:1663 (0:1237)
b_{Hebrew}	0:0542 (0:0252)	0:1274 (0:0614)	0:0506 (0:0270)
$b_{English}$	0:0340 (0:0183)	0:1311 (0:0363)	¡ 0:0100 (0:0217)
$b_{\text{age on arrival}}$	¡ 0:0003 (0:0019)	0:0132 (0:0052)	¡ 0:0029 (0:0020)
$b_{\text{years of schooling}}$	0:0068 (0:0062)	0:0214 (0:0225)	0:0083 (0:0062)
$b_{\text{training WC}}$	0:0339 (0:0480)	0:1146 (0:0796)	¡ 0:0010 (0:0625)
$b_{\text{training BC}}$	0:0209 (0:0515)	¡ 0:0485 (0:1301)	0:0642 (0:0550)
$b_{\text{accumulated experience}}$	0:0101 (0:0125)	0:0300 (0:0358)	0:0075 (0:0128)
$b_{\text{accumulated experience}^2}$	0:0008 (0:0007)	¡ 0:0007 (0:0019)	0:0009 (0:0007)
$b_{\text{white collar occupation}}$	0:3023 (0:0405)	¡ ¡	¡ ¡
Num. of Obs.	574	132	442
R^2	0.277	0.230	0.156

3 The Model

The model follows the dynamic programing models of labor supply and schooling (for example, Eckstein and Wolpin (1999) and Keane and Wolpin (1997)), where an individual chooses among a finite set of mutually exclusive alternatives in each period over a finite horizon. Search is represented by allowing immigrants to randomly receive job offers and training program offers in different occupations, which they can reject or accept. The random offer probabilities depend on the individual's current employment state, and working at the same occupation is random as well. The occupational choice allows workers to select between two broad occupational classes - white and blue-collar. Training programs are classified in the same way. Labor market conditions (such as job availability) are captured by allowing occupational specific time varying indicators to influence the offer probabilities of jobs and training programs. Finally, the model incorporates observed heterogeneity, such as schooling, occupation prior to immigration, and other demographic characteristics as well as unobserved heterogeneity (Heckman and Singer (1984)).

An immigrant i who arrives in Israel at time D_i 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 (quarter), $t;\ t = 1, 2 \ldots T_i$ he can choose one of five labor market alternatives. The index $j;\ j = 0, 1, 2 \ldots J$, $J = 4$; describes the alternatives. The index $j = 1, 2$; corresponds to working in the two alternative occupations; occupation 1 = white collar and occupation 2 = blue collar. The index $j = 3, 4$ denotes the two types of training programs, and $j = 0$ represents unemployment. Let d_{it}^j equal one if the individual chooses alternative j at time t, and be zero otherwise, When $d_{it}^j = 1$; and $j = 1, 2$; the individual works in occupation j. When $d_{it}^j = 1$; and $j = 3, 4$; the individual acquires training relevant for occupation $j - 2$. When $d_{it}^0 = 1$; the immigrant neither works nor does he attend a training program. We denote by d_{it} the row vector of length $J + 1$, consisting of a single one and J zeros to indicate which activity is chosen in period t.

A job offer is an opportunity to work in occupation j where we assume that there is an occupation specific separation rate. Regular jobs are usually associated with a wage path, including promotions. Subsidized training programs usually pay some fixed positive income and an opportunity to be offered a training program is also uncertain.

Consider an individual i who chose alternative r in period $t - 1$. At the end of this period he will receive offers from the set $J + 1 = 5$ alternatives. The conditional probability that this offer will be from alternative j is:

$$P^{rj}_{it} = P^{rj}(m^j_{D_i+t}, x_{it}, t). \tag{1}$$

The vector $m^j_{D_i+t}$ represents time varying occupation specific demand indicators, such as unemployment rates, number of immigrants relative to natives, and entry requirements for training programs. Note that chronological time is given by $D_i + t$, reflecting the fact that immigrants arrive on different dates and therefore the same tenure in Israel, t, may be associated with different market conditions. The vector x_{it} represents individual characteristics, such as occupation in the country of origin, knowledge of Hebrew or/and English, age on arrival and, most important, whether the individual has completed a training program in a certain occupation and has general work experience in the new labor market.

The dependence of the offer probability on the current work activity introduces a dynamic element whereby training or work in a particular job can influence the probability of alternative job offers. For instance, an immigrant who is working or is in training has less time to search for a new job. Therefore, his chance of receiving offers for alternative jobs is lower than if he would be unemployed. Similarly, the probability of receiving a job offer in an academic occupation may be lower if one works in a non-academic job than if he would be unemployed.

Time in the new country, t, is allowed to influence the offer probability in two ways. First, there is a seniority effect representing the immigrant's learning of local market conditions and acquisition of language. This individual learning process must be distinguished from the exogenous changes captured by $m^j_{D_i+t}$ which affect all individuals at a given chronological time. In addition to labor market conditions, these variables represent changes in the eligibility to a subsidized training program. Typically, eligibility expires after a period of 5 years. We assume that the immigrant can attain a training program if he had not been previously in training and he is allowed to attain only one training program in his life time. In our data, time in Israel is distinguished from the work experience. This allows us to identify the direct experience effect from the time effect.

The wage offered for jobs in occupation j, $j = 1,2$ in period t is a function of: (i) the person's occupation-specific human capital, K_t^j and (ii) a temporal i.i.d shock, z_t^j. The wage offered in occupation j, $j = 1,2$ at time t can be expressed by

$$\ln w_{it}^j = K_{it}^j + z_{it}^j \qquad (2)$$

The random variable z_{it}^j can be interpreted in two different ways. Under the search interpretation, it reflects heterogeneity in the distribution of wage offers, implying that the particular wage that an individual will receive, if an offer is received, is random. Under the human capital interpretation, z_{it}^j represents random shocks to productivity.

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

$$K_{it}^j = \alpha_{0j} + \alpha_{ej} EX_{it} + \alpha_{e1} d_{it}^1 EX_{it} + \alpha_{e2j} EX_{it}^2 + \alpha_{c1j} C_{it}^1 + \alpha_{c2j} C_{it}^2 + \alpha_{Hj} L_{it}^H + \alpha_{Fj} L_i^F + \alpha_{sj} K_i^f \qquad (3)$$

where EX_{it} is the general experience in the Israeli labor market, C_{it}^j is an indicator that equals one if the worker has taken a training course in occupation j, $j = 1,2$. The parameters α_{ej} and α_{cj} represent the contribution of on-the-job learning and formal training in the formation of human capital. The variables L_{it}^H and L_i^F indicate the level of Hebrew skill acquisition and the knowledge of English on arrival, respectively, which, for simplicity, we assume to be exogenous. The parameters α_{Hj} and α_{Fj} describe the contribution of the two languages to the earning capacity. The initial level of human capital from the foreign country on arrival to Israel is K_i^f. α_{sj} measures the value of that human capital on arrival to the new labor market. The imported human capital, K_i^f, depends on the immigrant's personal characteristics, x_{it}, which includes variables such as schooling, age or experience at arrival and the present knowledge of English.

The "wage" associated with a training program, $j = 3,4$ and with unemployment, $j = 0$, is determined exogenously by the government (typically, the government subsidizes these activities) and is indicated by tr^j, $j = 3,4$. The unemployment benefit is set as ue. Let K_{it} denote the vector of occupation specific human capital, i.e., $K_{it} = (K^1_{it}, K^2_{it})$. To be concrete, current utility from labor market state j for individual i at time t in the new country (U^j_{it}) is given by,

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

where the vector $\varepsilon_i = [\varepsilon^0_{it}, z^1_{it}, z^2_{it}, \varepsilon^3_{it}, \varepsilon^4_{it}] \sim N(0, \Omega)$; where Ω is not restricted.

The Optimization Problem

The immigrant is assumed to maximize the expected present value of life time utility

$$E\left[\sum_{t=\tau_i} \beta^{t-\tau_i} \sum_{j \in J+1} U^j_{it} d^j_{it} \mid S_{it}\right] \tag{5}$$

by the choice of d^j_t for all $t = \tau_i, \ldots, L$ and where S_{it} is the vector of all the relevant state variables. E denotes the expectation taken over the joint distribution of ε and the transition probabilities P^{rj}_{it}.[9] The state vector is given by $S_{it} = [EX_{it}, C^j_{it}, L^H_{it}, L^F_i, K^f_i, d^j_{t-1}, \varepsilon_i, \text{ for } j = 0, 1, 2, 3, 4]$. The state variables in t are the realized values of the shocks, ε_i, and the given values of the state variables in $t-1$, according to equations (2) and (3). Note that the realizations of the random variables occur at the beginning of period t. These shocks will influence, according to (2) the new wages that a person draws in each alternative. β is a discount factor, $0 < \beta < 1$.

Let $V^j_i(S_{it}, t)$ be the maximum expected life time utility given by equation (5) such that $d^r_t = 1$, for immigrant i. This value can be defined recursively, for $t = \tau_i, \ldots, L$ using the Bellman equation,

$$V^r_i(S_{it}, t) = U^r_{it} + \beta E \max\{V^j_i(S_{it+1}, t+1);\ \text{for } j = 0, \ldots, 4 \mid S_{it}, t, d^r_{it} = 1\}. \tag{6}$$

[9] The optimization problem (5) is in the same format as in Eckstien and Wolpin(1989).

To simplify the model we assume that the optimization problem is divided into two sub periods. During the first 20 quarters the model is solved explicitly. At the 21'st quarter the immigrant utility is given by $V_i^j(S_{iL+1}, t = 21)$, which is assumed to be a given function of (S_{iL+1}, τ_i) for $j = 0, 1, \ldots 4$ (see Eckstein and Wolpin(1999)). The operator E denotes the expectation taken over the joint distribution of ε.

Note that, for a given time in Israel, t, the value associated with each state depends on the immigrants date of arrival and on his age on arrival, respectively. The subscript t on the value function indicates that for given S_{it} changes in t are associated with changes in the demand shifters, $m^j_{D_i+t}$, as well as potential horizon effects. Furthermore, perfect foresight is assumed concerning the future behavior of the demand shifters.

Solution Method

The model does not admit to an analytical solution. Using the end conditions, and assuming a known distribution of ε_i 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. Specifically, we first separate between the expectation operator taken in (6) on the transition probabilities defined by (1) and the joint distribution of ϵ. Given the transition probabilities, P_{it}^{rj}, at each date t and state S there are at most 16 possible outcomes of feasible choice sets.[10] At each choice set we can choose between being unemployed, $j = 0$, and the possible outcome of the four alternative labor market activities. Let g_s be the feasible choice set s, $s = 1, \ldots, 16$, and $P(g^s_{it+1} \mid S_{it}, t, d^r_{it})$ the conditional probability of the choice set g^s_{it+1}, at time $t + 1$. Now we can rewrite (6) as follows,

$$V_i^j(S_{it}, t) = U_{it}^j + \beta \sum_{s=1}^{16} P(g^s_{it+1} \mid S_{it}, t, d^r_{it}) E(\max\{g^s_{it+1} \mid S_{it}, t, d^r_{it} = 1\}). \tag{7}$$

where E is the expectation operator taken only on the joint distribution of ϵ. The numerical

[10] We assume that the the individual can always choose to be unemployed. Therefore, there are only 16 possible independent transition probablities each given by (1)

complexity arises because of the value function requiring high-dimensional integrations for the computation of the Emax function on the right-hand-side of (7). We follow the procedure in Keane and Wolpin (1994), using Monte Carlo integrations to evaluate the integrals that appear in (7).[11]

In the analysis of the initial transition period in Israel, we will use quarterly data. Such data is available for a maximum of five years for each observation. The model assumes that decisions within the sample period reflect expected circumstances and choices in subsequent periods. As explained above, we split the planning horizon between the first 20 quarters in Israel and the rest of the lifetime. As indicated above, the value at $t = 21$ is assumed to be a linear function of the state vector S_{i20} and the remaining periods of life, $L - 21 - \tau_i$. We then apply the Bellman equation (6) and calculate the optimal policy backwards for $t = 20, \ldots, 1$ recursively.

Implications

The model has several predictions regarding the dynamic pattern of the proportion of immigrants to be observed in each of the labor market states of the model. Participation in a training course related to each occupation is an investment in skills that are rewarded in that occupation by a higher wage as well as an increase in receiving a job offer in that occupation. So far, the standard human capital theory emphasized the earning impact of training. On the other hand, labor market practice indicates that the impact of training might be more important as a formal screening and licencing instruments in affecting job availability than a direct wage gain. Both rewards to training investment are for the entire future, and it is therefore, expected that training participation will take place on arrival in Israel. In a dynamic setting, training can be viewed as a form of job search, and therefore, participation in training can be expected in later periods. Moreover, the availability of training is random and, it is possible therefore, to observe training in later periods.

The endogenous process of accumulating work experience can also be viewed in this model as an investment in skills which are used in the labor market, since job offers positively depend on the general experience. Assuming that the availability of blue collar jobs is higher than that of white collar jobs (more blue collar positions in the Israeli market), the model predicts

[11] To compute the Emax function we simulate 150 draws at each point of the state space.

that initially the workers who arrive with a high potential human capital (high schooling) will initially invest by working in blue collar jobs and attain training, and later will …nd a job in a white collar occupation. In general, the model predicts that the accumulation of work experience and participation in a training program a¤ect future wages faced by the individual as well as work possibilities which, in turn, a¤ect future participation and wages in the labor market.

Estimation Method

Conditional on values for the parameters and the observed state space of a given individual, the dynamic Bellman equation (6) looks like a standard indirect utility function in a multinomial choice model for panel data. The main complications here, compared to the multinomial logit case, stem from the theory that does not permit additivity and independence of the errors and, hence, the choices for each individual are correlated. Furthermore, we allow for measurement error in observed wages . Speci…cally, we assume the log of the observed wage of individual i at time t in occupation j , $\ln w^{jo}_{it}$; is of the form: $\ln w^{jo}_{it} = \ln w^{j}_{it} + \epsilon^{j}_{it}$, where $\epsilon^{j}_{it} \sim N(0; \sigma^2_\epsilon)$ is the multiplicative measurement error.

The model is estimated using smooth maximum likelihood (SML) (McFadden(1989) and Keane and Wolpin (1997)). Let I be the number of individuals in the sample and each individual observed over the sample periods 1 to t_i: The vector of observed outcomes for individual i at date t is given by $[d^{j}_{it}; w^{jo}_{it}]$: Note that the vector of model parameters enters the likelihood through its e¤ect on the choice probabilities, the wage being observed only while working and for each individual the sample truncated at time t_i. As such, the likelihood for a sample of I individuals is given by,

$$L(\theta) = \prod_{i=1} \Pr(d^{j}_{i1}; w^{jo}_{i1}; d^{j}_{i2}; w^{jo}_{i2}; :::::; d^{j}_{it_i}; w^{jo}_{it_i} \mid S_{i0}) \tag{8}$$

where θ is the vector of parameters to be estimated. Given the assumption of joint serial independence of the vector of errors, the likelihood function (8) can be written as a product of within-period conditional joint probabilities of the choices and the wage. These probabilities are computed from the solution of the dynamic programming as explained above. To achieve asymptotically efficient estimators using the simulated probabilities we smooth the probability in the way suggested by Keane and Wolpin(1997).[12]

Unobserved Heterogeneity

So far the heterogeneity in the model is captured by the imported skills of the immigrants, the knowledge of Hebrew and the arrival period. It is possible that an individual gains from working in certain occupation, the gain from training and the utility while being unemployed is valued differently among the immigrants. To capture the possible heterogeneity that is unobserved (by us), we allow for M types of individuals, each comprising a π_m fraction of the population (Heckman and Singer (1984)). We allow for this heterogeneity to enter into the utility from each of the five choices as well as affecting the job offer probabilities. As such, the model is independently solved for each type and the likelihood function is a weighted average of the likelihood of each type, i.e.,

$$L(\theta) = \prod_{i=1} \sum_{m=1} \Pr(d^j_{i1m}, w^{jo}_{i1m}, d^j_{i2m}, w^{jo}_{i2m}, \ldots, d^j_{it_i m}, w^{jo}_{it_i m} \mid S_{iM0}, type = m) \times \pi_m . \qquad (9)$$

Specific Parameterization

In this section we provide the explicit functional forms used by us in the estimation of the model.

The wage offer functions: A wage offer in occupation j, $j = 1, 2$, is as we specify in (3) with the following specific form:

$$\begin{aligned} w^j_{it} = \exp\{ & \alpha_{0jm} + \alpha_{ej} EX_{it} + \alpha_{e2j} EX^2_{it} + \alpha_{c1jm} C^1_{it} + \alpha_{c2jm} C^2_{it} + \alpha_{Hj} L^H_{it} + \alpha_{Fj} L^F_i + \\ & \alpha_{Aj} AGE_i + \alpha_{Sj} EDUC_i + z^j_{it}\} \end{aligned} \qquad (10)$$

where AGE_i (τ_i) indicates age on arrival and $EDUC_i$ is the imported years of schooling. Here

[12] For example, for the probability that $d^j_{it} = 1$, we use the Kernel smoothing function: $\exp\left(\frac{(V^j_i(S_{it},t) - \max(V^a_i(S_{it},t))}{\tau}\right) / \sum_{k=0}^{4} \exp\left(\frac{(V^k_i(S_{it},t) - \max(V^a_i(S_{it},t))}{\tau}\right)$

we assume that the unobserved types differently value work in WC and BC occupations. The natural way to model it is by adding a type specific parameter to the utility depending on the occupational choice. However, the linearity implies that this parameter cannot be identified separately from the constant in wages. Hence, we assume that the constant in the wage offer function and the return to training depends on the unobserved characteristic of type m.

The job offer rates: The probabilities of receiving job offers in WC and BC have the following logistic form:

$$P_{it}^{rj} = \frac{\exp\{Q_{ijt}\}}{1+\exp\{Q_{ijt}\}}, (j = 1, 2) \tag{11}$$

where the specification of Q_{ijt} depends on j as specified below.

The job offer rate in WC Occupation: During their first two quarters in Israel, only immigrants who had some knowledge of Hebrew upon arrival can obtain a job offer in a WC occupation. Otherwise, the probability that an individual i who chose alternative r in period $t-1$ would receive 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), knowledge of English, occupation in USSR ($UOCC_i$), accumulated experience in Israel, participation in a white-collar training course, age on arrival and knowledge of Hebrew. Specifically:

$$\begin{aligned} Q_{i1t} = {} & b_{01jm} d^1_{t-1,i} + b_{02jm} d^2_{t-1,i} + b_{03jm}(d^0_{t-1,i} + d^4_{t-1,i} + d^5_{t-1,i}) + b_1 L_i^F + \\ & b_2 UOCC_i + b_{31j} I(EX_{it} = 0) + b_{32j} I(1 \le EX_{it} \le 4) + b_{4j} C^1_{it} + \\ & b_{5j} L_i^H + b_{6j} AGE_i \end{aligned} \tag{12}$$

where $I(EX_{it} = 0)$ is an indicator equals one if individual i has accumulated no work-experience in Israel by time t, and $I(1 \le EX_{it} \le 4)$ is an indicator equals one if individual i has accumulated one to four quarters of work-experience in Israel by time t.

The job offer rate in BC Occupation: The probability that an individual i who chose alternative r in period $t - 1$; would receive a job offer in a blue collar occupation ($j = 2$) depends only on the activity the individual engaged in the previous period (r), the unobserved type of the individual, accumulated experience in Israel, participation a blue-collar training course, age on arrival and knowledge of Hebrew. Specifically:

$$\begin{aligned} Q_{i2t} = \; & b_{01jm} d^1_{t-1;i} + b_{02jm} d^2_{t-1;i} + b_{03jm}(d^0_{t-1;i} + d^4_{t-1;i} + d^5_{t-1;i}) + \\ & b_{31j} I(EX_{it} = 0) + b_{32j} I(1 \leq EX_{it} \leq 4) + b_{4j} C^2_{it} + \\ & b_{sj} L^H_i + b_{6j} AGE_i \end{aligned} \tag{13}$$

Note that the job offer rates in WC and BC occupations are independent. That is, an immigrant can get, at each period, an offer in each type of occupation. Furthermore, we assume that the constant terms, b_{01jm}; b_{02jm}; b_{03jm}; vary across the M unobserved type of immigrants ($m = 1; ...; M$). The above offer rates depend on the labor market state of the individual as we indicated in the specification of the model, by being a function of $d^r_{i;t-1}$, $r = 0; ...; 4$:

The training offer rates: The probabilities of receiving an offer to participate in a training program related to white or blue-collar occupations are constant and independent of job offers. An immigrant who has already participated in WC or BC training since his arrival, does not receive another training offer.

Utility from being unemployed and utility while participating in a training program ($ue; tr^j$; $j = 1; 2$) differ across the unobserved M types.

Value after five years: We assume that the present value of utility of the individual i at the 21st quarter takes the following approximation form of the state variables at that period, that is,

$$\begin{aligned} V^j_i(S_{iL+1}; t = 21) = \; & \delta_{1m} + \delta_2 EX_{i21} + \delta_{3m} C^1_{i21} + \delta_4 EDUC_i + \delta_5 AGE_i + \\ & \delta_6 L^H_{i21} + \delta_7 L^F_{i21} + \delta_8 d^1_{i20} + \delta_9 d^0_{i20} + \delta_{10m} C^2_{i21} \end{aligned} \tag{14}$$

where m indicates the type of individual.

4 Estimation Results and Model Fit

In this section we present the estimation results of the parameters and the fit of the model to the data. As a starting point for the estimated parameters and the fit of model to the data we construct an estimation method that provides the "best fit" of the model to the data. That is, the square difference between the aggregate choices (table 10) and the predicted aggregate choices, of immigrants at each labor market state, is minimized given the OLS estimates for the wage function. We call these estimates for a simple model specified below "best fit" which show how well the model can fit the main pattern of the data. Using the "best fit" estimated parameters as starting points, we present the results from the simulated maximum likelihood described above.

4.1 "Best Fit" Results

The OLS parameters of the wage in WC and BC (table 10) minimizes the sum of square errors from the regression line and therefore provides best fit for the observed wage. Given the wage parameters, we estimate the other parameters of the model under the following assumptions: (i) there is no unobserved heterogeneity in the population; (ii) Ω is diagonal and (iii) there are no shocks to preferences of attending training or of being unemployed. Let these parameters belong to the vector, θ^0: We estimate θ^0 by minimizing the distance between the predicted and the actual aggregate choice probabilities (table 4). We call this method Best Fit Estimator (BFE), since it solves the following objective function

$$J(\theta^0) = \underset{\theta}{\mathrm{Min}} \left\{ \sum_{t=1}^{20} \sum_{j=0}^{4} (prob^p_{jt} - prob^r_{jt})^2 \times obs(t) / \sum_{t=1}^{20} obs(t) \right\} \qquad (15)$$

where $prob^p_{jt}$ is the predicted simulated proportion of individuals in alternative j at time t, $prob^r_{jt}$ is the observed proportion of individuals in alternative j at time t in the data and obs(t) is the number of observations in the sample at time t. To obtain the predicted pattern for a given set of parameters, we solve the DP problem backwards for each point in the state space using 150 Monte-Carlo draws to calculate E max at each point as $\sum_{s=1}^{16} P(g^s_{it+1} | S_{it}, t, d^r_{it}) E(\max\{g^s_{it+1} | S_{it}, t, d^r_{it} = 1\}$ in (7). Solving forward for each immigrant in the sample requires simulating the choice set, g_s, the immigrant faced in each quarter and the offered wage. Since we do not observe the actual job and training offers, we simulate the choice set and build the immigrant's choice path.[13] The value of J, as defined by (15) stands on 49.653.

Figure 3a shows that the BFE provides a set of estimated parameters that fit very well the observed aggregate pattern of the fast reduction in unemployment, the large increase in the proportion of BC workers and the very slow, but steady, increase in the proportion of WC workers. Furthermore, figures 3b and 3c show that the model fits well the pattern of attending training programs soon after completion of learning Hebrew (attending "ulpan") as predicted by the human capital investment model.

Table 11 shows that a simple fit test for the labor market aggregate choices does not pass the test statistic with 0.05 significance level for the main two labor market outcomes of work in WT and unemployment for the entire model. The fit for BC is statistically significant and due to the few observations in the training programs, the fit for WT is also statistically significant. The BFE gives a good fit to the aggregate pattern of choices, but it does not necessarily match well the actual choices made by each immigrant and it does not necessarily fit well other aspects of the data, such as the hazard rates for each alternative, the transitions between the different states or even the joint labor market activity choice and the observed wage. In other words, BFE demonstrates that the model can reproduce the aggregate choices but not necessarily the individual choices. For example, predicting correctly that 20% immigrants are working in BC in a certain quarter does not imply that we predict this event correctly for people who were actually employed in BC occupation that quarter. Specifically, we correctly predict the choices for only 2404 observations out of 5778 (41.6%), which corresponds to a pseudo R^2 of 0.416.

The estimated parameters for the wage equations are given in table 10 and discussed in section 2. The estimated parameters for preferences, the job and training offer probabilities and

[13] For example, in order to decide if an unemployed immigrant received a job offer in WC occupation ($j = 1$) at time t, we take a draw from a uniform unit distribution [0,1] and compare it to the WC job offer probability, P^{01}_{it}, which is implied by the model. If the draw is smaller than P^{01}_{it}, we assume the immigrant received a WC job offer at time t.

terminal value are given in table 1A in the appendix. We see that the job o¤er probability is lower if the immigrant did not work in the previous period and is higher if the individual had training in the same occupation. The estimated probability to receive a training program is very low (0.103 in WT and 0.078 in BT). This result is most likely due to the high estimated return to training in wages. Furthermore, the utility gain from participation in training is higher then the one from unemployment. Hence, to match the observed participation in training patterns, we get low training o¤er rates.

Table 11: Chi-Square Test for "Best-Fit"

	Â^2	degrees of freedom	P-value
unemployment	81.3425	20	0.0000
WC	40.6341	20	0.0041
BC	13.7664	20	0.8421
WT	21.4920	18	0.1663
BT	87.8987	17	0.0000
All …ve states	240.6684	75	0.0000

4.2 Maximum Likelihood Results

We use the solution of the dynamic programming problem as input in the estimation procedure as explained above. Hence, the vector of the parameters of the model (µ) enters the likelihood function through its e¤ect on the choice probabilities and wages. Given a vector of initial values of the parameters, as estimated by the BFE, we solve the model for each individual at each possible point in the state space and compute the value of the Emax^{0}s (and hence, the value functions he faces in each period) at these points[14]. Using these values, we calculate the implied conditional

[14] 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 in 2,070 points in the state space that may arise during the 20 period planning horizon (which means 2,070 combinations of $EX; C^1$ and C^2). Each of these points, we use 150 draws to calculate the Emax. The state space increases linearly with the number of unobserved types. In this version of the model we assume only two unobserved types, which implies that for each person we calculate the value functions in 4,140 points in the state space. Since the solution of the DP problem and the calculation of the likelihood function is made for each observation independently, we take advantage of the parallel processing features of the super-computers and run the program simultaneously on 16-32 processors. The program runs on IBM super computer at Tel-Aviv University and on a Silicon Graphics super-computer (Origin2000) at Boston University.

joint probabilities of the immigrant's choices and observed wage that enter the likelihood. We than iterate on the vector of parameters until we reach maximum[15].

Model …t to choices

The actual and simulated estimated choice distribution is presented in …gures 4a, 4b and 4c. The model tends to overpredict the proportion of immigrants in unemployment and to underpredict the employment in WC and BC occupations, mainly during the …rst eight quarters in Israel. The discrepancies, with respect to unemployment, mainly occur during the …rst four quarters of residency in Israel. The model predicted that 83% (42%) of the immigrants would be unemployed during the …rst(fourth) quarter in Israel, although 72% (23%) actually are. The predicted rise in the share of immigrants who are employed in WC is too slow during the …rst two years, compared to the actual rise observed in the data. The model underpredicts employment in BC during the …rst two years and overpredicts employment in this occupation from the 15th quarter on. With respect to participation in training, the predicted pattern is roughly consistent with the data. The model predicts a peak in participation in WT (BT) in the third (…fth) quarter (6.7% in WT and 4.8% in BT), whereas the actual peak in WT (6.4%) occurs in the fourth quarter and the actual peak in BT (4.3%) occurs, as predicted, in the …fth quarter. In table 12 we present results from a simple Â^{2} tests for the model …t. We reject the hypothesis that there is no di¤erence between the actual and predicted proportions in unemployment, WC, BC and WT separately. We do not reject this hypothesis with respect to the BT training state. The …t test for the model as a whole shows rejection at the 1% level. In addition, we …nd a signi…cant di¤erence between the predicted and actual choice distribution for all the choices during the …rst seven periods and during the 12 and 13 quarters. The J value using the parameters of the maximum likelihood is ¡ 229:7:

[15] The current value of the log-likelihood is -2,657.7

Table 12: Chi-Square Test for ML

	χ^2	degrees of freedom	P-value
unemployment	162.1	18	0.0000
WC	248.2	20	0.0000
BC	144.2	20	0.0000
WT	40.6	15	0.0004
BT	20.1	13	0.0931
All five states	615.2	66	0.0000

Estimated Parameters

Wage Parameters

Table A2 presents the estimated wage parameters. Like the OLS WC wage regression estimates (table 10 column (3)), most of the estimators here are statistically insignificant at a 5% level. The return to training is almost identical for both types and is close in magnitude to the OLS estimator, around 12%. The coefficient of English is significant and large (13%) whereas the coefficient of Hebrew is smaller (10.8%) and insignificant.[16] The estimated wage constant is larger for the 2nd type, implying that type 2 faces a higher mean wage regardless of his characteristics. The ML estimates of the BC wage parameters are also insignificant as the OLS estimators (table 10 column (4)). The return to training is substantially greater for type 1 than for type 2, although as in wage in WC, the constant is higher for the 2nd type.

Job Offer Parameters

Table A1 presents the estimated parameters of the job offer probabilities. The interpretation of these parameters is not straightforward because of the logistic functional form of the job-offer probabilities.

WC offer Probability

Language skills in both Hebrew and English do not have a significant effect on the rate WC job offers. Holding a WC job in the USSR does not have a significant effect on the rate WC job offers as well. Participation in WT significantly increases the job offers in WC, and the same is

[16] Note that knowledge of English and Hebrew indices vary between 1 to 4 and the mean is 1.76 for English and 2.7 for Hebrew.

true with regard to the accumulated work experience of one to four quarters in Israel. Immigrants who did not accumulate any work experience in Israel face a lower job o¤er probability in WC occupation, though the coe¢ cient of no experience is insigni…cant. Immigrants who were older on arrival also face a lower job o¤er probability in WC occupation. Regardless of the immigrant's unobserved type and observed characteristics, immigrants who did not work in the previous quarter (either because they were unemployed or participated in one of the training programs) face a higher probability of receiving a job o¤er in WC (compared to immigrants who worked in BC occupation). Type 2 has a higher unconditional probability of receiving a job o¤er in WC occupation. The separation rate from WC jobs is close to zero. To demonstrate the quantitative e¤ect of the elements that a¤ect WC o¤er probability, consider an unemployed immigrant who was 38 on arrival, worked in WC in USSR and has an English skill index of 1.79 and Hebrew skill index of 2. If this immigrant had not accumulated work experience, he would receive a WC job-o¤er each quarter with a probability of 0.021 if he is of type 1 and 0.026 if he is of type 2. If the same immigrant had previously participated in WT, this o¤er probability would have increased by 136% for type 1 and by 134% for type 2. In the same manner, if this immigrant was only 30 years old on arrival, the WC job o¤er probability would have increased by 49%, regardless of his type. The job-o¤er probabilities are also in‡uenced from the accumulation of work experience. The same immigrant we considered above who has accumulated between 1 to 4 quarters of work experience in Israel, would receive a WC job-o¤er with a probability of 0.116 (0.143) if he is of type 1(2). The e¤ect of having some experience (compared to having no experience) is enormous as the WC job-o¤er probabilities increase by more than 440%.

BC O¤er Probability

Both age on arrival and Hebrew are insigni…cant. An immigrant who did not work in the previous period has a higher probability of receiving a BC job o¤er than an immigrant who worked in the previous period in WC ($b_{032h} < b_{012h}$ for $h = 1; 2$). BC job o¤er probability increases with training in BC occupation. Similarly to WC jobs, we …nd high persistence in BC jobs, as the separation rate from BC occupation is negligible. Again, to demonstrate the quantitative e¤ects of various variables on BC o¤er probability, we consider an unemployed immigrant who was 38 years old on arrival, has no experience and Hebrew skill index of 2. This immigrant would receive a BC job-o¤er each quarter with a probability of 0.113 if he is of type 1 and 0.109 if he is of type

2. If the same immigrant had previously participated in BT, this o¤er probability would have increased by 67% for both types. If this immigrant was only 30 years old on arrival, the WC job o¤er probability would have increased by 46% regardless of his type. The same immigrant but with 1 to 4 quarters of work experience in Israel, would receive a BC job-o¤er with probability of 0.46(0.45) if he is of type 1(2).

Training

The estimated probability of receiving an o¤er to participate in a training program which is related to WC occupation is 10.3% quarterly, whereas the probability of receiving an o¤er to participate in a training program which is related to BC occupation is 7.8% each quarter. Both probabilities are signi…cant. The utility while attending WT (BT) is -2.8 (0.03) for an immigrant of type 1 and 96.8 (96.3) if the immigrant is of type 2. The big di¤erence between the utilities of the two types, combined with the di¤erent return to BT training in wage in BC for the two types, leads to a di¤erent pattern of participation in training of the two types.

Terminal value

The estimated parameters of the terminal value function are shown in table A1. All the estimates are signi…cant at the 5% level. Every unit of work experience increases the discounted terminal value by 299NIS per hour. Training in WC increments the terminal value by about 49 NIS for both types whereas training in BC increments the terminal value by approximately 42 NIS. A unit in Hebrew skill or English skill increases the terminal value by 60 NIS each. Immigrants who worked in WC in the last quarter can expect an increase of 107 NIS in the terminal value whereas an immigrant who was unemployed in the last quarter faces a decrease of 130 NIS in his terminal value.

Transitions

Table 13 presents the predicted quarter to quarter transitions among the …ve alternative labor market states for each type of immigrant separately. The predicted transitions below are based on the same simulations of the choice probabilities that are presented in …gures 4a, 4b and 4c. That is, for each of the 419 observations we use the true exogenous variables and we simulate their lifetime decisions using the estimated parameters. The table shows that the main distinction between the transitions of the two types is with respect to persistence in employment in WC and BC. The main result is that type 1 is less persistence in WC jobs than type 2, but more persistence in BC jobs.

Table 13: Predicted Transitions by Type

From \ To	Unemployment		73 202 WC		BC		WT		BT		Total	
Type	1	2	1	2	1	2	1	2	1	2	1	2
Unemployment	1326	1333	59			189	80	88	62	58	1729	1741
WC	0	0	720	1209	20	5	0	0	0	0	740	1214
BC	0	0	31	69	2605	2074	0	0	0	0	2636	2143
WT	52	55	7	8	10	14	73	77	0	0	142	154
BT	48	45	0	0	12	11	0	0	52	51	112	107
Total	1426	1433	817	1359	2849	2293	153	165	114	109	5359	5359

Table 14 presents the average predicted transitions weighted by types' proportions and the actual transitions. The model predicts the persistence in WC occupation, in BT and in WT fairly well. However, it produces too much persistence in unemployment and correspondingly too little persistence in BC. The predicted transitions from training to the two employment states are lower than the actual transitions and there are no predicted transitions from the two employment states to training.

Table 14: Actual and Predicted Transitions

From \ To	Unemployment		WC		BC		WT		BT		Total	
	actual	ML	actual	ML	actual	ML	actual	ML	actual	ML	actual	ML
Unemployment	841	1352	89	65	275	195	34	86	19	60	1258	1759
WC	16	0	999	1059	15	7	12	0	4	0	1046	1065
BC	110	0	18	60	2646	2215	26	0	28	0	2828	2275
WT	25	55	25	7	17	13	70	75	0	0	136	150
BT	21	47	4	0	19	11	0	0	47	52	91	110
Total	1013	1454	1134	1191	2972	2441	142	161	98	112	5359	5359

5 Implications

The structural estimation of the model allows us to estimate the private (and social) impact of alternative government intervention regarding training on subsequent work and occupational choice. We consider the following …ve experiments, all with respect to the availability of training programs:

1) no training available

2) only BT available (probability of WT is the ML estimate)

3) only WT is available (probability of BT is the ML estimate)

4) an increase of 20% in probability of WT

5) an increase of 20% in probability of BT

We consider the impact of each of the above experiments on the hourly present value (PV) of four representative immigrants who di¤er by their age on arrival, years of schooling and occupation in the USSR. The knowledge of Hebrew and English are set at their sample means. The results of the experiments are presented in table 15. The estimated present value per hour of work in Israel is estimated to be between 3,293 NIS to 2,719 NIS depending on the individual characteristics.[17]

As expected, immigrants who were younger on arrival, face a higher PV than that of older immigrants. However, it is interesting to note that given age on arrival, years of education do not lead to higher PV. This …nding is surprising since wage increases with schooling level and one would expect that the more educated would gain more from immigrating. Nevertheless, the more educated tend to search more and are more choosy, so overall they spend more time being unemployed or attending training programs. Since not all of them succeed in eventually …nd a job in a WC occupation, this search leads to a loss rather than a gain. The loss in terms of PV from not having the option to participate in any training program (…rst experiment) ranges between 6 to 8.3 percent. This loss is greater for older and for more educated immigrants. Older immigrants have a lower probability to receive a job o¤er in either BC or WC occupations and participation in training overcompensate this loss and helps them to receive job o¤ers in both

[17] Assuming about 1800 hours of work per year, the value of immigration for that individual is about 5.4 million NIS.

occupations. More educated immigrants also suffer more since their human capital may be more specific and training can help them in adjusting their skills to the Israeli labor market. However, when we do not permit immigrants to attend WT programs only (second experiment), we find that the younger immigrants and the less educated immigrants experience greater loss in terms of PV. In the third experiment, we calculate the PV assuming BT programs only are not available. Blocking the entry to BT leads to a loss of between 2.1 to 4.7 percent. Here we find the loss is higher for older and for better-educated immigrants. Increasing the quarterly probability to receive a WT (BT) offer in 20%, leads to gains between 0.9%-2.4% (3.2%-7.5%).

From the various experiments we conclude that the gain from BT programs is larger, simply because most of the immigrants are eventually absorbed in BC jobs in the Israeli labor market. Younger immigrants and better educated immigrants tend to lose a larger fraction of utility if the BT programs were unavailable. Overall, the availability of the 6 month government-sponsored vocational training provides a return of 6% to 8% rate of increase in welfare (wages). This rate is approximately the same as the standard estimated rate of return on a year of schooling. Yet these numbers most likely have large standard errors which possibly means that we cannot reject the hypothesis that the rate of return is even close to zero.

Table 15: Counterfactual Simulations

% of change in parenthesis

Experiment	BC in USSR, schooling=12		WC in USSR, schooling=15	
	age on arrival 30	age on arrival 45	age on arrival 30	age on arrival 45
Present Value On Arrival*	3,293.10	2,799.63	3,171.00	2,719.02
No Training	3,094.30 (-6.04)	2,571.44 (-8.15)	2,961.15 (-6.62)	2,494.19 (-8.27)
No WT	3,218.77 (-2.26)	2,747.25 (-1.87)	3,113.92 (-1.80)	2,688.47 (-1.12)
No BT	3,224.50 (-2.08)	2,691.45 (-3.86)	3,078.66 (-2.91)	2,591.64 (-4.68)
WT offer +20%	3,370.74 (2.36)	2,849.71 (1.79)	3,226.98 (1.77)	2,743.30 (0.89)
BT offer +20%	3,396.71 (3.15)	2,963.85 (5.87)	3,307.37 (4.30)	2,921.47 (7.45)

*Hourly, August 1995 prices

References

[1] Bellman, R. (1957), "Dynamic Programming," Princeton, New-Jersey, Princeton University Press.

[2] Borjas, G.J. (1994), "The Economics of Immigration," Journal of Economic Literature, 32, 1667-1717.

[3] Chiswick, B. (1992), "The Performance of Immigrants in the Labor Market: A Review Essay," unpublished manuscript.

[4] Eckstein, Z. and Y. Weiss (1998), "The Absorption of Highly Skilled Immigrants: Israel 1990-1995," Foerder Institute Working Paper, 3-98.

[5] Eckstein, Z. and Y. Weiss (1999), "The Integration of Immigrants from the Former Soviet Union in the Israeli Labor Market," Foerder Institute Working Paper, 33-99.

[6] Eckstein and K.I. Wolpin (1999), "Why Youth Drop Out of High School: The Impact of Preferences, Opportunities and Abilities", Econometrica, 67(6), 1295-1339.

[7] Freidberg, R. (2000), "You Can't, Take it With You? Immigrant Assimilation and the Portability of Human Capital," Journal of Labor Economics, 18(2), 221-251.

[8] Heckman, J., LaLonde, R.J. and J.A.Smith (1999) "The Economics and Econometrics of Active Labor Market Programs," Handbook of Labor Economics, forthcoming.

[9] Heckman, J. and B. Singer (1984), "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," Econometrica, 52(2), 271-320.

[10] Keane, M. P. and K. I. Wolpin (1994), "The solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence", Review of Economics and Statistics, 76, 648-672.

[11] Keane, M. P. and K. I. Wolpin (1997), "The Career Decision of Young Men," Journal of Political Economy, 105, 473-522.

[12] LaLonde, R. J. and R. H. Topel (1994), "Economic Impact of International Migration and the Economic Performance of Migrants," mimeo., University of Chicago.

[13] LaLonde R.J. (1995) "The Promise of Public Sector-Sponsored Training Programs", Journal of Economic Perspectives 9(2), 149-168.

[14] McFadden, D. (1989), "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration," Econometrica, 57(5), 995-1026.

[15] Wiess, Y., Sauer, R.M. and M. Gotliboveski (1999), "Immigration, Search and Loss of Skill," Foerder Institute Working Paper, 26-99.

Table A1: "Best …t" and ML estimates

BC O¤er Probability	"Best …t"	Maximum Likelihood
b_{0221} ¡ worked in BC at t-1,type 1	2.6210	14:0513¤ 4:4721
b_{0222} ¡ worked in BC at t-1,type 2		13:8350¤ 4:4721
b_{0121} ¡ worked in WC at t-1,type 1	0.0010	¡ 3:2775¤ 0:5962
b_{0122} ¡ worked in WC at t-1,type 2		¡ 3:8065¤ 1:0962
b_{0321} ¡ worked in WC at t-1,type 1	-0.9978	¡ 1:4134¤ 0:4015
b_{0322} ¡ worked in WC at t-1,type 2		¡ 1:4525¤ 0:4425
b_{0312} ¡ No work experience in Israel		¡ 0:4169¤ 0:2145
b_{0322} ¡ Work experience in Israel 1-4		1:5000¤ 0:1499
b_{42} ¡ Training in BC	0.4790	0:6052¤ 0:1535
b_{52} ¡ Hebrew		0:0066 0:0783
b_{62} ¡ Age on arrival		¡ 0:0064 0:0060
WC O¤er Probability		
b_{0111} ¡ worked in WC at t-1,type 1	2.2178	15:9914¤ 4:4721
b_{0111} ¡ worked in WC at t-1,type 2		14:5064¤ 4:4721
b_{0211} ¡ worked in BC at t-1,type 1	-4.4977	¡ 3:7029¤ 0:8450
b_{0212} ¡ worked in WC at t-1,type 2		¡ 2:8429¤ 0:9005
b_{0311} ¡ worked in WC at t-1,type 1	-1.7662	¡ 2:3427¤ 0:7890
b_{0312} ¡ worked in WC at t-1,type 2		¡ 2:1064¤ 0:8391
b_{1} ¡ English	0.0020	¡ 0:0002 0:0497
b_{2} ¡ Occupation in Soviet Union	0.0202	0:4798 0:2768
b_{311} ¡ No work experience in Israel		¡ 0:2339 0:7812
b_{321} ¡ Work experience in Israel 1-4		1:5833¤ 0:2823
b_{41} ¡ Training in WC	0.0010	0:8881¤ 0:2653
b_{51} ¡ Hebrew		0:1066 0:1407
b_{61} ¡ Age on arrival		¡ 0:0516¤ 0:0115

	”Best …t’	Maximum likelihood
WC Training O¤er Probability	0.1225	0:1031¤ 0:0147
BC Training O¤er Probability	0.0727	0:0779¤ 0:0111
Terminal value parameters		
$\pm_{11}$ – Constant, type 1	1000.0000	1000:0267¤ 4:4721
$\pm_{12}$ – Constant, type 2	–	1000:0275¤ 4:4721
$\pm_{2}$ – Experience	60.0000	299:0676¤ 4:3732
$\pm_{31}$ – WC Training, type 1	60.0000	49:2532¤ 4:4717
$\pm_{32}$ – WC Training, type 2	–	49:6209¤ 4:4719
$\pm_{4}$ – Schooling	10.0000	10:4013¤ 4:4719
$\pm_{5}$ – Age on arrival	-10.0000	¡ 8:7038 4:4718
$\pm_{6}$ – Hebrew knowledge	60.0000	60:0767¤ 4:4721
$\pm_{7}$ – English knowledge	60.0000	60:0203¤ 4:4721
$\pm_{7}$ – worked in WC last period	60.0000	107:7968¤ 4:4699
$\pm_{8}$ – unemployed last period	-60.0000	¡ 130:8033¤ 4:4713
$\pm_{101}$ – BC Training, type 1	30.0000	42:3587¤ 4:4717
$\pm_{102}$ – BC Training, type 2	–	42:2711¤ 4:4719
unemployment bene…t, type 1	6.5650	¡ 186:6118¤ 4:3524
unemployment bene…t, type 2	–	¡ 177:0909¤ 4:4468
WT bene…t, type 1	8.4994	¡ 2:8028 4:4620
WT bene…t, type 2	–	96:7559¤ 4:4691
BT bene…t, type 1	8.4994	0:0312 4:4410
BT bene…t, type 2	–	96:3348¤ 4:4720
Type 1 Proportion	–	0:6959¤ 0:0638

Table A2: Wage Parameters

Wage parameters	BC		WC	
	best fit	ML	best fit	ML
b_{cons}; type1	2.1663 (0.1237)	2.1638^{*} 0.1238	1.0475 (0.4261)	1.1212^{*} 0.4704
b_{cons}; type2		2.5513^{*} 0.1362		1.6073^{*} 0.5010
b_{Hebrew}	0.0506 (0.0270)	0.0496 0.0317	0.1274 (0.0614)	0.1085 0.0681
$b_{English}$	-0.0100 (0.0217)	-0.0139 0.0258	0.1311 (0.0363)	0.1388^{*} 0.0418
$b_{\text{age on arrival}}$	-0.0029 (0.0020)	-0.0053 0.022	0.0132 (0.0052)	0.0095 0.0069
$b_{\text{years of schooling}}$	0.0083 (0.0062)	0.0089 0.0072	0.0214 (0.0225)	0.0179 0.0235
$b_{\text{trained in wc}}$; type1	-0.0010 (0.0625)	-0.0007 0.0736	0.1146 (0.0796)	0.1200 0.0939
$b_{\text{trained in wc}}$; type2				0.1230 0.1039
$b_{\text{trained in bc}}$; type1	0.0642 (0.0550)	0.0928 0.0694	-0.0485 (0.1301)	-0.0324 0.1560
$b_{\text{trained in bc}}$; type2		0.0261 0.2130		
$b_{\text{accumulated experience}}$	0.0075 (0.0128)	$5.3e-8$ 0.0004	0.0300 (0.0358)	$3.0e-7$ 0.0009
$b_{\text{accumulated experience}^2}$	0.0009 (0.0007)	-0.0018^{*} 0.0002	-0.0007 (0.0019)	-0.0017^{*} 0.0005
No. of Obs.	442	442	132	132

Figure 1a: Proportions in Unemployment, Blue Collar and White Collar

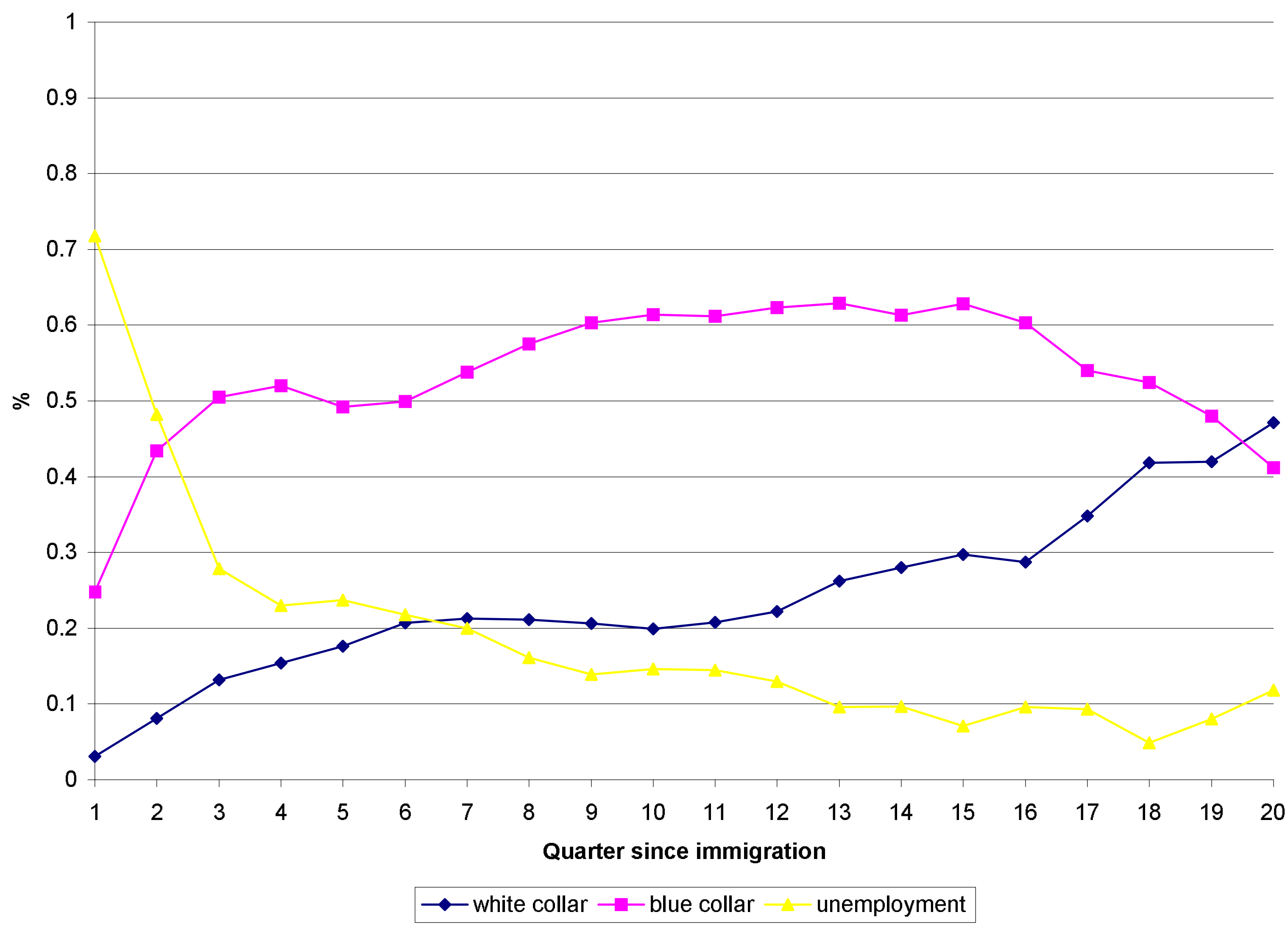

Figure 1b: Participation in Blue Collar and White Collar Training

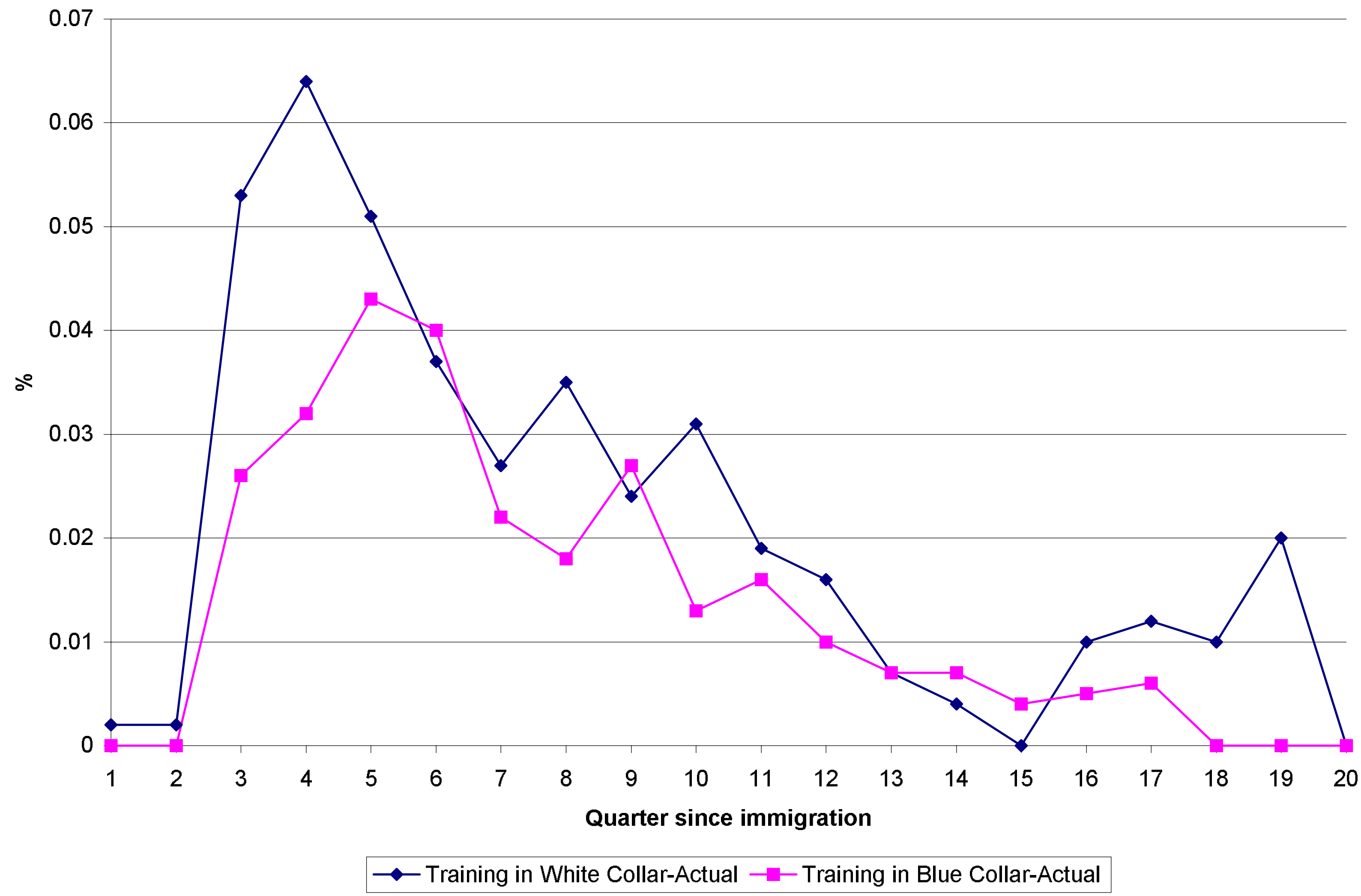

Figure 2: Average Wage by Occupation

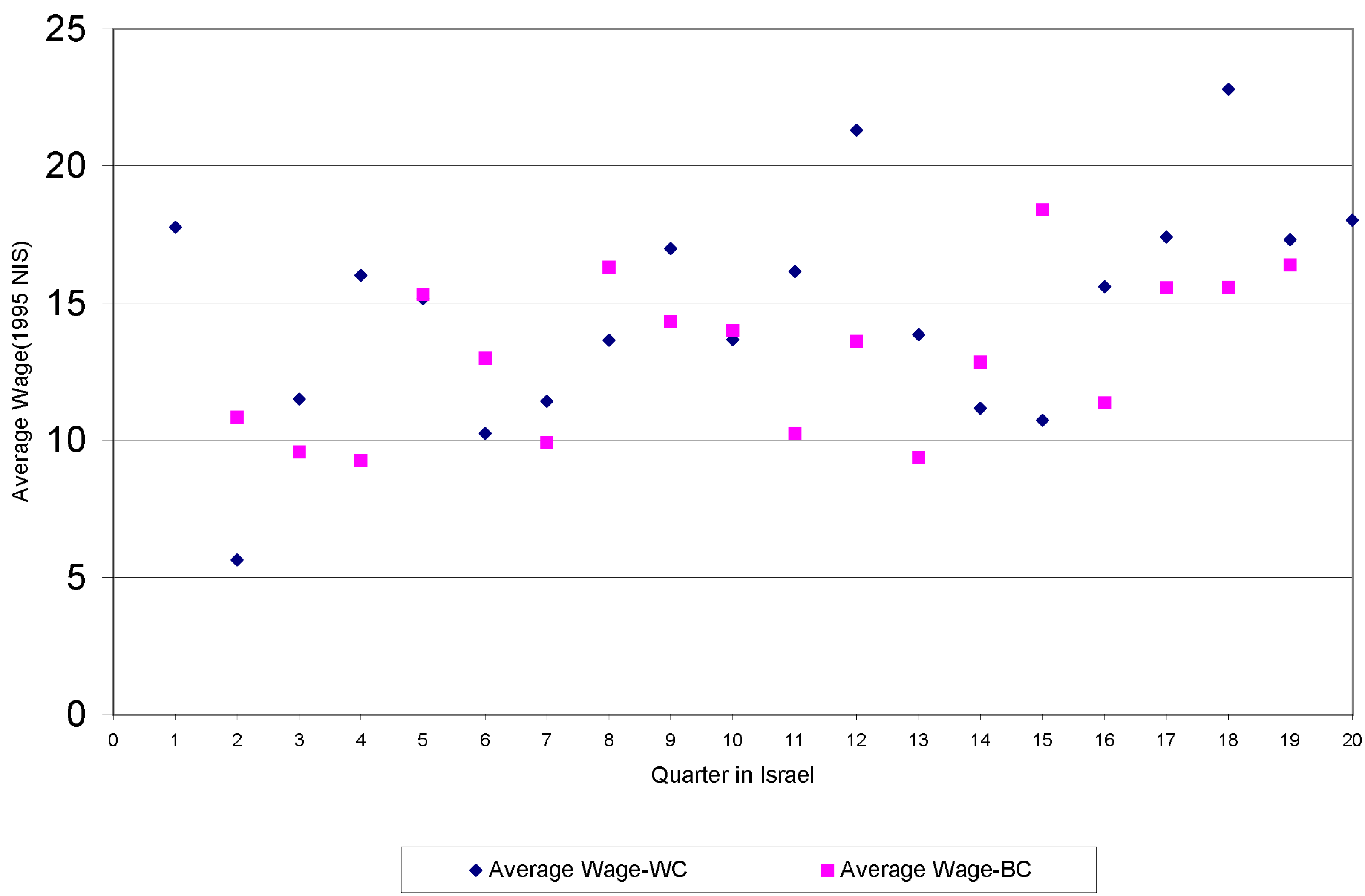

Figure 3a: Choice Distribution: Actual and Best-fit

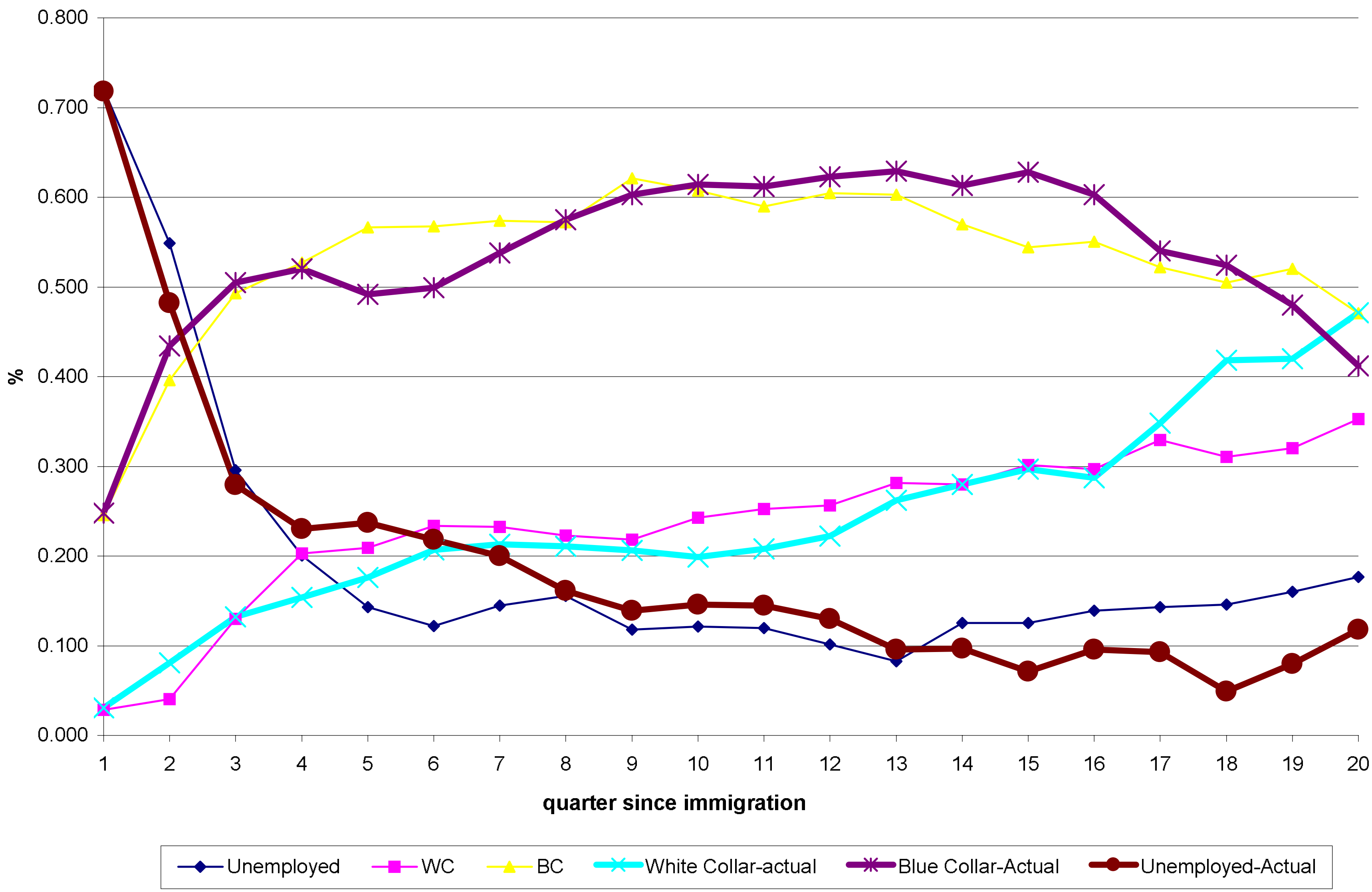

Figure 3b: Participation in White Collar Training: Actual and Best-fit

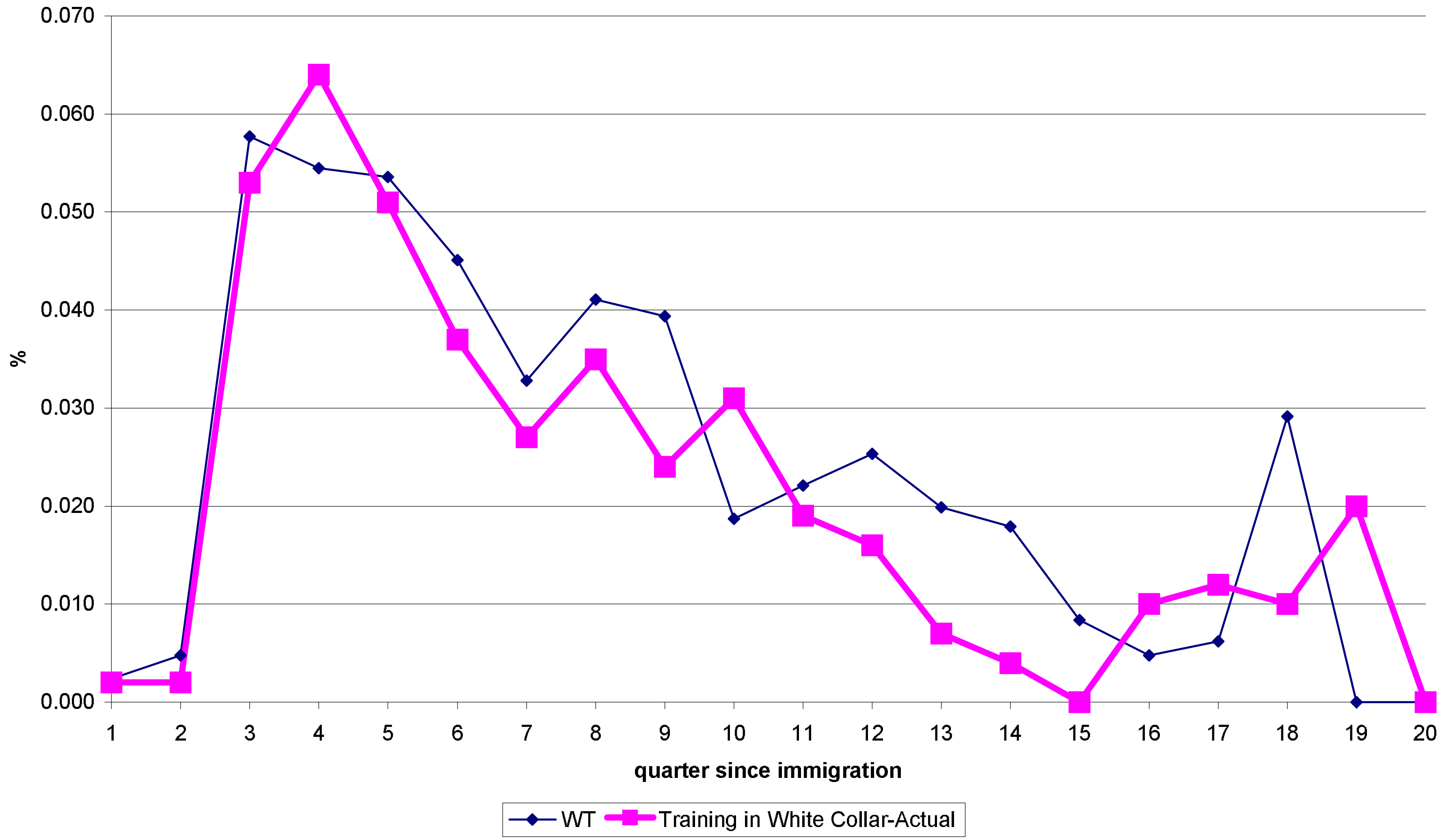

Figure 3c: Participation in Blue Collar Training: Actual and Best-fit

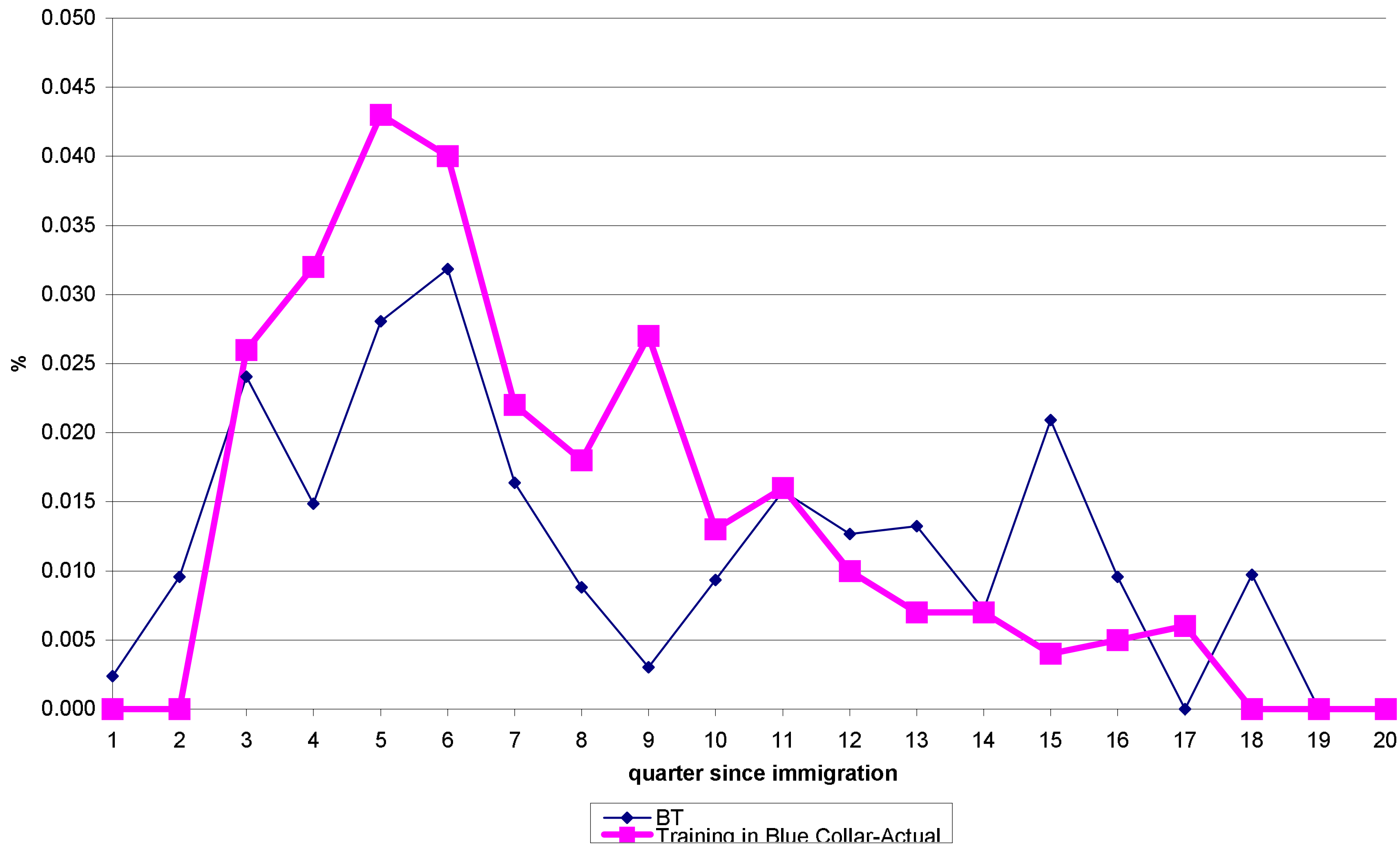

Figure 4a: Actual and ML Proportions in Unemployment, Blue Collar and White Collar

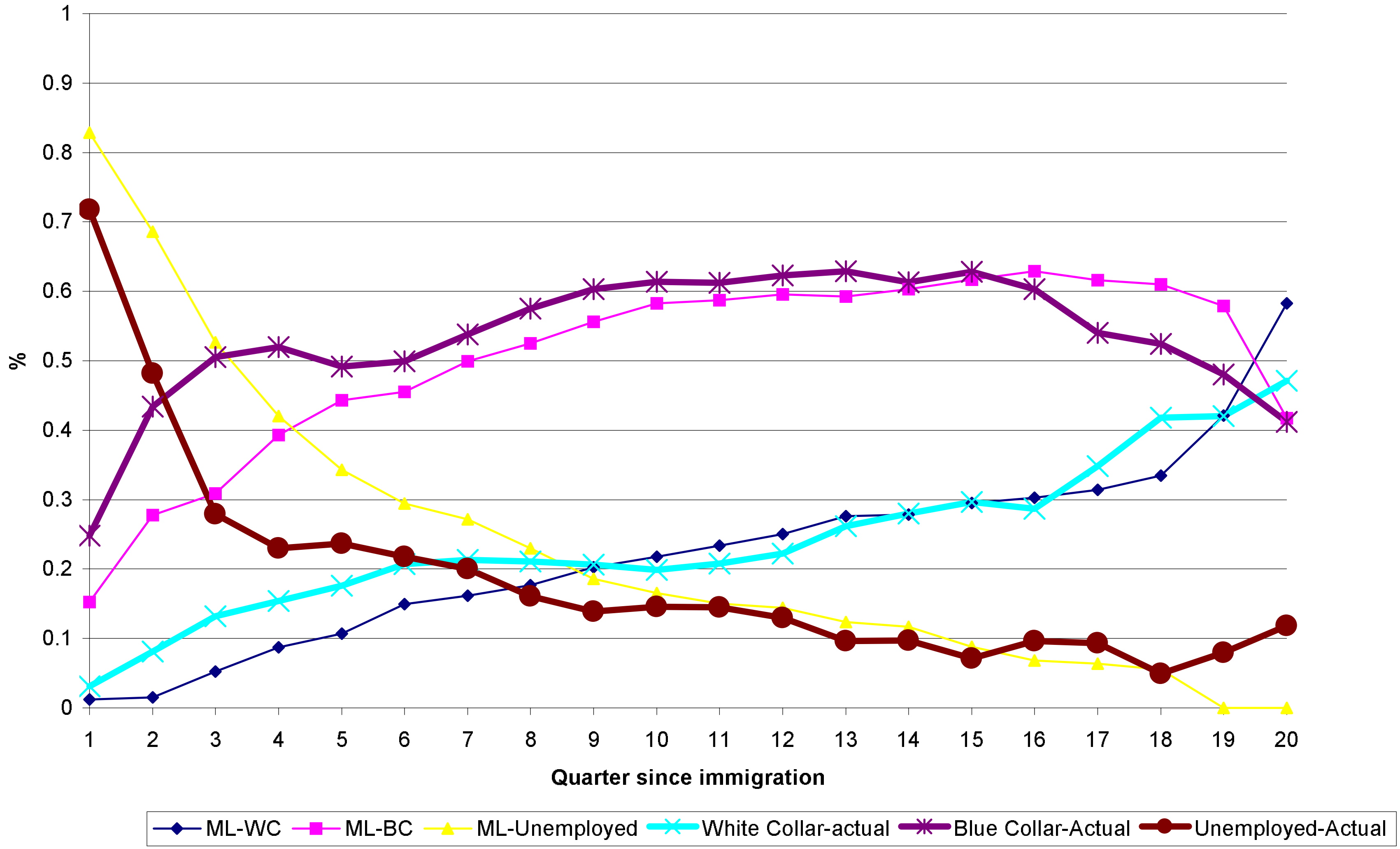

Figure 4b: Actual and ML Proportions in White Collar Training

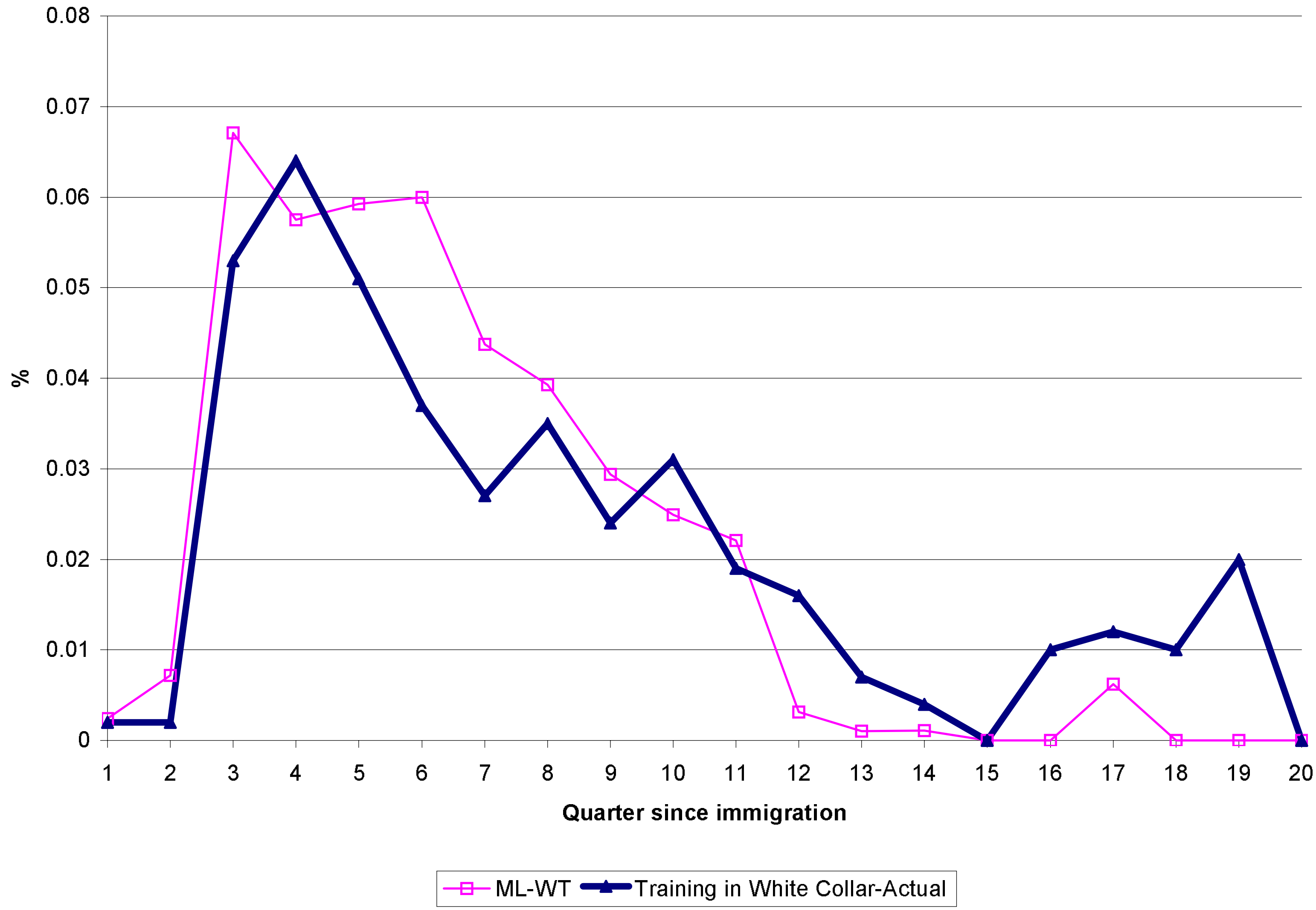

Figure 4c: Actual and ML Proportions in Blue Collar Training