Available online at www.sciencedirect.com
ScienceDirect
European Economic Review 51 (2007) 553–576
EUROPEAN ECONOMIC REVIEW
www.elsevier.com/locate/eer

A life-cycle model of outmigration and economic assimilation of immigrants in Germany

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Received 12 July 2004; accepted 6 March 2006
Available online 22 May 2006

Abstract

This paper estimates a forward-looking life-cycle model of outmigration and labor force participation. The estimated model is used to evaluate the impact of enforcing a maximum stay duration for newly admitted immigrants on labor force participation and outmigration. Restricting the migration duration is found to have little effect on the labor force participation of skilled immigrants, and a negative effect on that of unskilled immigrants. Restricting the migration duration is also found to encourage the departure of unskilled and unsuccessful immigrants before the maximum duration is reached. These results are obtained by estimating the model with data that contain no information on outmigration decisions. It is shown that the assumption of a continuous state variable affecting attrition only through outmigration allows the probability of outmigration to be identified from the panel attrition. This probability can then be estimated using standard dynamic programming techniques. The migration durations so estimated are found to differ substantially from those estimated under the assumption that immigrants are myopic decision makers.

JEL classification: J61; C61

Keywords: Outmigration; Structural dynamic programming models

1. Introduction

It is now well accepted that outmigration is a worldwide phenomenon. It has therefore become a central concern in the literature of immigration to characterize those immigrants

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0014-2921/$ - see front matter
doi:10.1016/j.euroecorev.2006.03.005

who choose to leave their host country, to infer the rules determining their decision, and find out how their duration of stay and participation in the host labor market are affected by policy changes.

In this paper, I specify a forward-looking model of labor force participation and outmigration decision made by immigrants over their life cycle. The model parameters are estimated using the immigrant sample of the German Socio-Economic Panel (GSOEP), which mainly consists of ''guest'' workers admitted to overcome cyclical labor shortages who have no restrictions on their duration of stay. One attractive feature of the GSOEP is that immigrants are followed over a long period, which helps to identify various life-cycle effects. Another advantage of this data source is that it contains detailed information on potential determinants of outmigration, such as the performance of immigrants in the German labor market, their age on arrival, and the number of years since their migration to Germany. These determinants enter the model through both pecuniary and non-pecuniary benefits of working and outmigration. The model's capacity to separately identify pecuniary and non-pecuniary benefits distinguishes it from more traditional migration models, which focus exclusively on differences in pecuniary benefits (e.g., Harris and Todaro, 1970). This model also distinguishes itself from other works (e.g. Pessino, 1991) by including explicitly uncertainty about future work and earnings in the host and home countries, which allows immigrants to revise the duration of stay over their lifetime. Another important feature of the model is it highlights differences in consumption preferences between the home and host countries, which is one of the reasons usually put forward to explain why outmigration occurs despite persistently higher expected earnings in the host country (see Carrington et al., 1996, for related evidence).

This model is used to provide new insights to the recent debate about whether imposing a maximum duration of stay on visas should be an important component of Germany's immigration policy.[1] One of the reasons that policy makers are attracted to the short-term visa solution is that it allows the host country to more easily adjust its stock of immigrants to fluctuations in the labor market. It also provides a means of preventing the immigration of (possibly unskilled) family members (see Bauer and Zimmermann, 2000, for a discussion). One possible disadvantage of short-term visas is that they may lower incentives for immigrants to accumulate skills and experience. This aspect depends on the transferability of skills and experience acquired in the host country to the home country, as well as on the initial skill levels of the immigrants. Accordingly, policy analysis is performed in this paper for both highly skilled and unskilled immigrants. It is important to use a forward-looking model to measure the effects of this policy change, because a short-term visa affects behavior by restricting the horizon over which agents benefit from accumulating skills and experience, and thus affects the future benefits of remaining in the host country as perceived by immigrants. Imposing a maximum duration of stay is found to expedite the departure of skilled immigrants only if they experience spells of unemployment after their entry. Because skilled immigrants are unlikely to experience such spells, their accumulation of experience and integration into the German labor market are not likely to be strongly affected by such a policy change. The policy is found to

[1] Some insights on German guest workers have already been obtained by modeling data on stated intentions of stay (e.g. Dustmann, 1996, 2000). There, the skill levels of immigrants declaring the intent to stay permanently are compared to the skill levels of immigrants declaring the intent to remain in Germany temporarily.

be more successful at encouraging low-skilled, unemployed immigrants to outmigrate before expiration of their visa.

The lack of high-quality outmigration indicators to estimate the underlying model has been one of the main problems in simulating the effects of this and other policy changes on outmigration. This problem is also present in the GSOEP data.[2] This paper develops an econometric framework to overcome this problem, using sample attrition as a baseline proxy variable for outmigration and incorporating in the sample likelihood the probability that sample attrition is confounded for outmigration. To identify this probability and hence separate outmigration from other forms of attrition, it is critical to assume the existence of at least one continuous state variable affecting attrition only through the probability of outmigration. This exclusion restriction makes it possible to decrease the outmigration probability to zero for appropriate values of the excluded state variable while keeping the probability of other forms of attrition constant. The required separation is thus identified by immigrants whose value of the state variable generates a zero outmigration probability but who still have a positive probability of attrition due to other factors. This paper shows how this assumption can be used to estimate the model and empirically measure outmigration probabilities using standard dynamic programming methods.

Because such methods are computationally intensive, I also compare the life-cycle migration duration profiles of various immigrants as predicted by this model to those predicted by a simpler model. The simpler model is estimated under the assumption that immigrants are myopic decision makers who do not discount future utility, an assumption which removes the need to solve a dynamic programming problem for each immigrant within the estimation procedure. Despite the fact that both models provide similar parameter estimates, the myopic and forward-looking models generate very different life-cycle migration duration profiles. These differences result from the fact that forward-looking agents take into account their future well-being when making decisions, which in turn depends on future state variables that are influenced by their current decisions.

The rest of this paper is organized as follows. Section 2 presents the data used. Section 3 presents the model. Section 4 presents the estimation approach and discusses how to identify the outmigration probability using attrition data. Section 5 discusses the results, compares the predicted migration durations of the dynamic and myopic models, and discusses the policy experiment. Section 6 concludes.

2. Data

The data used here are taken from the immigrant sample of the 1984–2001 public release of the GSOEP, and cover the 1985–1999 period. The data mainly consist of an oversample of immigrants living in West Germany and coming from countries that had signed a bilateral migration agreement with Germany in the 1950s and 1960s, namely Greece, Italy, Spain, Turkey and former Yugoslavia.[3] These data contain detailed information on labor supply, labor market earnings, education, age on arrival in Germany, and knowledge of German, all tracked over a very long period of time.

[2] Dustmann (1996) discusses this point in the context of the GSOEP, while Dustmann (2000) discusses it in a more general context.

[3] Immigrants of Portuguese nationality are not present in the panel.

Despite these advantages, the GSOEP data suffer from several limitations which will affect the model presented in the next section. First, information on savings was only available after 1991. Second, these data do not contain information on the potential earnings of immigrants in their native country. Third, no distinction about the country of origin is made beyond whether the immigrant came from an EU (Greeks, Italians, and Spaniards) or non-EU (Turks and immigrants from former Yugoslavia) state. Fourth, while information on speaking fluency was given in consecutive waves from 1984 until 1987, after 1987 this information was only gathered every other year. In order to keep a constant time interval between individual observations, I have chosen to retain eight waves of the panel where information on speaking fluency was available, each spanning 1 year, starting in 1985 and ending in 1999. I consider only males between 18 and 64 years of age who did not die during the 1985 and 1999 period, and provide complete information in any of the eight waves on the variables entering the empirical model. This selection results in a sample of 727 immigrants observed in 1985.

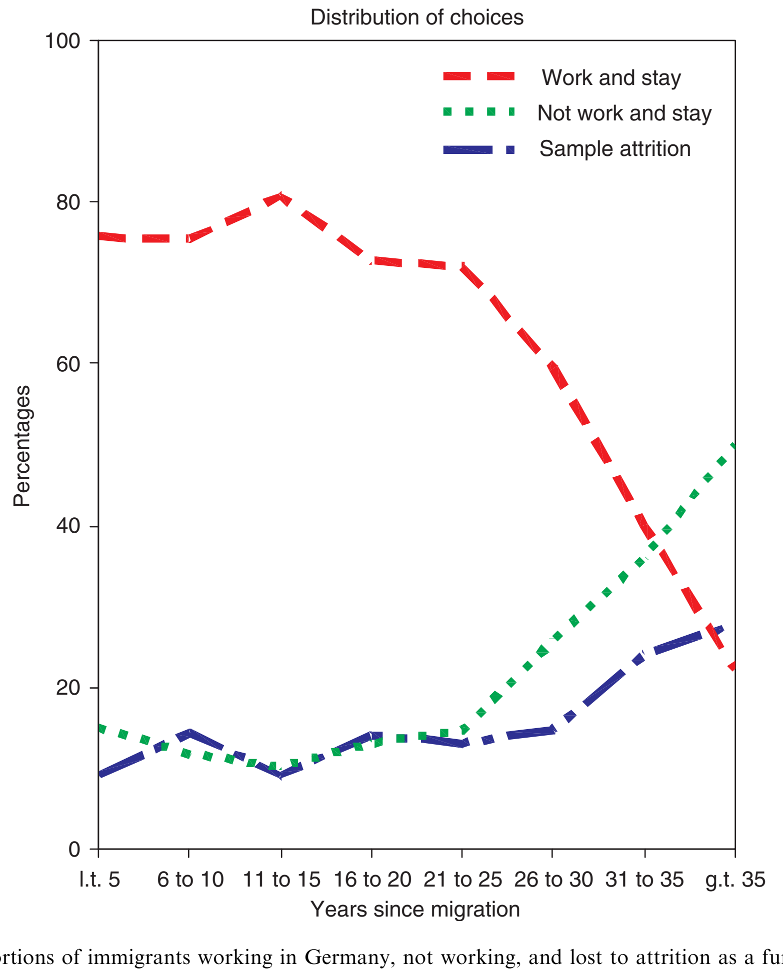

Fig. 1. Proportions of immigrants working in Germany, not working, and lost to attrition as a function of the number of years since migration.

Table 1
Descriptive statistics (sample means)

Variable description		
Europe	0.495	1 = Spain, Italy or Greece, 0 = Former Yugoslavia and Turkey
Age	44.688	
Experience	28.598	Number of years of labor market experience
Education	9.39	Number of years
German speaking fluency	2.58	1 = bad, 5 = excellent
Age at immigration	23.61	
Years since immigration in 1985	15.74	

Fig. 1 presents the proportions of sample immigrants who were working, not working, or left the panel as a function of the number of years they spent in Germany. It can be seen that the working proportion is close to 80% for immigrants who have spent 15 years or less in Germany. This proportion quickly decreases as the number of years spent in Germany increases further, dropping to as little as 20% for immigrants who have spent more than 35 years in Germany. The proportion of immigrants not working is between 12% and 17% for those who have stayed for 25 years or less, then steadily increases and eventually passes the 40% mark for those who have spent 35 years or more in Germany. The proportion of sample attrition has a similar pattern, averaging around 15% for immigrants with 25 years or less of residence then rising steadily to a point just over 25% for immigrants with more than 35 years of residence.

Table 1 presents the variables and associated summary statistics. Most immigrants migrated to Germany early in their productive lives. The average age at the time of immigration is only 23.61 years, indicating that most immigrants were of an age to autonomously decide to move to Germany. The number of years of education is an important variable, which is assumed to be exogenous in the model presented in the next section. To determine whether this assumption is realistic, the number of immigrants in 1985 who stopped to accumulate education over the period observed was counted. Of the 727 immigrants in the data, only 18 increased their education level between 1985 and 1999. This suggests that most immigrants had completed their education at the beginning of the observation window.

3. The model

Conditional on the information set $\boldsymbol{\Omega}_{i1}$, an immigrant i at time $t = 1$ will maximize his expected lifetime utility over a finite horizon T,

$$\mathbf{E}\left[\sum_{t=1}^{T} \beta^{t-1} U(d_{it}^{\mathrm{W}}, d_{it}^{\mathrm{NW}}, d_{it}^{\mathrm{O}}) \middle| \boldsymbol{\Omega}_{i1}\right], \tag{1}$$

by choosing the sequence $\{d_{it}^{*\mathrm{W}}, d_{it}^{*\mathrm{NW}}, d_{it}^{*\mathrm{O}}\}_{t=1}^{T}$, where $d_{it}^{\mathrm{W}} = 1$ if the immigrant works in the host country, $d_{it}^{\mathrm{NW}} = 1$ if the immigrant does not work but remains in the host country, and $d_{it}^{\mathrm{O}} = 1$ if the immigrant outmigrates. These decisions are binary and mutually exclusive (i.e., $d_{it}^{\mathrm{W}} + d_{it}^{\mathrm{NW}} + d_{it}^{\mathrm{O}} = 1$).[4] It is further assumed that outmigration is

[4]In this paper, I treat return migration and outmigration as equivalent concepts since most outmigration movements are believed to be return movements. The model above does not, however, rule out other departure destinations.

irreversible, which implies that the control variable d_{it}^{O} acts as a stopping rule.[5] Hence, Eq. (1) is assumed to be maximized according to the constraint that $d_{it}^{*\mathrm{O}} = 1$ if $d_{it-1}^{*\mathrm{O}} = 1$. The expectation of (1) is taken over a joint distribution of the stochastic future state variables (see below), where β is a subjective discount factor.

The instantaneous utility function is given by

$$\begin{aligned} U(d_{it}^{\mathrm{W}}, d_{it}^{\mathrm{NW}}, d_{it}^{\mathrm{O}}) = d_{it}^{\mathrm{W}}\left[\theta^{\mathrm{Host}}\ln(c_{it}) + \delta_{it}^{\mathrm{W}} + \varepsilon_{it}^{\mathrm{W}}\right] + d_{it}^{\mathrm{NW}}\left[\theta^{\mathrm{Host}}\ln(c_{it}) + \varepsilon_{it}^{\mathrm{NW}}\right] \\ + d_{it}^{\mathrm{O}}\left[\theta^{\mathrm{Home}}\ln(c_{it}) + \delta_{it}^{\mathrm{O}} + \varepsilon_{it}^{\mathrm{O}}\right], \end{aligned}$$

where c_{it} denotes consumption of a composite good, θ^{Host} and θ^{Home}, respectively, denote the marginal utility of consumption in the host and home country, and $\varepsilon_{it}^{\mathrm{W}}$, $\varepsilon_{it}^{\mathrm{NW}}$, and $\varepsilon_{it}^{\mathrm{O}}$ consist of time-specific shocks to utility. The direct utility of working in the host country δ_{it}^{W} and the direct utility of living in the home country δ_{it}^{O} are permitted to depend on individual characteristics:

$$\begin{aligned} \delta_{it}^{\mathrm{W}} &= \alpha_0^{\mathrm{W}} + \alpha_1^{\mathrm{W}} Europe_i + \alpha_2^{\mathrm{W}} Ageatim_i + \alpha_3^{\mathrm{W}} Ageatim_i \times Europe_i \\ &\quad + \alpha_4^{\mathrm{W}} Exper_{it} + \alpha_5^{\mathrm{W}} Exper_{it}^2 + \alpha_6^{\mathrm{W}} Ysm_{it}, \\ \delta_{it}^{\mathrm{O}} &= \alpha_0^{\mathrm{O}} + \alpha_1^{\mathrm{O}} Europe_i + \alpha_2^{\mathrm{O}} Ageatim_i + \alpha_3^{\mathrm{O}} Ageatim_i \times Europe_i \\ &\quad + \alpha_4^{\mathrm{O}} Exper_{it} + \alpha_5^{\mathrm{O}} Exper_{it}^2 + \alpha_6^{\mathrm{O}} Ysm_{it}, \end{aligned}$$

where $Europe_i$ is a binary indicator taking a value of 1 if the immigrant is from Spain, Italy, or Greece, and 0 otherwise; $Ageatim_i$ is the age in years on arrival in Germany; $Educ_{it}$ is the number of years of education; $Exper_{it}$ is the number of years of labor market experience; and Ysm_{it} is the number of years since migration.[6]

The budget constraint which is assumed to be satisfied in each period is given by

$$c_{it} = w_{it}^{\mathrm{W}} d_{it}^{\mathrm{W}} + \tau d_{it}^{\mathrm{NW}} + w_{it}^{\mathrm{O}} d_{it}^{\mathrm{O}}, \tag{2}$$

where w_{it}^{W} is the income of immigrants in Germany, w_{it}^{O} is their income in the home country, and τ denotes any transfers obtained when not working.[7] Eq. (2) implies that immigrants do not save, an admittedly restrictive assumption in light of recent theoretical and empirical models of asset accumulation and return migration (e.g., Dustmann and Kirchkamp, 2002). One of the reasons for retaining this assumption is that information on savings was collected only after 1991, exactly halfway through the observation window. Another reason is that relaxing this assumption would result in a considerable expansion of the choice set and state space, and greatly increase the complexity of the calculations.[8]

[5]In the present data, reversible outmigration is negligible (Pannenberg, 1998). In other countries, however, this assumption is not likely to be satisfied. Jasso and Rosenzweig (1990), for example, find that reversible outmigration is particularly important for Mexican immigrants living in the United States.

[6]A more complete specification of the direct utility of outmigration would incorporate the variation of social and political circumstances in the home country over time. Since I do not have data on these factors, they are not included in the model.

[7]Outmigration costs do not enter this budget constraint, reflecting the fact that the German federal government reimbursed outmigration costs from 1984 to 1992 (see Section 2 for details). I do not model the regime change after 1992.

[8]The effects of savings on outmigration may be partially captured by the non-pecuniary benefit functions δ_{it}^{W} and δ_{it}^{O}. This will be the case if, for example, those who have more labor market experience are also more likely to save and start businesses once they return. Dustmann and Kirchkamp (2002) present evidence of this for Turkish return migrants.

Labor market earnings in the host country are assumed to be determined by

$$w_{it}^{\mathrm{W}} = \exp\big(\varphi_0^{\mathrm{W}} + \varphi_1^{\mathrm{W}} Europe_i + \varphi_2^{\mathrm{W}} Educ_{it} + \varphi_3^{\mathrm{W}} Fluency_{it} + \varphi_4^{\mathrm{W}} Exper_{it} + \varphi_5^{\mathrm{W}} Exper_{it}^2 + \varphi_6^{\mathrm{W}} Ysm_{it} + \eta_{it}^{\mathrm{W}}\big) \tag{3}$$

and depend on the number of years of education, the number of years of labor market experience, the number of years since migration, the fluency in German $Fluency_{it}$, and a shock factor η_{it}^{W}.

It is important to note that labor market experience and the number of years since migration affect the utility of working in the host country through two channels: Once through a direct effect on δ_{it}^{W}, and again through their indirect effect on the utility of consumption $\theta^{\mathrm{Host}} w_{it}^{\mathrm{W}}$ due to changes in earnings w_{it}^{W}. The signs of the direct and indirect effects of these variables need not be the same, a situation that can explain voluntary retirement from the labor force. When the labor market earnings profile grows flat at high levels of experience, for example, working an extra year in the host labor market will have a very small effect on utility via changes in consumption. The immigrant will then have an incentive to retire from the labor force if he suffers greater direct disutility from working an additional year in the host country.

The earnings in the home country are determined by

$$w_{it}^{\mathrm{O}} = \exp\big(\varphi_0^{\mathrm{O}} + \varphi_1^{\mathrm{O}} Europe_i + \varphi_2^{\mathrm{O}} Educ_{it} + \varphi_3^{\mathrm{O}} Fluency_{it} + \varphi_4^{\mathrm{O}} Exper_{it} + \varphi_5^{\mathrm{O}} Exper_{it}^2 + \varphi_6^{\mathrm{O}} Ysm_{it} + \eta_{it}^{\mathrm{O}}\big), \tag{4}$$

where the variables and parameters used are analogous to those of Eq. (3).

In any given period, $\boldsymbol{\Omega}_{it}$ contains all the state variables entering the earnings and utility functions for each choice, as well as all shocks $(\varepsilon_{it}^{\mathrm{W}}, \varepsilon_{it}^{\mathrm{NW}}, \varepsilon_{it}^{\mathrm{O}}, \eta_{it}^{\mathrm{W}}, \eta_{it}^{\mathrm{O}})$. This information set is updated over time as decisions are made. The two endogenous state variables, $Exper_{it}$ and Ysm_{it}, have the following laws of motion: $Exper_{it} = Exper_{it-1} + d_{it-1}^{\mathrm{W}}$ and $Ysm_{it} = Ysm_{it-1} + \mathrm{Max}[d_{it-1}^{\mathrm{W}}, d_{it-1}^{\mathrm{NW}}]$. The initial values of $Exper_{it}$ and Ysm_{it} are zero. Education and fluency in German are both assumed to be time-varying exogenous variables.

4. Estimation procedure

The structural model is estimated using the three-step strategy proposed by van der Klaauw (1996). The main advantage of this approach over a direct likelihood estimation of the full structural model is that it allows several of the structural specifications to be estimated without having to estimate the time-intensive dynamic programming step.

In the first step, let $\boldsymbol{\Omega}_{it} = [\mathbf{Y}_{it}, (\varepsilon_{it}^{\mathrm{W}}, \varepsilon_{it}^{\mathrm{NW}}, \varepsilon_{it}^{\mathrm{O}}, \eta_{it}^{\mathrm{W}}, \eta_{it}^{\mathrm{O}})]$, where $\mathbf{Y}_{it}$ is the vector containing all state variables and is assumed to be observed by the econometrician. When incorporating the earnings Eqs. (3) and (4) into the budget constraint (2), and the budget constraint into the objective function (1), the contemporary utilities of each alternative can be expressed as the following reduced form equations[9]:

$$U^{\mathrm{W}}(\mathbf{Y}_{it}) + \varepsilon_{it}^{\mathrm{W}} = z_{it}' \boldsymbol{\lambda}^{\mathrm{W}} + \varepsilon_{it}^{\mathrm{W}},$$

[9]The transfer τ is normalized to 1. As for the other two choices, it would be possible to specify the utility of staying without working as a function of the direct component of utility $\delta_{it}^{\mathrm{NW}}$ (which in turn depends on observable state variables), and the utility of transfer consumption $\theta^{\mathrm{W}}\tau$. Because these coefficients would not be identified, they are normalized here to zero. Hence, the estimated structural parameters α^{W} and α^{O} should be interpreted as measuring their effects on the utility of a particular choice relative to their effects on the utility of staying and not working.

$$U^{\mathrm{NW}}(\mathbf{Y}_{it}) + \varepsilon_{it}^{\mathrm{NW}} = \varepsilon_{it}^{\mathrm{NW}},$$

$$U^{\mathrm{O}}(\mathbf{Y}_{it}) + \varepsilon_{it}^{\mathrm{O}} = \boldsymbol{z}_{it}'\boldsymbol{\lambda}^{\mathrm{O}} + \varepsilon_{it}^{\mathrm{O}},$$

where $\boldsymbol{z}_{it}$ is a vector containing the distinct state variables of the earnings and non-pecuniary benefit equations, and $\boldsymbol{\lambda}^j = [\lambda_0^j, \lambda_1^j, \ldots, \lambda_8^j]'$ for $\{j = \mathrm{W}, \mathrm{O}\}$ are vectors of the reduced form parameters.[10] Following van der Klaauw (1996), I assume that the composite error terms

$$\varepsilon_{it}^{\mathrm{W}} = \theta^{\mathrm{Host}}\eta_{it}^{\mathrm{W}} + \varepsilon_{it}^{\mathrm{W}},$$

$$\varepsilon_{it}^{\mathrm{NW}} = \varepsilon_{it}^{\mathrm{NW}},$$

$$\varepsilon_{it}^{\mathrm{O}} = \theta^{\mathrm{Home}}\eta_{it}^{\mathrm{O}} + \varepsilon_{it}^{\mathrm{O}}$$

have a conditional mean of zero, are independently distributed over time and individuals, and follow an extreme-value type I distribution.

The solution of (1) can be decomposed into the solution of T separate problems, where for each $t = 1, 2, \ldots, T$, one determines

$$\left\{ \max_{d_{it}^{\mathrm{W}}, d_{it}^{\mathrm{NW}}, d_{it}^{\mathrm{O}}} (d_{it}^{\mathrm{W}}[V_t^{\mathrm{W}}(\mathbf{Y}_{it}) + \varepsilon_{it}^{\mathrm{W}}] + d_{it}^{\mathrm{NW}}[V_t^{\mathrm{NW}}(\mathbf{Y}_{it}) + \varepsilon_{it}^{\mathrm{NW}}] + d_{it}^{\mathrm{O}}[V_t^{\mathrm{O}}(\mathbf{Y}_{it}) + \varepsilon_{it}^{\mathrm{O}}]) \right\}, \quad (5)$$

where $V_t^j(\mathbf{Y}_{it})$ are the value functions associated with the choices $j = \mathrm{W}, \mathrm{NW}, \mathrm{O}$. The value functions associated with $(j = \mathrm{W}, \mathrm{NW})$ are given by

$$V_t^j(\mathbf{Y}_{it}) = U^j(\mathbf{Y}_{it}) + \beta \mathbf{E} \max\{V_{t+1}^{\mathrm{W}}(\boldsymbol{\Omega}_{it+1}), V_{t+1}^{\mathrm{NW}}(\boldsymbol{\Omega}_{it+1}), V_{t+1}^{\mathrm{O}}(\boldsymbol{\Omega}_{it+1}) | \mathbf{Y}_{it}, d_{it}^j = 1\}, \quad (6)$$

where the expectation is taken over the triplet $(\varepsilon_{i,t+1}^{\mathrm{W}}, \varepsilon_{i,t+1}^{\mathrm{NW}}, \varepsilon_{i,t+1}^{\mathrm{O}})$ contained in the information set $\boldsymbol{\Omega}_{it+1}$. Finally, the outmigration decision acts as a terminal control variable whose associated value function has the following simple form:

$$V_t^{\mathrm{O}}(\mathbf{Y}_{it}) = U^{\mathrm{O}}(\mathbf{Y}_{it}) + \beta \mathbf{E}\{V_{t+1}^{\mathrm{O}}(\boldsymbol{\Omega}_{it+1}) | \mathbf{Y}_{it}, d_{it}^{\mathrm{O}} = 1\}.$$

In the finite horizon case, solutions to the value functions are computed through backward recursion starting with the terminal period T. In order to simplify the computations, I assume that throughout the recursion an immigrant expects that future values of $Educ_{it+j}$ and $Fluency_{it+j}$ for any $j = 1, 2, \ldots, T - t$ will be equal to the time t values. This assumption seems reasonable given the characteristics of the present data. Most immigrants have completed their education at the start of the observation window (see Section 2). As for speaking fluency, Dustmann and van Soest (2001) find that most of an individual's variation in reported speaking fluency in the GSOEP data is due to misreporting errors, suggesting that any actual improvements over time are small. This could result from the fact that the average time spent in Germany at the start of the observation window was already more than 15 years in this sample; the subjects had thus already stopped improving their speaking fluency. I do not attempt to control for measurement error in the speaking fluency indicator.

[10]One example of a reduced form parameter is $\lambda_0^{\mathrm{W}} = \alpha_0^{\mathrm{W}} + \theta^{\mathrm{Home}}\varphi_0^{\mathrm{W}}$.

The model presented above does not admit an analytical solution. By taking advantage of the terminal conditions and distributional assumptions regarding the stochastic model components, however, it is possible to solve for a set of optimal decisions numerically using backward induction for given values of β and $\boldsymbol{\lambda}$.[11] Given that the Bellman equations have been solved for a given set of parameter values and the serial independence of the unobservable state variables, the decision rule (5) can be applied to determine the choice probabilities as follows:

$$\Pr(d_{it}^{j} = 1|\mathbf{Y}_{it}) = \Pr(V_t^j(\mathbf{Y}_{it}) + \varepsilon_{it}^{j} > V_t^l(\mathbf{Y}_{it}) + \varepsilon_{it}^{l};\ \text{for all } l \neq j).$$

When combined with the distributional assumptions, this equation takes on a familiar multinomial logit form. The probabilities are then used to form the sample likelihood

$$\prod_{i=1}^{N}\prod_{t=1}^{T_i}\left[\sum_{j=\mathrm{W,NW,O}} d_{it}^{j}\Pr(d_{it}^{j} = 1|\mathbf{Y}_{it})\right],$$

where T_i is the number of periods observed for immigrant i.

In the second step of the estimation procedure, the reduced form estimates of the dynamic programming model are used to estimate the earnings (3), correcting for selectivity due to work and attrition.[12]

Finally, given consistent estimates of the reduced form parameters $\boldsymbol{\lambda}^{\mathrm{W}}, \boldsymbol{\lambda}^{\mathrm{O}}$ and the earnings equation estimates from the second step, consistent estimates of the structural parameters are obtained using a minimum distance estimator (Chamberlain, 1984). This estimator is defined as

$$\min_{\boldsymbol{\psi}}(\widehat{\boldsymbol{p}} - g(\boldsymbol{\psi}))'\boldsymbol{C}^{-1}(\widehat{\boldsymbol{p}} - g(\boldsymbol{\psi})),$$

where $\boldsymbol{\psi}$ denotes the vector of structural parameters and the function $g(\cdot)$ imposes the structural restrictions of the model on the vector of reduced form parameter estimates $\widehat{\boldsymbol{p}}$.[13] $\boldsymbol{C}$ is the covariance matrix of $\widehat{\boldsymbol{p}}$, which can be computed using the estimated covariance matrices and the outer product of the scores from the estimates of the first two steps. The resulting estimate $\widehat{\boldsymbol{\psi}}$ is consistent and has an asymptotic normal distribution (see van der Klaauw, 1996, for more details).

4.1. Identification and estimation with partial observability of outmigration

So far, it has been assumed that d_{it}^{O} was perfectly observed. In the data, however, it is sample attrition rather than true outmigration that is perfectly observed. Sample attrition may differ from actual, unobservable outmigration because some attrition may result from immigrants leaving the sample but not the country. Immigrants who remain in the panel, on the other hand, have clearly decided to remain in the host country. In this sense, sample attrition partially reveals outmigration. It is well known that measurement error in a discrete left-hand side variable can lead to biased parameter and variance estimates in non-linear models (see Bound et al., 2001, for a survey of this literature). This suggests that one

[11] Given my distributional assumptions, the $\mathbf{E}\max$ functions have a familiar log sum form (e.g. van der Klaauw, 1996).

[12] Technical details of this step are provided in the Appendix.

[13] One example of such a restriction is $\widehat{\lambda}_0^{\mathrm{W}} = \alpha_0^{\mathrm{W}} + \theta^{\mathrm{Host}}\widehat{\varphi}_0^{\mathrm{W}}$.

cannot simply use sample attrition as a proxy variable for outmigration without accounting in some way for the partial observability problem.

Let the attrition indicator d_{it}^{A} take the value 1 when immigrant i drops out of the panel, and 0 otherwise. By the law of total probability, it can be shown that the probability that an immigrant i will drop out of the sample, conditional on state variables $\mathbf{Y}_{it}$, is given by

$$\Pr(d_{it}^{\mathrm{A}} = 1|\mathbf{Y}_{it}) = \pi(\mathbf{Y}_{it}) + [1 - \pi(\mathbf{Y}_{it})] \cdot \Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it}), \tag{7}$$

where $\pi(\mathbf{Y}_{it}) \equiv \Pr(d_{it}^{\mathrm{A}} = 1|d_{it}^{\mathrm{O}} = 0, \mathbf{Y}_{it})$ represents the probability that an immigrant drops out of the panel but remains in the country.[14]

The quantity $\Pr(d_{it}^{\mathrm{A}} = 1|\mathbf{Y}_{it})$ is in principle directly identified by the data. Given the left-hand side of (7), one could then solve for $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ if the function $\pi(\mathbf{Y}_{it})$ were also identified. Inspection of (7) reveals, however, that without further restrictions on how state variables enter $\pi(\mathbf{Y}_{it})$ and $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ it is not possible to separately identify $\pi(\mathbf{Y}_{it})$ and $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ using the variation of $\Pr(d_{it}^{\mathrm{A}} = 1|\mathbf{Y}_{it})$ and $\mathbf{Y}_{it}$.

Let $\mathbf{Y}_{it} = [\overline{\mathbf{Y}}_{it}, v_{it}]$, where v_{it} is a continuous state variable. v_{it} is restricted to significantly affect the attrition probability only through $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ (i.e. $\pi(\mathbf{Y}_{it}) = \pi(\overline{\mathbf{Y}}_{it})$). It is also required that the effect of the state variables $\mathbf{Y}_{it}$ on the outmigration probability $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ operates through a parametric linear index $\Psi_{it} = \mathbf{Y}_{it}'\boldsymbol{\Lambda}$, where $\boldsymbol{\Lambda}$ is an appropriately scaled parameter vector. Given these conditions, $\pi(\overline{\mathbf{Y}}_{it})$ can be identified nonparametrically.[15]

I now review an explanation of this result as given by Lewbel (2000). Given (7) and the exclusion of the continuous variable v_{it} from $\pi(\cdot)$, it follows that the following functional:

$$\frac{\partial^2 \Pr(d_{it}^{\mathrm{A}} = 1|\mathbf{Y}_{it})/\partial^2 v_{it}}{\partial \Pr(d_{it}^{\mathrm{A}} = 1|\mathbf{Y}_{it})/\partial v_{it}} = \frac{\partial^2 \Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})/\partial^2 v_{it}}{\partial \Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})/\partial v_{it}} \tag{8}$$

is independent of $\pi(\cdot)$. Lewbel (2000, Lemma 1) exploits the fact that the left-hand side of (8) is nonparametrically identified, and that its expectation is a function of Ψ_{it} alone, to identify and estimate $\boldsymbol{\Lambda}$ using appropriate semiparametric single index estimators. Given an identification of the index Ψ_{it}, Lemma 2 of Lewbel (2000) implies that the outmigration probability $\Pr(d_{it}^{\mathrm{O}} = 1|\cdot)$ can be identified using an integrated version of the preceding functional and then estimated at an arbitrary point on its support, again using a sequence of conventional nonparametric estimators. Next, given that Ψ_{it} and $\Pr(d_{it}^{\mathrm{O}} = 1|\cdot)$ are known and that v_{it} affects $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ but not $\pi(\cdot)$, $\pi(\overline{\mathbf{Y}}_{it})$ can be identified using immigrants with extreme values of v_{it} conditional on $\overline{\mathbf{Y}}_{it}$.[16] Lewbel (2000, Lemma 4) shows how $\pi(\overline{\mathbf{Y}}_{it})$ can be estimated using a series of nonparametric density and conditional expectation estimators. This discussion shows that $\pi(\overline{\mathbf{Y}}_{it})$ and the outmigration probability $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ can be separately identified, provided that an exclusion restriction is placed on $\pi(\overline{\mathbf{Y}}_{it})$ and a single index restriction on $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$.

[14] The structure of Eq. (7) is mathematically equivalent to the class of binary choice models with misclassification of the dependent variable (Hausman et al., 1998; Lewbel, 2000). The main difference is that here the "misclassification" is one-sided, and results from the partial observability of the outcome rather than a misreporting mechanism.

[15] A general limitation of the present framework, however, is that $\pi(\cdot)$ cannot depend on unobservable individual characteristics.

[16] This follows from (7) since $\lim_{v_{it}\to\infty} \Pr(d_{it}^{\mathrm{A}} = 1|\Psi_{it}) = \pi(\overline{\mathbf{Y}}_{it})$ when the coefficient of v_{it} is negative. The opposite limit applies when the coefficient of v_{it} is positive.

In the following empirical analysis, I assume that $\mathbf{Y}_{it}$ affects the outmigration probability but not the probability of dropping out of the panel and remaining in the country ($\pi(\mathbf{Y}_{it}) = \pi$).[17]

4.2. Identification of remaining model parameters

The parameters of the earnings (3) are identified from the observable earnings data in the host country. The vectors of reduced form parameters $\boldsymbol{\lambda}^{\mathrm{W}}$ and $\boldsymbol{\lambda}^{\mathrm{O}}$ are identified from the choice data. θ^{Host} is identified by excluding $Fluency_{it}$ and $Educ_{it}$ from the direct utility of working. As a result, the parameters $(\alpha_0^{\mathrm{W}}, \alpha_1^{\mathrm{W}}, \alpha_2^{\mathrm{W}}, \alpha_3^{\mathrm{W}}, \alpha_4^{\mathrm{W}}, \alpha_5^{\mathrm{W}}, \alpha_6^{\mathrm{W}})$ are identified.

One limitation of this model is the omission of all time-varying social and political circumstances which could affect the non-pecuniary benefits of staying, working, and outmigration. Correlation of these variables over time would introduce serial correlations across the unobserved state variables $(\varepsilon_{it}^{\mathrm{W}}, \varepsilon_{it}^{\mathrm{NW}}, \varepsilon_{it}^{\mathrm{O}})$, which are ruled out by the distributional assumptions. This would result in biased parameter estimates.

A second limitation is that no data on home country earnings are available. This prevents separate identification of the non-pecuniary benefits of the outmigration parameters $(\alpha_O^{\mathrm{W}}, \alpha_1^{\mathrm{O}}, \ldots, \alpha_6^{\mathrm{O}})$, and the corresponding φ_j^{O} parameters in the home country earnings equation (4). This implies that for state variables appearing in both the direct utility of outmigration and the equation for home country earnings, only the sum of both effects $(\alpha_j^{\mathrm{O}} + \theta^{\mathrm{Home}}\varphi_j^{\mathrm{O}})$ can be identified.

5. Estimation results

T was set to 65 years of age in estimating the model. This section compares the estimated parameters and predicted migration durations for two specific models: A myopic (static) model which sets β equal to 0, and a forward-looking (dynamic) model where β reflects an annual discount rate of 4%, adjusted to the two-year span between individual observations.[18] The differences observed between the myopic and forward-looking models indicate the importance of allowing for dynamics in the model. Such a comparison is important as the numerical simplicity of the myopic model and its capacity to estimate the structural parameters make this an attractive alternative.

5.1. Model fit

Table 2 reports predicted choice distributions and expected labor market earnings for various durations of stay in Germany.[19] Panel A presents within-sample predictions based on parameter estimates computed using all the available data. Panel B presents out-of-sample predictions for 25% of the original observations, using parameters estimated from

[17]The assumption that 'misclassification' is independent of observable characteristics is often maintained in this class of models (see, e.g. Dustmann and van Soest, 2001; Hausman et al., 1998; Poterba and Summers, 1995).

[18]I ran into numerical problems when attempting to estimate this discount factor.

[19]To compute the expected earnings, I make use of the fact that earnings in (3) have the exponential form $w_{it}^{\mathrm{W}} = e^{\boldsymbol{x}_{it}'\boldsymbol{\varphi}} \cdot e^{\eta_{it}^{\mathrm{W}}}$. Taking the expectation conditional on $\boldsymbol{x}_{it}$ and assuming homoscedasticity of η_{it}^{W} implies $e^{\boldsymbol{x}_{it}'\boldsymbol{\varphi}} \cdot \mathbf{E}(e^{\eta_{it}^{\mathrm{W}}})$. An estimator of the expected earnings is obtained using $e^{\boldsymbol{x}_{it}'\widehat{\boldsymbol{\varphi}}} \cdot (1/N - \dim(\boldsymbol{x}_{it}))\sum_N^1 e^{\widehat{\eta}_{it}^{\mathrm{W}}}$, where $\widehat{\eta}_{it}^{\mathrm{W}}$ are the fitted residuals from the earnings equation and $\widehat{\boldsymbol{\varphi}}$ are the estimated earnings parameters.

Table 2

Years since immigration	Sample size	Stay and work		Stay and not work		Attrition		Outmigration	Monthly labor earnings	
		Actual	Predicted	Actual	Predicted	Actual	Predicted	Predicted	Actual	Predicted
Panel A										
$years \leqslant 5$	33	0.757	0.780	0.151	0.111	0.091	0.108	0.000	2051.4	2038.7
$5 < years \leqslant 10$	187	0.754	0.761	0.118	0.128	0.144	0.109	0.001	2583.8	2569.6
$10 < years \leqslant 15$	571	0.807	0.790	0.102	0.098	0.091	0.111	0.003	2943.3	2945.8
$15 < years \leqslant 20$	1000	0.728	0.747	0.131	0.131	0.141	0.122	0.016	3207.8	3209.3
$20 < years \leqslant 25$	997	0.721	0.691	0.147	0.173	0.132	0.133	0.028	3516.3	3514.7
$25 < years \leqslant 30$	682	0.594	0.597	0.258	0.241	0.148	0.161	0.059	3959.3	3957.6
$30 < years \leqslant 35$	269	0.401	0.449	0.361	0.328	0.238	0.232	0.139	4225.5	4255.8
$35 < years$	54	0.222	0.274	0.500	0.430	0.278	0.305	0.221	4321.0	4312.0
Panel B										
$years \leqslant 5$	11	0.636	0.754	0.273	0.137	0.091	0.109	0.001	1848.1	1886.4
$5 < years \leqslant 10$	42	0.738	0.745	0.142	0.146	0.119	0.109	0.001	2534.0	2508.9
$10 < years \leqslant 15$	142	0.788	0.782	0.113	0.106	0.098	0.113	0.005	2901.1	2906.1
$15 < years \leqslant 20$	249	0.735	0.750	0.116	0.126	0.149	0.124	0.018	3191.9	3193.5
$20 < years \leqslant 25$	239	0.732	0.684	0.126	0.180	0.142	0.136	0.031	3579.1	3590.2
$25 < years \leqslant 30$	187	0.626	0.604	0.246	0.239	0.128	0.156	0.054	3809.8	3820.2
$30 < years \leqslant 35$	68	0.471	0.482	0.279	0.309	0.250	0.209	0.113	4458.8	4510.0
$35 < years$	12	0.167	0.229	0.500	0.422	0.333	0.346	0.267	3821.0	3818.9

Panel A presents actual and predicted choice frequencies based on the model estimated using the entire sample. Panel B presents the out-of-sample actual and predicted choice frequencies for 25% of the original observations. Panel B is computed using dynamic model parameters estimated from the remaining 75% of the sample. Predicted earnings are in Deutschmarks. The samples used to calculate average actual and predicted labor earnings use only data on workers, so are smaller than those reported in the table. The predicted outmigration probabilities are obtained by solving (7) with the corresponding predicted attrition rates and an estimated value for π of 0.108.

the remaining 75% of the observations.[20] The latter set of predictions will be used to investigate the robustness of the model in predicting sample attrition and outmigration.

In panel A, one finds that the model effectively captures the growth of earnings for immigrants in Germany with stays ranging from 5 years or less to more than 35 years. With respect to the distribution of choices, the model accurately predicts the pattern that a decreasing proportion of immigrants stays and works as the duration of residence increases. In particular, it matches both the value and location of the peak in the working and staying proportion, which occurs between 11 and 15 years of residence. The model's worst performance is in predicting the proportions of working and staying immigrants who have been in Germany for 31–35 years (predicted 44.9%, actual 40.1%), and of immigrants who have been in Germany for more than 35 years (predicted 27.4%, actual 22.2%).

The predicted proportion of immigrants staying and not working in Germany is lower than observed for those who have spent less than 5 years in Germany (predicted 11.1%, actual 15.1%), and higher than observed for immigrants who have spent more than 35 years in Germany (predicted 43.0%, actual 50.0%). The model correctly predicts the

[20]These estimated parameters were very similar to those reported for the full data set in the following section. In particular, the estimated values of π was identical in the two cases. The parameter estimates used for the out-of-sample predictions are available upon request.

lowest proportion of immigrants staying and not working, however, which is reached for stays between 11 and 15 years.

The predicted probabilities of attrition are within 2 percentage points of actual rates for immigrants who have spent 30 years or less in Germany. The model also successfully captures the relatively higher attrition proportion for immigrants who have spent between 31 and 35 years in Germany. The model slightly overpredicts the attrition proportion for immigrants who have spent more than 35 years in Germany (predicted 30.5%, actual 27.8%).

The results of panel B indicate that the quality of out-of-sample predictions is similar to that of within-sample predictions. In particular, the rise in attrition with the number of years since migration is again well captured. This suggests that the present empirical model replicates patterns observed both in and out of a sample.

Finally, the fit provided by the myopic model was very similar to that of the dynamic model. Because of these close similarities, the fit results of the myopic model are not reported in this paper.[21]

5.1.1. Predicted outmigration rates

This econometric model corrects for the fact that attrition may not distinguish between immigrants staying in and leaving the host country. This confounding effect is captured by the magnitude of π, which represents the probability that an immigrant drops out of the panel but remains in Germany. A direct implication of (7) is that the value of π provides an estimated lower bound on the attrition probability $\Pr(d_{it}^{\mathrm{A}} = 1|\mathbf{Y}_{it})$.[22] A second implication is that (7) can be used to solve for predicted outmigration rates, given estimated values of π and the level of attrition. Table 2 presents the predicted outmigration probabilities as a function of the number of years spent in Germany. All numbers in Table 2 are computed using an estimated π value of 0.108 (see Table 5). The predicted outmigration rate is close to zero for immigrants who have spent 15 or fewer years in Germany. The probability progressively increases after the number of years spent in Germany exceeds 15, eventually reaching 13.9% for the 30–35 year bracket and 22.1% for immigrants who have spent more than 35 years in Germany. Panel B reports the out-of-sample predicted outmigration rates. These have magnitudes similar to the rates of Panel A when the number of years spent in Germany is less than or equal to 35. For durations of stay exceeding 35 years, however, the predicted out-of-sample outmigration rate of 26.7% is higher than the rate obtained in Panel A (22.1%).

Another out-of-sample verification can be obtained by checking the characteristics of outmigrants as predicted by the model against other data sources over the same time period. Dustmann and Kirchkamp (2002) analyze data on Turkish outmigrants who left Germany during the year 1984. They notably report (see their Table 5) the average age of outmigrants in 1984 (42.42 years), the average age on arrival in Germany (28.56), and the average number of years these outmigrants spent in Germany (14.76). The data used in this paper include information on Turkish immigrants living in Germany in 1985, a complementary set to the outmigrants analyzed in Dustmann and Kirchkamp (2002).

A nonparametric prediction of the differences between outmigrants and non-outmigrants can be obtained by comparing the average age, age at entry, and stay duration of

[21]A complete table is available upon request.

[22]This can be seen by setting $\Pr(d_{it}^{\mathrm{O}} = 1|\mathbf{Y}_{it})$ to zero in (7).

outmigrants in the Dustmann and Kirchkamp (2002) data and non-outmigrants in the GSOEP data at approximately the same point in time. A restricted sample of the GSOEP data was constructed containing only 1985 immigrants from non-EU member countries, who were mostly Turks. In this restricted sample the average age of immigrants is 38.41 years, the average age at entry is 24.45 years, and an the average duration of stay is 13.96 years. Comparing these numbers to those given above for the Dustmann and Kirchkamp (2002) data, Turkish non-outmigrants at approximately the same point in time were younger, migrated earlier in life to Germany, and had spent fewer years in Germany.

These predicted differences between outmigrants and non-outmigrants are nonparametric since they are obtained without using the structural model estimated here. We next check whether the structural model can predict similar differences in the observable characteristics of outmigrants and non-outmigrants. To proceed, the model estimates are used to separate immigrants from the restricted 1985 sample into two groups: The predicted outmigrants and the predicted non-outmigrants.[23] For each group I computed the average age, the average age at entry, and the average number of years spent in Germany. The predicted non-outmigrants are younger (38.27 years vs. 50.37 years), have migrated earlier in life to Germany (24.34 years vs. 32.47 years), and have spent fewer years in Germany (13.93 years vs. 17.90 years) relative to predicted outmigrants. These model-based predictions are all in line with the nonparametric predictions obtained using the Dustmann and Kirchkamp (2002) data.

5.2. Estimated parameters

5.2.1. Partial observability of outmigration

The parameter π is estimated to be 0.108, a value significantly different from zero and relatively similar to the estimate provided by the myopic model. To check whether $\widehat{\pi}$ has a reasonable magnitude, I compare it to the attrition rate in a sample of native Germans also drawn from the GSOEP.[24] Assuming that the outmigration probability in the native sample is negligible, and that the propensities of immigrants and natives to participate in the survey are similar, the estimated value of π should be close to the average biannual attrition rate in the native sample. Table 3 presents the attrition rates per wave, relative to the preceding year, and the corresponding attrition rate of the native sample. Averaging over the sample period, one finds that the attrition rate in the sample of Germans (11.6% per two years) agrees with the estimated value of π.

5.2.2. Earnings parameters

Table 4 presents estimates of all parameters in the earnings equation for Germany. The parameter estimates of the myopic model are very similar to those of the dynamic model. Focusing on the dynamic model, immigrants originating from EU countries have significantly lower expected earnings (8.8%), holding other factors constant. The effect of education is small but positive, with an extra year of education increasing expected earnings by 0.4%. The relationship between labor market experience and expected earnings has the usual increasing, downward-concave profile, with a predicted peak at

[23]The proportion was calculated by simulating each immigrant's choice 100 times. The predicted choices and associated immigrant characteristics were then recorded.

[24]For more information on the native GSOEP sample, see Haisken-DeNew and Frick (2003).

Table 3
Panel attrition for samples of West Germans and immigrants relative to the 1985 sample size

	West Germans			Immigrants		
	N	% 1985	Attrition rate	*N*	% 1985	Attrition rate
1985	1987	100	–	727	100	–
1987	1648	82.9	17.1	578	79.6	20.4
1989	1408	70.8	14.6	468	64.6	18.9
1991	1253	63.1	11.0	411	56.8	12.1
1993	1122	56.4	10.5	353	48.4	14.7
1995	1002	50.4	10.7	289	39.7	18.0
1997	919	46.3	8.3	240	33.1	16.8
1999	834	41.9	9.3	193	6.7	19.4
Mean 1985–1999			11.6			17.2

Table 4
Parameters of the earnings function, as estimated under the ordinary least-squares (OLS), myopic, and dynamic models

Parameter	Variable	OLS		Myopic		Dynamic	
		Est.	SE	Est.	SE	Est.	SE
Earnings function in Germany							
φ_0^W	Constant	7.313	0.049***	7.219	0.078***	7.222	0.079***
φ_1^W	Europe	−0.067	0.012***	−0.091	0.013***	−0.088	0.013***
φ_2^W	Education	0.010	0.003**	0.014	0.004**	0.014	0.004**
φ_3^W	Speaking fluency	−0.040	0.008***	−0.032	0.008***	−0.040	0.007***
φ_4^W	Experience/10	0.321	0.024***	0.260	0.042***	0.253	0.045***
φ_5^W	Experience^2/1000	−0.615	0.045***	−0.514	0.078***	−0.503	0.081***
φ_6^W	Years since immigration/10	0.226	0.012***	0.251	0.012***	0.247	0.012***

The column labeled SE gives asymptotic standard errors, with ***, **, and * denoting, respectively, significance at the 10%, 5% and 1% levels.

25.13 years of experience. The expected return from an additional year spent in the host country is 2.4%, suggesting that economic assimilation in the sense of LaLonde and Topel (2000) is indeed taking place. Finally, improvements in the speaking fluency of immigrants have a positive and significant effect on labor market earnings.

The accumulation of labor market experience and time spent in the home country (years since migration) are endogenously determined in the model. The impact of endogeneity is assessed by comparing the earnings parameters of the structural model with those obtained using the ordinary least-squares estimator (OLS). The first two columns of Table 4 present OLS estimates of the earnings equation. All coefficients have approximately the same magnitude and levels of significance for both specifications, suggesting little endogeneity bias.

Table 5
Estimated parameters for the utilities of working in Germany and outmigration, and the partial observability correction, for the dynamic and myopic models

Parameter	Variable	Myopic model		Dynamic model	
		Est.	SE	Est.	SE
Utility of working and staying					
α_0^W	Constant	−336.76	0.486***	−217.65	0.068***
α_1^W	Europe	4.903	0.284***	2.888	0.244***
α_2^W	Age at migration	−7.662	0.268***	−4.228	0.157***
α_3^W	(Age at migration/10) × Europe	−0.057	0.106	0.012	0.081
α_4^W	Experience/10	−2.755	0.340***	−5.217	0.351***
α_5^W	Experience^2/1000	20.345	0.385***	17.008	0.395***
α_6^W	Years since migration/10	−19.896	12.277	−12.015	4.536**
θ^{Host}	Marg. utility consumpt.	47.632	0.259**	31.144	0.146***
Utility of outmigration					
$\alpha_0^O + \theta^{Home}\varphi_0^O$	Constant	−7.059	2.335**	14.438	2.217***
$\alpha_1^O + \theta^{Home}\varphi_1^O$	Europe	1.273	1.800	0.507	1.181
α_2^O	Age at migration/10	0.689	0.451	0.017	0.329
α_3^O	(Age at migration/10) × Europe	−0.248	0.496	−0.107	0.347
$\theta^{Home}\varphi_2^O$	Education	0.329	0.094***	0.155	0.065**
$\theta^{Home}\varphi_3^O$	Speaking fluency	0.164	0.194	−0.048	0.159
$\alpha_4^O + \theta^{Home}\varphi_4^O$	Experience/10	−2.258	0.779**	−8.892	1.131***
$\alpha_5^O + \theta^{Home}\varphi_5^O$	Experience^2/1000	5.081	1.247***	11.915	1.485***
$\alpha_6^O + \theta^{Home}\varphi_6^O$	Years since migration/10	1.365	1.201	0.698	0.555
π	Partial obs. probability	0.109	0.030***	0.108	0.031***
β	Discount factor	0	–	0.924	–
Distance		0.004			

Asymptotic standard errors are given in the column labeled SE. ***, **, * denote, respectively, significance at the 10%, 5% and 1% level. The discount factor listed in the dynamic model is biannual, and consistent with an annual discount rate of 4%.

5.2.3. *Utility parameters*

Estimated structural utility parameters and their asymptotic standard errors for the myopic and dynamic models are presented in Table 5.[25] Each parameter estimate is fairly similar for both models. One notable difference between the models lies in the effect of years since migration on the direct utility of working and staying, which is significantly negative in the dynamic model and consistent with zero in the myopic model. Moreover, the marginal utility of consumption in the host country is significantly smaller in the dynamic model than in the myopic model (31.14 vs. 47.63). As the overall difference between the two models is slight, the following discussion will limit itself to the parameters of the dynamic model (Table 6).

The estimated marginal utility of consumption θ^{Host} is positive and significant, indicating that increased earnings in the host country have a significant impact on the

[25] Corresponding estimates of the reduced form choice and earnings parameters are presented in Table 6.

Table 6
Maximum likelihood and OLS estimates of the reduced form model parameters

Parameter	Variable	Myopic		Dynamic	
		Est.	SE	Est.	SE
λ_0^W	Constant	6.906	0.486***	7.343	0.693***
λ_1^W	Europe	0.517	0.284*	0.191	0.244
λ_2^W	Age at migration/10	−7.814	0.356***	−4.285	0.220***
λ_3^W	Europe × age at migration/10	−0.061	0.106	0.003	0.081
λ_4^W	Education level	0.700	0.041***	0.442	0.023***
λ_5^W	Speaking fluency	−0.210	0.069**	−0.069	0.037*
λ_6^W	Experience/10	9.722	0.414***	2.663	0.361***
λ_7^W	Experience^2/1000	−4.125	0.363***	1.360	0.382**
λ_8^W	Years since migration	−8.028	0.337***	−4.354	0.213***
λ_0^O	Constant	−7.203	2.336**	14.685	2.221***
λ_1^O	Europe	1.218	1.800	0.685	1.182
λ_2^O	Age at migration/10	0.653	0.451	0.011	0.332
λ_3^O	Europe × age at migration/10	−0.245	0.496	−0.159	0.347
λ_4^O	Education level	0.338	0.095***	0.172	0.073**
λ_5^O	Speaking fluency	0.243	0.194	0.053	0.160
λ_6^O	Experience/10	−2.239	0.779**	−9.187	1.148***
λ_7^O	Experience^2/1000	5.022	1.247***	12.144	1.510***
λ_8^O	Years since migration	0.299	0.671	0.223	0.555
α	Partial obs. probability	0.109	0.031***	0.108	0.031***
Log-L		−2591.83		−2589.10	
φ_0^W	Constant	7.328	0.078***	7.330	0.078***
φ_1^W	Europe	−0.082	0.014***	−0.079	0.014***
φ_2^W	Education level	0.009	0.004**	0.009	0.004**
φ_3^W	Speaking fluency	−0.034	0.007***	−0.036	0.008***
φ_4^W	Experience/10	0.282	0.042***	0.282	0.045***
φ_5^W	Experience^2/1000	−0.546	0.078***	−0.543	0.081***
φ_6^W	Years since migration	0.237	0.013***	0.232	0.012***
	Work selection	0.183	0.097*	0.151	0.083*
	Attrition selection	−0.184	0.122	−0.162	0.107

Asymptotic standard errors are given in the column labeled SE. ***, **, * denote, respectively, significance at the 10%, 5% and 1% level.

utility of working and staying there. Neo-classical models assume that outmigration is exclusively driven by an earnings differential between the host and home countries. A test of the hypothesis that all the parameters entering the non-pecuniary direct utility function δ_{it}^W are jointly equal to zero is easily rejected (p-value $= 0.012$). In particular, holding host country earnings constant, immigrants from European Union (EU) member countries have a significantly higher utility of working in the host country than immigrants from non-EU countries. Immigrants who entered Germany later in life have a relatively lower utility of staying and working, which could reflect the fact that older migrants have less time to establish solid roots and networks in Germany. The interaction effect (α_3^W) between age at immigration and country of origin is not statistically significant. Finally, psychic costs of working and staying were captured by including labor market experience and years since migration in the direct utility of working. Under constant earnings, the utility from working in the host country decreases with the number of years of labor market experience. This finding is consistent with previous work indicating that the disutility of work increases with labor market experience for a given level of earnings (e.g. Eckstein and Wolpin, 1989). Furthermore, the disutility of working in the host country increases with the total number of years spent in Germany. An alternative explanation for this increasing disutility is that the non-pecuniary benefit parameters of staying and working reflect the omitted effect of savings. For example, those who have more labor market experience or have stayed longer in Germany are more likely to save in order to start up businesses in their home country.[26]

As discussed in the previous section, the lack of data on immigrant earnings after their return prevents separation of the earnings equation parameters and the non-pecuniary benefit equation parameters α^{O}. In the case of experience, for example, one is limited to making inferences on the compounded linear $(\alpha_4^{\mathrm{O}} + \theta^{\mathrm{Host}}\varphi_4^{\mathrm{O}})$ and quadratic $(\alpha_5^{\mathrm{O}} + \theta^{\mathrm{Host}}\varphi_5^{\mathrm{O}})$ effects of experience on the utility of outmigration. The number of years of education has a positive and significant effect on the utility of outmigration, an effect which possibly reflects the returns from education in the home country. There is also a significant, convex relationship $(\widehat{\alpha}_4^{\mathrm{O}} + \widehat{\theta}^{\mathrm{Host}}\widehat{\varphi}_4^{\mathrm{O}} < 0$ and $\widehat{\alpha}_5^{\mathrm{O}} + \widehat{\theta}^{\mathrm{Host}}\widehat{\varphi}_5^{\mathrm{O}} > 0)$ between labor market experience and the utility of outmigration. Under the plausible assumption that $\widehat{\theta}^{\mathrm{Home}} > 0$,[27] and earnings in the host country are an increasing, concave function of experience $(\widehat{\varphi}_4^{\mathrm{O}} > 0, \widehat{\varphi}_5^{\mathrm{O}} < 0)$, this suggests the presence of non-pecuniary outmigration benefits which are convex with respect to experience and dominate the utility from consumption of earnings in the host country $(\widehat{\alpha}_4^{\mathrm{O}} < -\widehat{\theta}^{\mathrm{Host}}\widehat{\varphi}_4^{\mathrm{O}} < 0$ and $\widehat{\alpha}_5^{\mathrm{O}} > -\widehat{\theta}^{\mathrm{Host}}\widehat{\varphi}_5^{\mathrm{O}} > 0)$. Finally, country of origin, age at immigration, years since migration, and speaking fluency do not have a significant effect on the utility of outmigration.

5.3. Quantitative differences between myopic and dynamic models

Tables 4 and 5 indicate that the myopic and forward-looking models, with few exceptions, provide parameter estimates with similar signs and magnitudes. The two models will generally differ, however, on the likelihood of making a specific choice over the life cycle. This results from the fact that forward-looking decision makers not only compare the relative contemporary utility of each alternative they face, but also the relative impact these alternatives have on their future utility. Moreover, the discounted streams of future utility will change as decision makers get closer to the terminal date, a feature not present in the myopic model. For these reasons, the predicted choices made over the life cycle may differ between the two models.

In order to compare life-cycle predictions, the distribution of predicted remaining migration durations for two different immigrants was computed for each model. The first immigrant has observable characteristics approximately equal to those of the average immigrant in the sample in 1985: A 39-year old immigrant from a European Union

[26] Dustmann and Kirchkamp (2002) present evidence of this trend among Turkish return migrants.

[27] The outmigration literature (e.g. Djajic and Milbourne, 1988) typically assumes that $\theta^{\mathrm{Home}} > \theta^{\mathrm{Host}}$. Given that $\widehat{\theta}^{\mathrm{Host}} = 31.144$, this suggests that $\widehat{\theta}^{\mathrm{Home}} > 0$ should hold.

member country, who migrated to Germany at the age of 23 and has 9 years of education, average speaking fluency (*Fluency* $= 3$), and 24 years of labor market experience. The second subject is a newly arrived, 27-year old immigrant from a European Union member country, who has 9 years of education, average speaking fluency, and no labor market experience. Each distribution is computed using 2000 choice sequences simulated with the estimates of the relevant model. The predicted remaining length of stay in Germany was recorded for each sequence.

Fig. 2 presents the predicted migration durations. The upper two graphs show the distributions of expected remaining length of stay for the average immigrant, for both the myopic model (left) and the dynamic model (right). It can be seen that the probability mass of the distribution under the myopic model is concentrated in the range of 20–26 additional years of stay. In particular, the myopic model predicts that a representative immigrant is more than 60% likely to stay 26 more years, i.e. until he reaches 65 years of age. The dynamic model, on the other hand, predicts a wider distribution with a significantly higher probability of staying for fewer than 20 additional years. As a result the

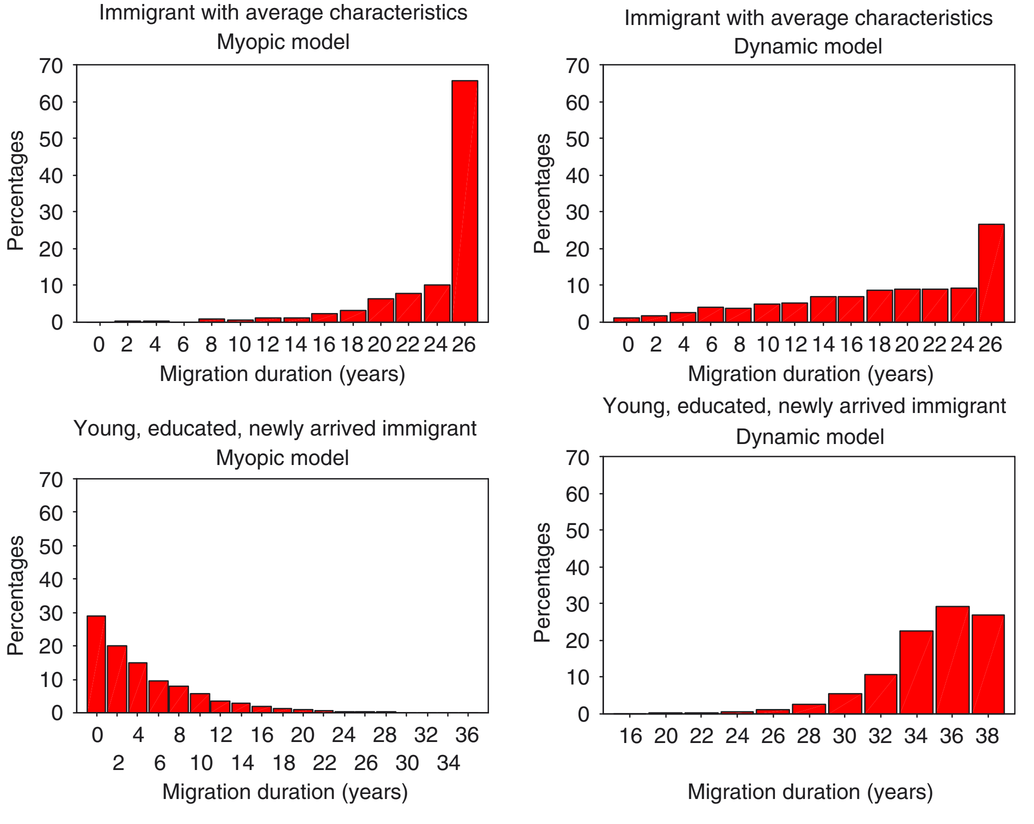

Fig. 2. Predicted migration duration probabilities for the myopic and forward-looking models. Percentages are obtained by simulating 2000 choice sequences and normalizing the distribution of predicted migration durations. Top two graphs: Predicted distribution for a 39-year-old immigrant from a EU member country, who migrated to Germany at the age of 23 with average speaking fluency (*Fluency* $= 3$) and 9 years of education. Bottom two graphs: Predicted distribution for a newly arrived 27-year-old immigrant from a EU member country, with average speaking fluency (*Fluency* $= 3$) and 9 years of education.

probability of staying until 65 years of age predicted by the dynamic model is below 30%, less than half that predicted by the myopic model.

Differences between the myopic and dynamic models are even more pronounced in the predicted migration duration distributions of newly arrived immigrants (the bottom two graphs of Fig. 2). The myopic model predicts a migration duration distribution concentrated towards short-term stays, with a very small probability of staying more than 20 years after arrival. The dynamic model, on the other hand, predicts a distribution concentrated towards long-term durations of stay, with little probability of staying less than 20 years.

5.4. Policy analysis

In this section, I compare the labor force participation and migration duration of immigrants entering Germany under two different visas: A permanent visa, and a short-term visa restricting the duration of their stay to at most 10 years. In each scenario the following two types of immigrants are compared:

1. A skilled immigrant, 25 years of age at entry, who comes from an EU member country with 10 years of education, 10 years of labor market experience, and speaking below average German (*Fluency* $= 4$ out of 5).
2. An unskilled immigrant, 25 years of age at entry, who comes from a EU member country with 6 years of education and 4 years of labor market experience, and speaking below average German (*Fluency* $= 4$ out of 5).

Under a permanent visa, immigrants can choose their optimal duration of stay up to the terminal age of 65. This was the relevant policy for the cohort of guest workers analyzed in this paper. Under a short-term visa, immigrants must leave after its expiration; this is similar to the policy implemented by Germany in 2000 for the admission of skilled guest workers in specific technological sectors (see Bauer and Kunze, 2004, for details).[28] I compare the predicted probabilities of working and staying, of not working and staying, and of outmigration under the short-term and permanent visa scenarios. For both skilled and unskilled immigrants I computed all three probabilities in the entry year, as well as the probabilities for all possible states (according to their labor market experience and years since migration) 4 and 8 years after entry. The results are presented in Table 7. The upper and lower panels present the predicted choice probabilities for the skilled and unskilled immigrant, respectively. The cell with 10 years of experience and 0 years since migration in the top panel describes the entry state of the highly skilled immigrant, while the cell with 4 years of experience and 0 years since migration in the bottom panel presents the entry state of the unskilled immigrant. The diagonal elements are associated with states where each immigrant has worked since entry in Germany: Increases of 4 years since migration are matched with corresponding increases of 4 years of labor market experience. Off-diagonal elements represent states with varying degrees of unemployment. Each cell presents the relevant choice probabilities under both short-term (numbers in parentheses) and permanent visas.

[28]Switzerland, amongst others, has had a long tradition of issuing short-term visas (see Dustmann, 1996, for details).

Table 7
Predicted choice probabilities of newly arrived immigrants according to the number of years since migration and experience

Ysm	Pr(Working) *Exper*			Pr(Not working) *Exper*			Pr(Outmigration) *Exper*		
	10	14	18	10	14	18	10	14	18
High skilled									
0	0.892 (0.889)	–	–	0.008 (0.002)	–	–	0.000 (0.001)	–	–
4	0.875 (0.739)	0.891 (0.879)	–	0.016 (0.152)	0.000 (0.012)	–	0.001 (0.005)	0.000 (0.002)	–
8	0.382 (0.087)	0.883 (0.447)	0.891 (0.849)	0.506 (0.042)	0.010 (0.051)	0.000 (0.012)	0.032 (0.762)	0.000 (0.393)	0.000 (0.030)
Low skilled									
	4	8	12	4	8	12	4	8	12
0	0.281 (0.280)	–	–	0.611 (0.611)	–	–	0.000 (0.000)	–	–
4	0.065 (0.066)	0.241 (0.236)	–	0.825 (0.825)	0.649 (0.653)	–	0.000 (0.000)	0.012 (0.011)	–
8	0.012 (0.000)	0.053 (0.008)	0.213 (0.064)	0.878 (0.014)	0.835 (0.037)	0.667 (0.079)	0.001 (0.877)	0.017 (0.847)	0.020 (0.748)

Numbers in parentheses correspond to the short-term visa scenario. Both skilled and unskilled immigrants are 25 years old, come from an EU country, and have below average speaking fluency (*Fluency* = 4). The skilled immigrant has 10 years of experience on entry, and 9 years of education. The unskilled immigrant has 4 years of experience on entry, and 6 years of education.

For the skilled immigrant, the main findings are the following. First, restricting the migration duration has a limited effect on the probability that a skilled immigrant works *if* this immigrant has worked since entry. In particular, all diagonal elements associated with uninterrupted accumulation of labor market experience are high (between 84.9% and 88.9%) for both short-term and permanent visas. When the skilled immigrant experiences unemployment spells, on the other hand, differences in the probability of working appear. This can be seen in the off-diagonal elements under the probability of working column, all of which are smaller in magnitude for the short-term visa than for the permanent visa. The short-term visa also seems to affect the alternative adopted by skilled immigrants. In particular, when the skilled immigrant does not accumulate any labor market experience 8 years after entry ($Exper = 10$, $Ysm = 8$), his probability of working falls to 38.2% under a permanent visa, and to 8.7% under a short-term visa. Under a permanent visa, the low probability of working in that state is matched by a relatively high probability of not working (50.6%), and a negligible outmigration probability (3.2%). Under the short-term visa, the low probability of working in that state is accompanied by a small probability of not working (4.2%), and a substantial outmigration probability (76.2%). It is important to put these results in the perspective that they apply to states with a relatively small probability of being visited, as the skilled immigrant has a high probability of working immediately on entry as well as in subsequent years. The skilled immigrant has a relatively low probability of suffering unemployment spells, and consequently he also has a relatively low probability of suffering the disincentive aspects of the short-term visa.

For the unskilled immigrant, it is useful to compare predictions under the short-term and permanent visa scenarios separately for states of labor market experience associated with a migration duration of 4 years of less, and states of labor market experience associated with a migration duration of 8 years. For states of labor market experience associated with having been in Germany 4 years or less, there is a negligible difference between short- and permanent visas. In particular, the probabilities of working are below 30% under both visas, and lower than the corresponding probabilities for the skilled immigrant. The probabilities of not working are above 60% under both visas, higher than those of the skilled immigrant. Finally, the outmigration probabilities are close to zero under both visas, and similar to those of the skilled immigrant.

The biggest differences between short-term and permanent visas appear after 8 years of stay, with only 2 years remaining before reaching the maximum allowed duration under a short-term visa. Under a permanent visa, in all states of labor market experience, the unskilled migrant is predicted to have an outmigration probability of 2% or less but a significantly high probability of not working (87.8%, 83.5%, and 66.7%, respectively, for states with 4, 8, and 12 years of experience). Under a permanent visa there remain long-term expected benefits from staying, apparently resulting from the possibility of acquiring skills later. Under a short-term visa, on the other hand, unemployment during the last 2 years is no longer a valuable option in terms of reaping future benefits in the host country. Outmigration consequently appears more attractive, as reflected by the high outmigration probabilities for all states associated with 8 years spent in Germany.

6. Conclusions

This paper specifies and estimates a structural, dynamic model of the work and outmigration decisions that immigrants make over their life cycle. The model distinguishes itself from the existing literature by allowing immigrants to progressively revise their migration duration decisions during the migration period. Non-pecuniary benefits are found to be important, indicating that outmigration is not entirely driven by earnings differentials. Several migration duration distributions predicted by the model were compared to those provided by a simpler and less realistic model with myopic decision makers. Despite the fact that both models provide similar parameter estimates, they predict remarkably different migration duration distributions. This result illustrates the importance of dynamics in the context of outmigration, and the need for careful evaluation of an immigrant's subjective discount rates when making inferences on the migration duration of immigrants.

Estimates of the dynamic model were used to assess the effect of limiting immigrant visas on labor force participation and integration into the labor market. Short-term visas do not provide important work disincentives for relatively skilled immigrants. For low-skilled immigrants, who have a high probability of being unemployed, a short-term visa policy appears to be successful in increasing the probability of outmigration before they reach the end of their allowed stay. It is interesting to examine these results in the context of the new German policy of delivering short-term visas to highly skilled immigrants in specific technological sectors. While caution must be taken when extrapolating these findings to the new cohort of immigrants, they suggest that the length of the visa per se will not affect the incentives of these new immigrants to work during their stay in Germany.

Finally, both the predicted characteristics of outmigrants and the estimated attrition rate of immigrants who leave the panel but remain in the host country proved a reasonable match to facts reported elsewhere. This suggests the possibility of exploiting the identification strategy proposed here to estimate more general models of outmigration (e.g. including savings behavior) using panel data sets containing either partial or no information about outmigration decisions.

Acknowledgments

I would like to thank Arthur van Soest, Sabine Kröger, Pierre-Carl Michaud, Christian Dustmann, Jan van Ours, seminar participants at the Immigration and Economics Workshop in Tilburg, Laval, Penn State, IZA, Bocconi, Warwick, and York University, three anonymous referees and an editor for useful comments and suggestions. The author thanks the Canada Chair of Research in the Economics of Social Policies and Human Resources for support.

Appendix A. Details of the second estimation step

Following Dubin and McFadden (1984), I assume that the conditional expectation $\mathbf{E}(\eta_{it}^{\mathrm{W}}|\varepsilon_{it}^{\mathrm{W}},\varepsilon_{it}^{\mathrm{NW}},\varepsilon_{it}^{\mathrm{O}})$ is linear in $\varepsilon_{it}^{\mathrm{W}},\varepsilon_{it}^{\mathrm{NW}}$ and $\varepsilon_{it}^{\mathrm{O}}$. Given the distributional assumptions on the unobservable state variables, it follows from Dubin and McFadden (1984) that the conditional expected earnings of immigrants who work in Germany is given by

$$\begin{aligned}&\mathbf{E}(w_{it}^{\mathrm{W}}|d_{it}^{\mathrm{W}}=1,\mathbf{Y}_{it})\\&\quad=\varphi_0^{\mathrm{W}}+\varphi_1^{\mathrm{W}}\mathit{Europe}_i+\varphi_2^{\mathrm{W}}\mathit{Educ}_{it}+\varphi_3^{\mathrm{W}}\mathit{Fluency}_{it}\\&\qquad+\varphi_4^{\mathrm{W}}\mathit{Exper}_{it}+\varphi_5^{\mathrm{W}}\mathit{Exper}_{it}^2+\varphi_6^{\mathrm{W}}\mathit{Ysm}_{it}\end{aligned}$$

$$+\tau_2\left[\frac{\Pr(d_{it}^{\mathrm{NW}}=1|\mathbf{Y}_{it})\log(\Pr(d_{it}^{\mathrm{NW}}=1|\mathbf{Y}_{it}))}{1-\Pr(d_{it}^{\mathrm{NW}}=1|\mathbf{Y}_{it})}+\log(\Pr(d_{it}^{\mathrm{W}}=1|\mathbf{Y}_{it}))\right]$$
$$+\tau_3\left[\frac{\Pr(d_{it}^{\mathrm{A}}=1|\mathbf{Y}_{it})\log(\Pr(d_{it}^{\mathrm{A}}=1|\mathbf{Y}_{it}))}{1-\Pr(d_{it}^{\mathrm{A}}=1|\mathbf{Y}_{it})}+\log(\Pr(d_{it}^{\mathrm{W}}=1|\mathbf{Y}_{it}))\right].$$

The parameters $(\varphi_0^{\mathrm{W}},\dots,\varphi_6^{\mathrm{W}},\tau_2,\tau_3)$ of this equation can be consistently estimated using OLS by replacing the choice probabilities which enter the conditional expectation with consistent estimates obtained from the reduced form dynamic programming step.

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