Wage Mobility of Foreign-Born Workers in the United States

Seik Kim

Department of Economics

University of Washington

seikkim@uw.edu

http://faculty.washington.edu/seikkim/

September 14, 2010

Abstract

This paper presents new evidence on whether foreign-born workers assimilate. While the existing literature focuses on the convergence/divergence of average wages, this study extends the analysis to the distribution of wages by looking at wage mobility. We measure the foreign-native gap in year-to-year transition probabilities from one decile group to another of a wage distribution, where the deciles are determined by a native sample. Our results, based on the matched Current Population Survey for 1996 to 2008, suggest that the majority of foreign-born workers fail to assimilate. Immigrants in middle and bottom decile groups, who are the majority of immigrants, tend to fall behind relative to natives in the same decile groups. Only those in top decile groups seem to keep up or improve relative to their native counterparts. The widening foreign-native gap in mean wages with the time spent in the U.S. is mostly driven by middle and bottom decile group immigrants from Central and South America and bottom decile group immigrants from Asia.

Keywords: Economic Assimilation, Immigration, Wage Mobility

JEL Classification Number: C13, C23, J31, J61

[0] I have benefited from helpful comments from Joseph Altonji, Yoram Barzel, Jennifer Hunt, Chang-Jin Kim, Fabian Lange, Shelly Lundberg, and participants in seminars at the annual meetings of the American Economic Association, University of Carlifornia-Davis, University of Washington, Washington State University, and the UW Center for Studies in Demography and Ecology (CSDE). I am grateful for the support from the Tim Jenkins Faculty Career Development Fund and the CSDE seed grant 549802.

1 Introduction

This paper presents new evidence on whether foreign-born workers assimilate.[1] Economic assimilation is defined as the degree to which the wages of foreign-born workers approach those of native-born workers with additional time spent in the United States. Assimilation rates are the net result of several offsetting factors. Upon entry into the U.S. labor market, foreign-born persons may earn lower wages than their native counterparts to the extent that human capital is not perfectly transferable across economies and cultures. On the other hand, some groups of foreign-born workers might outperform natives if they possess superior skill endowments, stronger work ethics, or more powerful incentives. As immigrants stay longer in the United States, their wages might converge to those of natives.

A large literature studies whether an average foreign-born worker assimilate, focusing on the convergence/divergence of mean wages (Chiswick, 1978; Borjas, 1985, 1995; Jasso and Rosenzweig, 1988; Lubotsky, 2007; Kim, 2010b). However, a more informative question would be how foreign-born workers in different locations of wage distribution assimilate as they accumulate U.S. experience. Butcher and DiNardo (2002), for example, analyze how changes in the wage structure affect differences at various point in the wage distributions between immigrants and natives. This paper extends the literature on average wages to the distribution of wages by looking at wage mobility. We measure the foreign-native gap in year-to-year transition probabilities from one decile group to another in the wage distribution, where the deciles are determined by native samples.

The estimation strategy draws on a first-order Markov-switching model. We apply the method using the Current Population Survey (CPS) for 1996 to 2008. The methodology is motivated by Buchinsky and Hunt (1999). They examine the wage mobility in the United States by estimating the probabilities of transition from one quintile to another and outside the distribution of wages. In this paper, instead of estimating the entire transition matrix, we reduce its dimension by estimating the probabilities of moving up (moving to higher decile

[1] In U.S. immigration law the term "immigrant" or "permanent resident alien" denotes a person admitted to this legal classification. For expositional convenience, we use the terms "foreign-born person" and "immigrant" interchangeably although our sample possibly includes aliens in an illegal status.

groups), moving down (moving to lower decile groups), and staying in the same decile group. This reduction is useful since the immigrant sample size per group is small. This paper analyzes the foreign-native gap in the reduced transition probabilities rather than summarizing the gap into a single mobility measure.

Our results suggest that there is little evidence of assimilation of foreign-born workers. Immigrants in middle (4th, 5th, 6th, and 7th) and bottom decile (1st, 2nd, and 3rd) groups, who are the majority of immigrants, tend to fall behind relative to natives in the same decile groups.[2] Only those in top decile (8th, 9th, and 10th) groups seem to keep up or improve relative to their native counterparts. We find that age, marital status, and education as well as continent of origin play a significant role in explaining wage mobility and the foreign-native gap in wage mobility.

Immigrants from Central and South America in middle and bottom decile groups and immigrants from Asia in bottom decile groups tend to move to lower decile groups as compared to natives in the same groups. Among immigrants in top decile groups, those from Europe and Asia are more likely to outperform their native counterparts. Top decile group immigrants from Central and South America do worse than natives and other immigrants in the same decile groups. Overall, the widening foreign-native gap in mean wages with the number of years spent in the United States in recent years is mostly driven by Central and South American and Asian immigrants in lower decile groups, who are the majority of the foreign-born population.

The paper proceeds as follows. Section 2 reviews the literature and provides background of this study. Section 3 is about the data set. It introduces the CPS and reports summary statistics. Section 4 discusses conceptual framework of the methodology and presents wage mobility by years since migration, by continent of origin, and by education. In Section 5, we develop an estimation strategy based on a standard first-order Markov-switching scheme and estimate the model. Section 6 offers conclusions.

[2] While immigrants may fall behind natives, they may still do better than those who stay in their home countries.

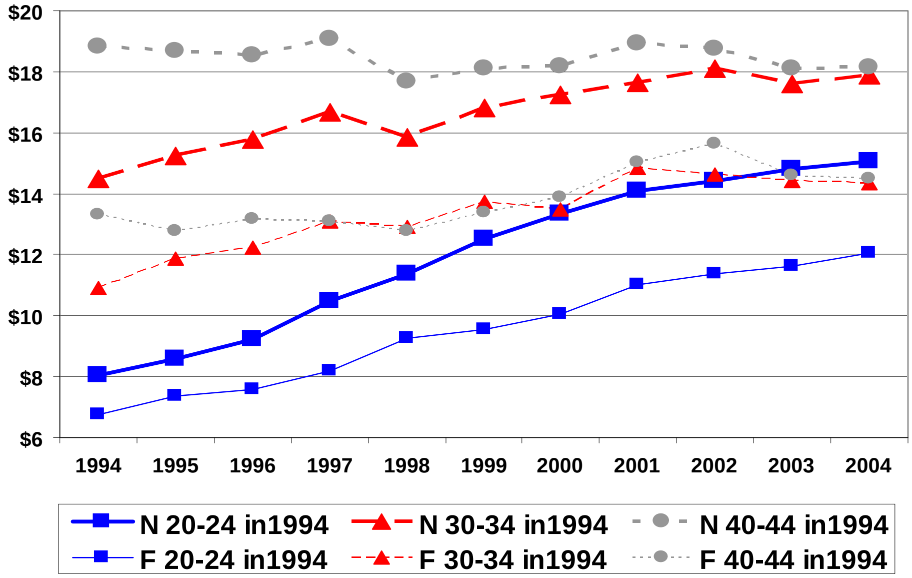

Figure 1: Average Wages (in 1994 Dollars) of Native-Born and Foreign-Born Workers

2 Background

Chiswick (1978) has pioneered the literature of assimilation using the 1970 Census. He finds that immigrants initially earn less than natives, but their earnings exceed those of natives after 10 to 15 years of arrival to the United States. Borjas (1985) notes that assimilation estimates based on a single cross-section are biased if the quality of immigrants vary by entry year cohort. Using the 1980 and 1990 Censuses, he finds slower assimilation rates. Immigrants have faster earnings growth rates than natives, but they do not outperform natives. Lubotsky (2007) fully controls for individual heterogeneity by using the CPS and the Survey of Income and Program Participation (SIPP) linked to the Social Security Earnings data for 1951-1997. He finds evidence of a slower rate of assimilation than those of repeated-cross-section studies.

Assimilation patterns have changed in recent years. Figure 1 illustrates wage growth paths for average immigrant and native workers. The figure depicts the mean hourly wages of foreign-born and native-born male workers of various age groups during 1994-2004. The foreign-born workers in the figure are confined to those who arrived between 1980 and 1991. For the time being, assume that selective return migration is negligibly small. The three thicker lines with larger symbols indicate the mean wages of native-born workers and the three thinner lines with smaller symbols indicate the mean wages of foreign-born workers. The solid lines with squares track the mean wages of those who were 20-24 years old in 1994. The dashed lines with triangles are the mean wages of those who were 30-34 years old in 1994. The dotted lines with circles correspond to the mean wages of those were 40-44 years old in 1994.

We observe that the wage gap between the immigrants and the natives in the "20-24 in 1994" cohort widens as the foreign-born workers stay longer in the United States. Foreign-born workers who were 20-24 years old in 1994 fail to assimilate economically during the 1994-2004 period. The foreign-born workers in the "30-34 in 1994" cohort also fail to catch up over the 1994-2004 period–the wage gap remains stable. The foreign-born workers in the "40-44 in 1994" cohort seem to experience assimilation over the 1994-2004 period as the wage gap narrows. These patterns are very different from what is known from the previous literature that looks at earlier periods.

To see whether foreign-born workers indeed fail to assimilate into the U.S. labor market, Kim (2010b) compares cross-section and panel analyses of assimilation using the same CPS sample for 1994-2004. The longitudinal model exploits the two-year panel aspect of the sample, whereas the cross-section model ignores its panel structure. The former is specified by simply adding individual fixed effects to the latter. The results suggest that controlling for this individual heterogeneity reverses the conventional results of assimilation. While the cross-section results are consistent with those of earlier studies, the longitudinal results suggest that the foreign-native gap in average wages widens with time since migration.

Exploiting the longitudinal dimension is really the source of the difference. For example, the wage growth rate of immigrants at age 24 is 1.17-1.49% points slower than that of native-born workers based on panel specifications. At age 32 the gap in growth rates is between 0.55-0.75% points. In contrast, according to cross-section models, immigrants' wage growth is faster than that of natives by 0.70-0.93% points at age 24 and by 0.69-0.74% points at age 32. In sum, there is little evidence of economic assimilation for 1994-2004 and using cross-section data to estimate assimilation for this period is misleading.

The current study is motivated by Kim (2010b). Given that an average foreign-born worker does not assimilate, we look at whether there are any groups of immigrants who assimilate. For these purposes, transition probability analyses are more useful than distribution analyses. For example, consider two economies with the same wage distribution: a half of workers earn \$6/hour and the other half earn \$8/hour. Suppose that the wage of a given worker is fixed in the first economy, but is alternating in the second economy. In the first economy, the worker's rank in the wage distribution is fixed over time and will result in a large inequality. In the second economy, the rank changes every period and the resulting inequality is not great. Moreover, the economic performance of an average worker of each economy is identical, but wage mobility is very different across the two economies. Distribution analyses will treat the two economies identical.

3 Data Description

3.1 The CPS: Cross-Section and Panel Samples

The CPS is a collection of representative cross-sections. It is a monthly survey designed to collect information on demographic and labor force characteristics of the civilian non-institutionalized population 16 years of age and older. As of July 2005, approximately 72,000 assigned housing units from 824 sample areas are in the sample. A housing unit is interviewed for four consecutive months, dropped out of the sample for the next eight months, interviewed again in the following four months, and then is retired from the sample. If the occupants of a dwelling unit move, the new occupants of the unit are interviewed. Nevertheless, the CPS provides a representative cross-section of each year's population because the random sample of housing units remains fixed.

The outgoing rotation groups, or the individuals in the fourth and the eighth interviews, are of interest because interviewees are asked their labor market outcomes, such as usual weekly earnings and usual weekly hours worked. In the outgoing rotation groups, an individual appears only once in a year, but may reappear in the following year if the individual does not move. One may append data from the two interviews and get repeated observations on the same individuals.

The appended sample is called the Merged Outgoing Rotation Group (MORG) or the matched CPS.

The matched CPS is a collection of two-year panels. The 1996-1997 panel, for instance, contains the individuals in the households which enter the survey scheme between October 1995 and September 1996. These two-year panels, however, are not representative of the U.S. population because they exclude those who move. What makes it more complicated is missing foreign-born respondents in the second period because it is not possible to tell whether the person is in the United States or has gone back to his or her home country. If the person is still in the United States, we call it sample attrition because this person will have an equal probability of being selected in a cross-section as all other U.S. residents. However, if the person has emigrated from the United States, we call it population attrition since this person has no chance of being selected in the cross-section.

The non-representative two-year CPS panels, if combined properly, can mimic a regular representative longitudinal sample. Suppose that there is no population attrition, i.e., attrition is caused by residential mobility within the United States. Since the CPS cross-sections are representative, a method developed by Hirano, Imbens, Ridder, and Rubin (2001) and Bhattacharya (2008) can be applied. Their method exploits the availability of representative cross-sections as the basis for weighting the persons in a balanced panel. The attrition-correcting weighting function is given by the inverse of one minus the probability of sample attrition. When there is attrition in the population, however, the second period cross-section is not representative of the first period population, and the existing method should not be applied. To account for sample attrition in the presence of population attrition, this paper uses a method developed by Kim (2010a).

The key estimation strategy is generating a counterfactual, but representative second period cross-section (where there is no outmigration) prior to applying the existing sample attrition correcting scheme. For example, suppose that the two-year panel of 1996-1997 is of interest. The CPS provides 1996 and 1997 cross-sections, but the 1997 cross-section is not representative of the 1996 population due to population attrition. First, we use the 1996 cross-section as the basis for generating a representative counterfactual 1997 cross-section. The counterfactual sample is obtained by weighting the second period cross-section by one minus the probability of population attrition. Then the two representative cross-sections (the 1996 actual and 1997 counterfactual cross-sections) are used as the basis for estimating attrition-correcting weighting functions. This step is identical to Bhattacharya (2008). Finally, we assign weights to the persons in the balanced part of the 1996-1997 panel. The resulting estimators are consistent.

The matched CPS with proper weights shares most of the advantages of usual panel data sets and is superior in some dimensions. First, the sample consists of panel sample. Usual panel data models, such as the first difference or the fixed effects models, can be used to control for individual-specific permanent components. Second, the sample has the crucial advantage of being much larger than alternative panel data sets such as the Panel Study of Income Dynamics (PSID) or National Longitudinal Survey of Youth 1979 (NLSY79). Sample sizes matter in immigration studies because foreign-born persons, after all, are minorities. Finally, the CPS cross-section is representative of the U.S. population for any given year. This property is the key to correct for sample attrition in the presence of unobserved population attrition.

3.2 Data and Summary Statistics

Since 1994, the CPS includes information on international migration, such as year of entry into the United States and country of birth along with demographic and labor market information, such as age, schooling, marital status, earnings per hour or week, usual hours of work, and labor market status.[3] The sample used in this analysis is drawn from the matched CPS between 1996 and 2008. We drop 1994 and 1995 because matching is not possible between June to December 1994 and 1995 and between January to August 1995 and 1996 due to the sample redesign of the CPS.

We take a sample of foreign-born and native-born men of ages 24-60 for 1996 to 2008.[4] In

[3] Prior to 1994, CPS supplements on immigration were administered to all households participating in the survey in November 1979, April 1983, June 1986, June 1988, and June 1991.

[4] The foreign sample includes foreign-born men who were not U.S. citizens at the time of birth. Following Warren and Peck (1980), our foreign sample consists of persons born outside the United States, the Commonwealth of Puerto Rico, and the outlying areas of the United States. Foreign-born persons may have acquired U.S. citizenship by naturalization or may be in illegal status. The reference group consists of native-born white

order to examine differences based on ethnic origin, we divide the foreign sample into four groups: immigrants from Central and South America, from Europe (including Australia, New Zealand, and Canada), from Asia, and from other countries.[5] The group of "other" countries consists of immigrants from Africa, Oceania, and unclassified ones. The last group is of little interest due to its small sample size and heterogeneity. Details on how the data are processed are explained in the Appendix. This section provides a general picture.

Table 1 reports summary statistics for cross-section/matched samples. The matched sample consists of two year panels. The wage information in the CPS sample is mostly self-reported, but also involves imputed wages. As the imputation rule does not account for the country of origin, the imputed wages of immigrant workers tend to be biased toward the wages of native workers. Consequently, our preferred way to handle the imputed wages is simply dropping them.[6]

We find substantial attrition. About 21% of native interviewees and 29% of immigrant interviewees drop out of the sample in the second period. The gap between natives and immigrants in the attrition rates may be partly explained by outmigration, but it is also due to differential residential mobility within the United States. For these reasons, we estimate the attrition-correcting weighting functions for immigrants and natives separately. Moreover, attrition rates vary by year. According to Table A1 in the Appendix, the matching rates are 74-82% among the native samples and 67-73% among the immigrant samples between 1996 and 2008. Therefore, we estimate the weighting functions for 1996-2008 year by year.

men. The native sample includes persons born in the Unites States, but excludes persons born in the Puerto Rico and the outlying areas. We use native-born white individuals because it gives the most conservative assimilation measure. Even with the most conservative definition, Kim (2010b) shows that immigrants have faster wage growth than natives when cross-section samples are used.

[5] We combine Australia, New Zealand, and Canada with Europe because of sample size considerations and so that immigrants from countries that are predominantly white and are at a similar stage of political and economic development are grouped together. We refer to the group as Europe. The data do not identify mother tongue. The impact of language proficiency has been studied in a large literature. LaLonde and Topel (1997) provide a survey.

[6] Hirsch and Schumacher (2004) find that regression estimates including variables not used in imputation rules, such as union status, are biased. As country of origin is not used as imputation criteria, using the whole sample may bias the results. Bollinger and Hirsch (2006) propose a weighting scheme to correct for the bias.

Table 1. Summary Statistics

	Cross-Section Sample		Matched Sample			
	Natives	Immigrants	Natives		Immigrants	
			1st year	2nd year	1st year	2nd year
Age	40.9	39.0	41.4	42.4	39.5	40.5
	(9.9)	(9.4)	(9.3)	(9.3)	(9.0)	(9.0)
Education	14.1	11.9	14.1	14.1	12.0	12.1
	(2.2)	(4.4)	(2.2)	(2.2)	(4.4)	(4.3)
C.S.America		10.0 (4.1)			10.0 (4.1)	10.1 (4.1)
Europe		14.5 (2.9)			14.5 (2.9)	14.6 (2.9)
Asia		14.8 (3.1)			14.9 (3.0)	15.0 (3.0)
Wage	16.9	13.3	17.2	17.5	14.1	14.3
	(13.9)	(12.2)	(13.2)	(12.7)	(13.0)	(12.6)
C.S.America		9.8 (6.6)			10.2 (6.6)	10.4 (6.4)
Europe		20.2 (17.7)			21.2 (19.1)	21.3 (18.0)
Asia		18.0 (15.6)			18.9 (16.2)	19.3 (15.7)
Hours	43.5	41.6	43.6	43.5	41.8	41.7
	(8.9)	(7.8)	(8.4)	(8.2)	(7.5)	(7.0)
Marital Status	0.692	0.682	0.739	0.744	0.785	0.789
U.S. Citizen	1.000	0.367	1.000		0.413	0.413
C.S.America		0.583			0.566	
Europe		0.130			0.144	
Asia		0.234			0.242	
Others		0.054			0.048	
N	435,721	71,533	115,968		15,721	

Standard deviations are reported in parentheses. N: sample size

Wage: hourly rate of pay; Hours: usual hours worked per week

Marital Status: 1 if married; U.S. Citizen: 1 if U.S. citizen; C.S.America: Central and South America;

Europe: Europe, Australia, New Zealand, and Canada; Others: Africa, Oceania, and other countries

The persons in the matched sample are a nonrandom subset of the cross-section sample. Table 1 reveals that persons in the matched samples, for all ethnic groups including natives, tend to earn more and work longer than those in the cross-section samples. It implies that more successful workers are more likely to be matched (or have lower residential mobility) than unsuccessful ones. Foreign-born persons from Central and South America tend to attrite more than those from Europe and Asia. Therefore, applying the attrition-correcting weights to the matched CPS is critical for proper wage mobility analyses.

Years of education provides a rough measure of skill endowment. Foreign-born persons have lower mean and a much larger standard deviation of education. In the cross-section sample, the average education level is 14.1 years for native-born persons and is 11.9 years for foreign-born persons. Immigrants from Central and South America have 10.0 years of average education, those from Europe 14.5 years, and those from Asia 14.8 years. Estimates of years of education are virtually not different between the matched and the cross-section samples.

In the cross-section sample, the average hourly wage of native-born workers is $16.9, in 1994 dollars, while the average foreign-born worker earns $13.3. Immigrants from Central and South America make $9.8 per hour, those from Europe $20.2, and those from Asia $18.0. Immigrant workers work 1.8-1.9 more hours per week than native workers. Although not reported in the table, 95.9% and 95.3% of the foreign-born and native-born populations are full-time workers, while 4.1% and 4.7% are part-time workers, respectively, among those who are employed. The proportions of full-time and part-time workers are relatively stable over the sampling period.

Among immigrants, 56.6-58.3% are from Central and South America, 13.0-14.4% are from Europe, and 23.4-24.2% are from Asia. The estimates also indicate that foreign-born persons are about 2 years younger than native-born persons on average. An average native and an average is 40.9 years old and an average immigrant is 39.0 years old in the cross-section sample. Individuals in the matched sample are older than those in the cross-section sample. It implies that older individuals are more likely to be matched in the second year interview. A larger proportion of the foreign-born population is married.

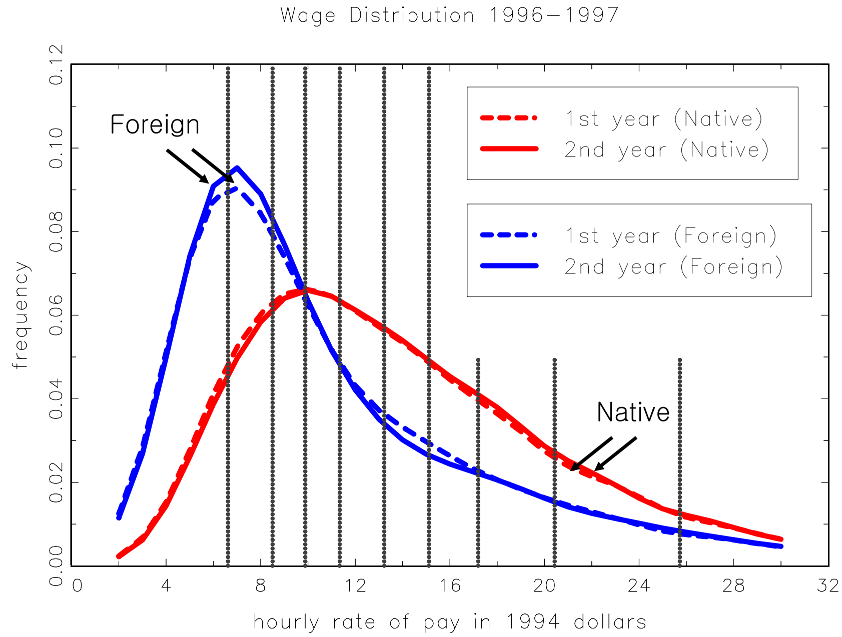

Figure 2: Wage Distribution of Natives and Immigrants

4 Unconditional Wage Mobility

4.1 Conceptual Framework

Figure 2 presents the wage distributions of native-born and foreign-born workers in 1996 and 1997 using the 1996 and 1997 CPS cross-sections. Broken lines are the 1996 wage distributions and solid lines are the 1997 wage distributions. The native distributions are the ones with a mode around $10 (and are in red color). The immigrant distributions are the ones with a mode around $7 (and are in blue color). Vertical lines indicate the decile points for the 1996 native wage distribution. For example, native-born workers with hourly wages between $8.5-$9.9 in 1996 are in the 20-30th percentile group. The decile points for the 1997 native wage distribution are omitted, but are similar to those for the 1996 distribution. For example, to be in the 20-30th percentile group in 1997, the hourly wage has to be between $8.6-$10.2. We do not obtain decile points for immigrants. Instead, immigrants are assigned to the native decile groups. The wage distribution of natives is more dispersed and has higher mean than that of immigrants. The majority of foreign-born workers are located at the bottom decile of the native wage distribution.

In principle, we can obtain the foreign-native gap in year-to-year transition probabilities from one decile group to another of a wage distribution, where the deciles are determined by the native sample. It requires one to estimate a ten-by-ten transition matrix for every two-year pair. For illustration purposes, take native-born and foreign-born workers who were in the 20-30th percentile of native wage distribution in 1996. First, assign attrition-correcting weights to the matched CPS. Then, take native-born workers in the 20-30th percentile group in 1996 and observe which proportion of workers move to each of the ten decile groups in 1997. Finally, repeat the exercise for foreign-born workers and analyze the foreign-native gap in the proportions for each of the ten decile groups in 1997.

While it is not very difficult to estimate these matrices, a more parsimonious model would be estimating the probabilities of moving to higher decile groups, moving to lower decile groups, and staying in the same decile group. More precisely, for the workers in the 20-30th percentile group in 1996, one may observe which proportion moves to the 30-100th percentile group, which to the 0-20th percentile group, and which stay in the 20-30th percentile group in 1997. For the 1996-1997 sample, we find that 36% of native-born workers moved to higher deciles, 21% moved to lower deciles, and 43% stayed. Among foreign-born workers, 25% moved to higher deciles, 32% moved to lower deciles, and 43% stayed.[7]

The results are visualized in Figure 3. The horizontal axis depicts percentile values representing the decile groups. The 20-30th percentile groups lie between 20 and 30. The solid line corresponds to native-born workers and the dashed line is for foreign-born workers. The length of these lines represents the probability of staying. Since the staying probabilities of native-born and foreign-born workers are identical, the two lines in Figure 3 are of the same length. The vertical distance between 1 and the upper triangle indicates the probability of moving to higher decile groups. The triangle for foreign-born workers lies below of that of native-born workers, meaning that foreign-born workers between the 20-30th percentiles have a smaller probability of moving higher deciles than native-born workers. The vertical distance between 0 and the lower triangle indicates the probability of moving lower decile groups. The inverse triangle for

[7] Since the matched CPS is a nonrandom subsample of the CPS cross-section, attrition-correcting weights are applied to obtain these estimates. The next section explains how to calculate the weights.

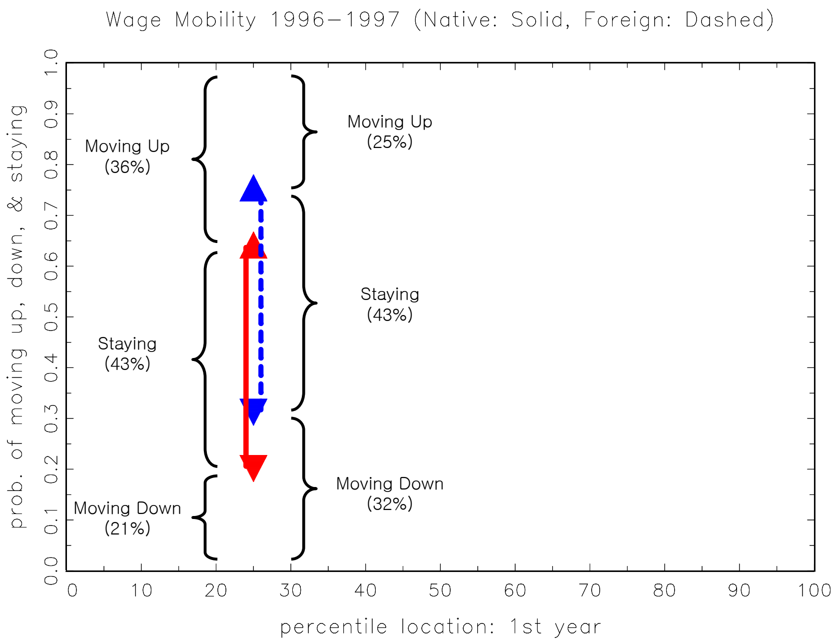

Figure 3: Probability of Moving Up, Down, and Staying

foreign-born workers lies above of that of native-born workers, meaning that foreign-born workers between the 20th-30th percentiles have a higher probability of moving to lower deciles than native-born workers in the same group.

4.2 Wage Deciles from Cross-Sections

This section presents native and immigrant wage distributions for 1996 to 2008 to see whether there is cross-sectional evidence of assimilation at different deciles of the distributions. Transition probabilities are influenced by changes in the wage structure. If changes in wage structure affects immigrants and natives differently, then the probability of moving up (or down) will be different for immigrants and natives. For example, if immigrants in a certain decile group are disproportionately hurt by changes in the wage structure, they will be more likely to move down to lower decile groups than their native counterparts in the same decile group.

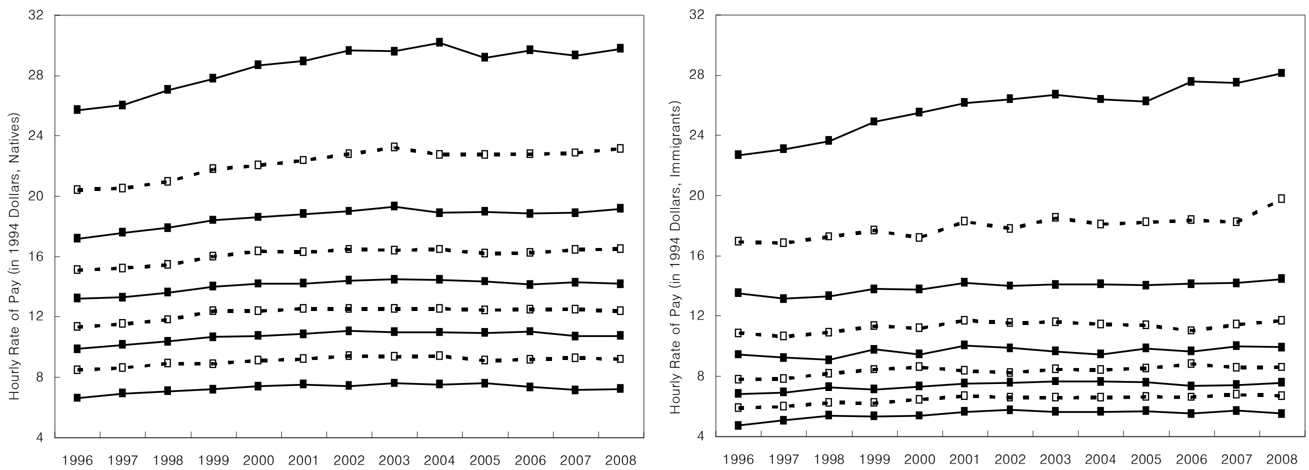

Figure 4. Wage Decile Points for Natives/Immigrants by Year

Figure 4 illustrates the time series of nine wage decile points for natives and immigrants. The left figure shows that the real wages of a 10th percentile native worker are \$6.61 in 1996, \$6.93 in 1997, ..., and \$7.23 in 2008. In general, the the native wage distributions are relatively stable over time except for the 80th and 90th wage percentiles. From the right figure, we see that the immigrant wage distributions are even more stable than the native wage distributions, although the 90th wage percentile is rising rapidly. Overall, wages distributions are stable for both natives and immigrants. Later, we look at how this is changed when we apply the transition data analyses using the longitudinal data.

4.3 Wage Mobility by Years Since Migration

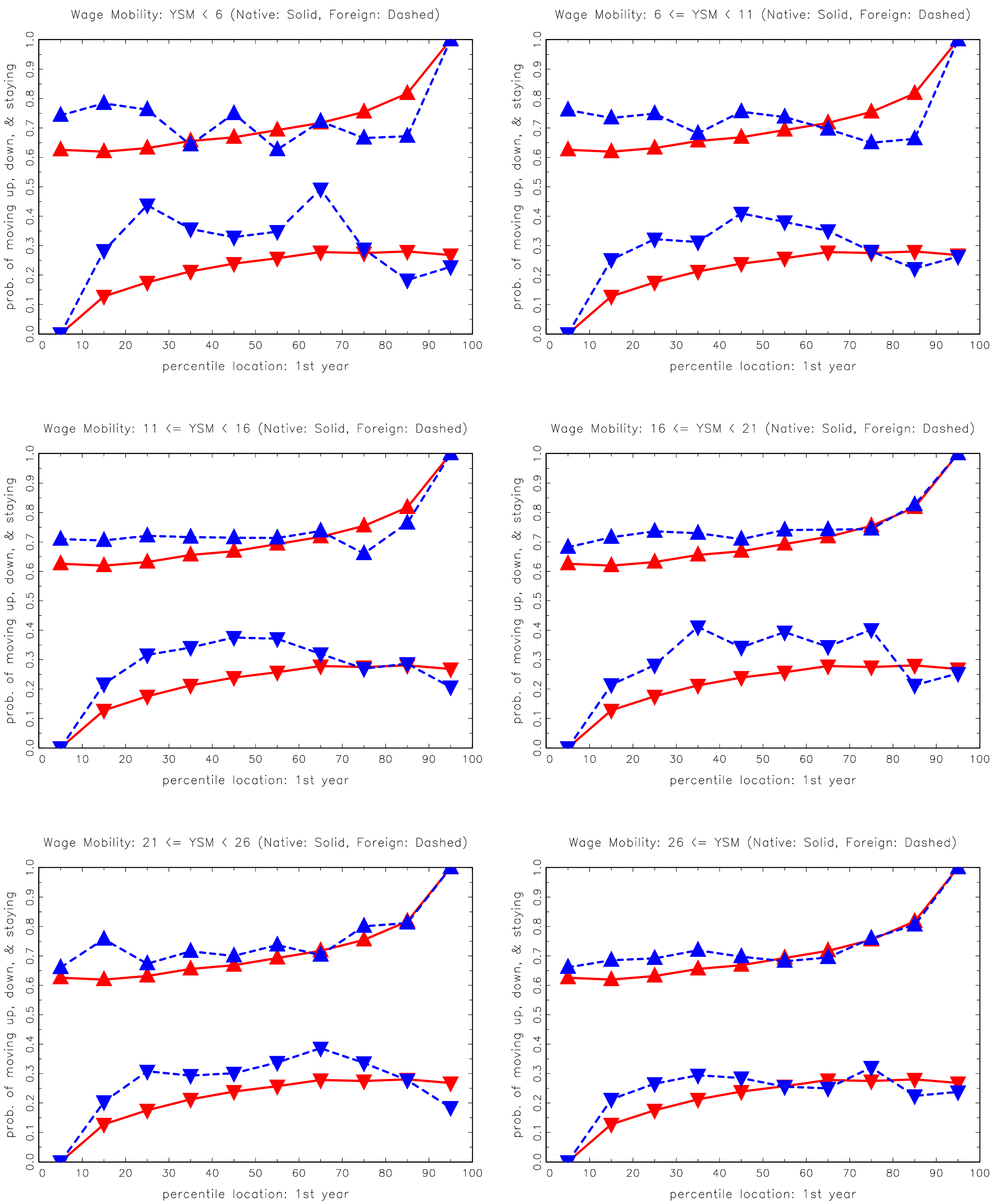

Figure 5: Wage Mobility by Years Since Migration

We apply the strategy to immigrants with different years of U.S. experience for 1996-2008. The six figures in Figure 5 classify immigrants by years since migration: less than 6 years, 6 to less than 11 years, ... , 21 to less than 26 years, and 26 years and above. We account for both sample attrition and population attrition in the two panel years to obtain these estimates. One can interpret the estimates as if there is no sample attrition and no population attrition in two year panels. No population attrition means that conditional on an immigrant is in the United States in the first panel year, the immigrant is in the United States in the second panel year. For example, for those who have stayed in the United States for 5 years and are in the sample in the first panel year, the counterfactual is that the immigrants are in the sample (and in the United States) in the second panel year.

The first figure (top left) with immigrants with less than 6 years of U.S. experience shows the followings. Immigrants in bottom decile groups have a smaller probability of moving up and a larger probability of moving down than their native counterparts. Immigrants in middle decile groups have more or less the same probability of moving up as natives, but have a higher probability of moving down. Immigrants in top decile groups tend to stay in higher deciles relative to natives, although it is not very clear whether their probability of moving to lower deciles is smaller than that of natives.

In general, immigrants in top decile groups are more likely to keep up or improve relative to natives, while those in middle and bottom decile groups tend to fall behind. Since most immigrants are located in bottom decile groups (based on the native samples), we conclude that the majority of foreign-born workers fails to assimilate into the U.S. labor market.

4.4 Wage Mobility by Continent of Origin

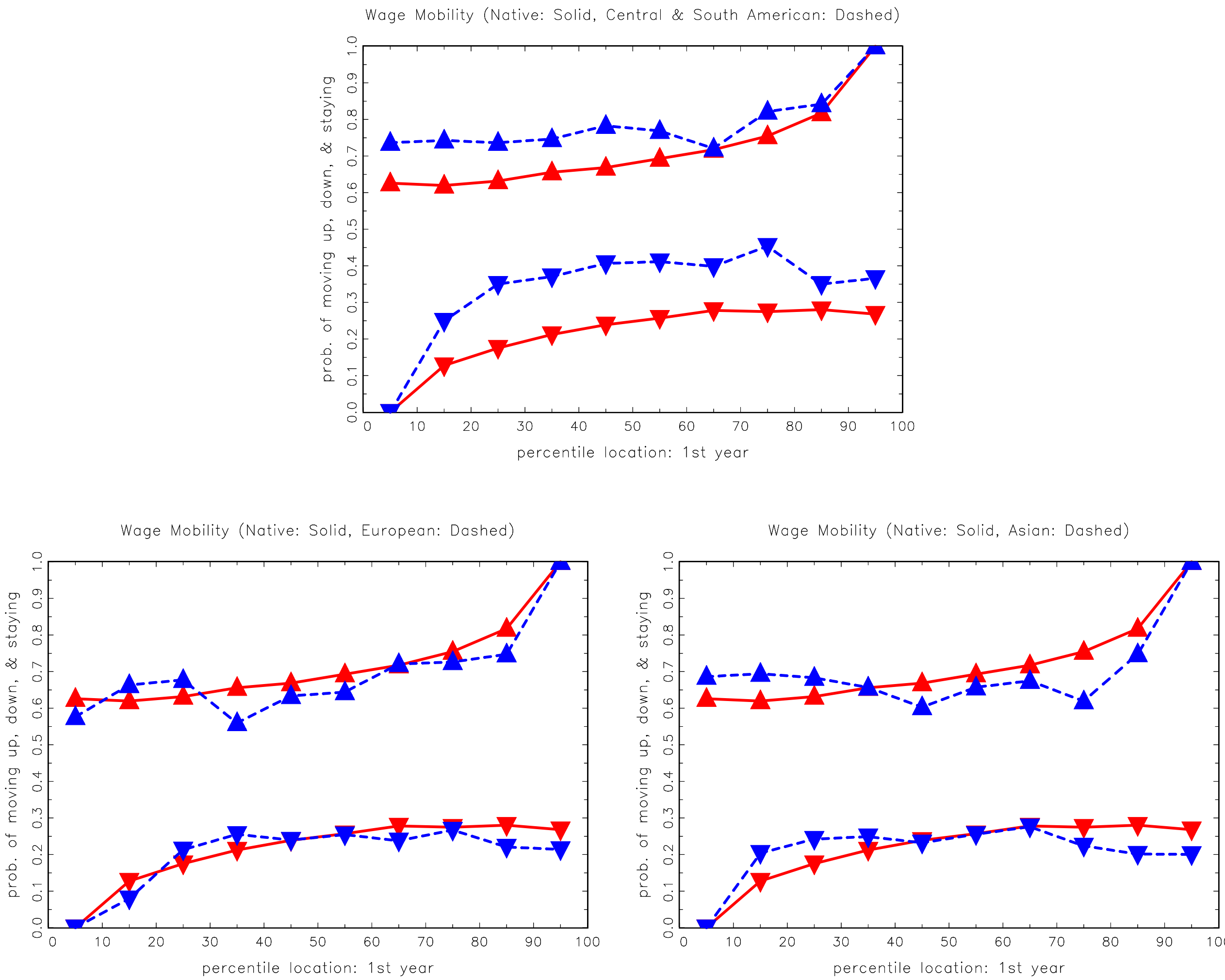

Figure 6: Wage Mobility by Continent of Origin

We conduct a similar analysis for immigrants from different continents in Figure 6.[8] First, immigrants from Central and South America tend to fall behind unless they are in the top two decile groups. Second, immigrants from Asia exhibit clear divergence. Asian immigrants with above-median wages have a higher chance of moving up and a lower chance of moving down than natives with above-median wages. For Asian immigrants with below-median wages, the exact opposite is true. Finally, immigrants from Europe are very similar to natives in terms of wage mobility. Our results suggest that the widening foreign-native gap in mean wages with U.S.

[8] In the United States, more than half of the foreign-born population is from Central and South America, about a quarter from Asia, and about one sixth from Europe.

experience is mostly driven by middle and bottom decile group immigrants from Central and South America and bottom decile group immigrants from Asia. This is confirmed later when we present conditional transition probability estimates.

4.5 Wage Mobility by Education

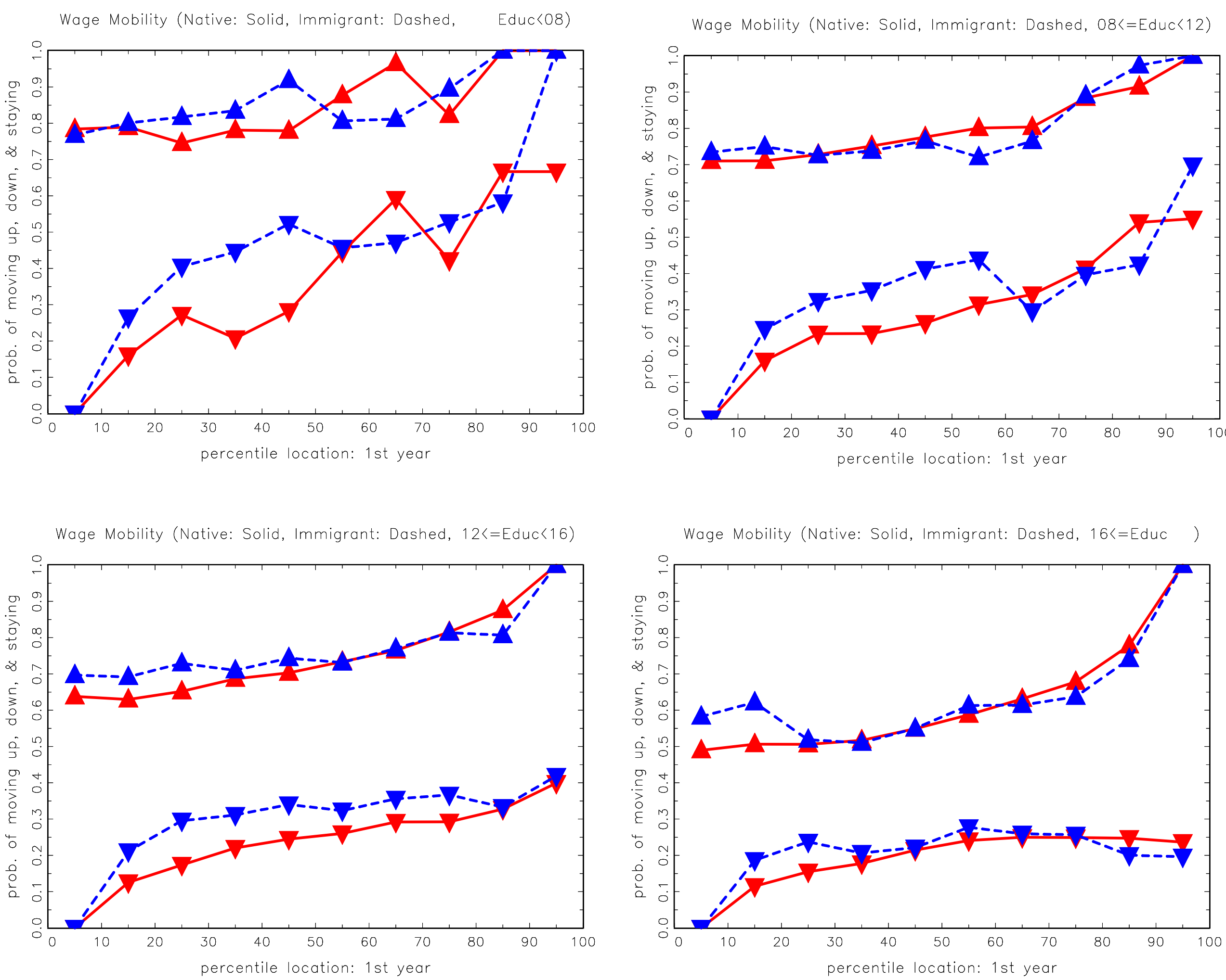

Figure 7: Wage Mobility by Education

In this section, we conduct a similar analysis for natives and immigrants of different education levels. Individuals are assigned to four different groups of years of education: $[0, 8)$, $[8, 12)$, $[12, 16)$, and $[16, \infty)$. The results are in Figure 7. The first education group with less than eight years of education includes 2% of natives and 19% of immigrants. Due to the small sample size of the native sample, native results (the solid lines) are relatively poorly estimated. Immigrant workers with wages below median have higher chance of moving down and lower chance of moving up than their native counterparts.

The second education group with $[8, 12)$ years of education consists of 6% of natives and 12% of immigrants. Immigrant workers with below-median wages are more likely to move to lower deciles than native workers in the same decile groups, but the chances of moving to higher deciles are not different from those of natives. Among the above-median wage workers, the foreign-native differences in the probabilities of moving up, moving down, and staying are small.

The members in the third education group have $[12, 16)$ years of education. 60% of natives and 41% of immigrants are in this group. Below-median wage immigrant workers have a smaller probability of moving to lower deciles than below-median wage native workers. Above-median wage immigrant workers have a greater (or similar) probability of moving to higher deciles than above-median wage native workers. The probability of moving down is always larger for immigrants unless they are in the top two decile groups.

Finally, the highest education group with 16 or more years of education includes 32% of natives and 28% of immigrants. In lower decile groups, immigrants have a lower probability of moving up and a higher probability of moving down. In middle decile groups, wage mobility is not very different between native and immigrant workers. In upper decile groups, immigrants have a higher probability of moving up and a lower probability of moving down. Overall, the education results suggest that the below-median wage immigrant workers with less than 16 years of education can explain the widening foreign-native gap in mean wages.

5 Estimation of Conditional Probabilities

5.1 A First-Order Markov-Switching Model

Consider a first-order Markov-switching variable S_{it} that has ten states. The ten-state S_{it} represents the ten decile groups, where i is individual and t is calendar year. A standard first-order

Markov-switching model defines a transition probability from state s_{t-1} to state s_t by

$$\Pr\left[S_{it} = s_t | S_{i,t-1} = s_{t-1}\right], \tag{1}$$

for $s_{t-1}, s_t \in \{1, 2, ..., 10\}$. In principle, the joint probability, $\Pr\left[S_{i,t-1} = s_{t-1}, S_{it} = s_t\right]$, can be estimated, but what we need for our analysis is the transition probabilities of moving up, moving down, and staying, which are even simpler than estimating the entire ten-by-ten transition matrix given by (1). The probability of moving up is given by

$$\begin{aligned} p_{s,up} &= \Pr\left[S_{it} > s | S_{i,t-1} = s\right], \qquad \text{for } s = 1, 2, ..., 9 \\ &= 0, \qquad \text{for } s = 10, \end{aligned} \tag{2}$$

and the probability of moving down by

$$\begin{aligned} p_{s,down} &= \Pr\left[S_{it} < s | S_{i,t-1} = s\right], \qquad \text{for } s = 2, 3, ..., 10 \\ &= 0, \qquad \text{for } s = 1. \end{aligned} \tag{3}$$

The probability of staying is simply the residual:

$$p_{s,stay} = 1 - p_{s,up} - p_{s,down}, \qquad \text{for } s = 1, 2, ..., 10. \tag{4}$$

Now suppose that the probabilities (2)-(3) are functions of a vector of covariates, X, and are given in parametric forms. We estimate the transition probabilities for each of the ten decile groups. For any given state, $S_{i,t-1} = s$, let the vector of parameters be θ_s. One may estimate the probabilities by maximum likelihood (ML) estimation. Conditional on $S_{i,t-1} = s$ the ML estimator is given by the maximizer of

$$L\left(\theta_s\right) = \sum_{i=1}^{n} \left[1\left\{S_{it} > s\right\} \log p_{s,up}\left(X_i; \theta_s\right) + 1\left\{S_{it} < s\right\} \log p_{s,down}\left(X_i; \theta_s\right) + 1\left\{S_{it} = s\right\} \log p_{s,stay}\left(X_i; \theta_s\right)\right].$$

For each $s = 1, 2, ..., 10$, apply a separate maximum likelihood estimation procedure and obtain

$\widehat{\theta}_{s,ML}$. Then, the estimated probabilities are

$$
\begin{aligned}
\widehat{p}_{s,up}\left(X_i\right) &= p_{s,up}\left(X_i;\widehat{\theta}_{s,ML}\right), \\
\widehat{p}_{s,down}\left(X_i\right) &= p_{s,down}\left(X_i;\widehat{\theta}_{s,ML}\right), \\
\widehat{p}_{s,stay}\left(X_i\right) &= 1-\widehat{p}_{s,up}\left(X_i\right)-\widehat{p}_{s,down}\left(X_i\right).
\end{aligned}
$$

5.2 Empirical Specification

A maximum likelihood estimation procedure can be used to estimate equations (2)-(3) using a multinomial logit model. In our specific model, partition the parameter vector θ_s by $\theta_s = (\gamma_s', \delta_s')'$. The probability of moving up is given by

$$
\begin{aligned}
p_{s,up}\left(X_i;\theta_s\right) &= \frac{e^{x'\gamma_s}}{1+e^{x'\gamma_s}}, \qquad \text{for } s=1, \\
&= \frac{e^{x'\gamma_s}}{1+e^{x'\gamma_s}+e^{x'\delta_s}}, \qquad \text{for } s=2,...,9, \\
&= 0, \qquad \text{for } s=10,
\end{aligned}
$$

and the probability of moving down is given by

$$
\begin{aligned}
p_{s,down}\left(X_i;\theta_s\right) &= 0, \qquad \text{for } s=1, \\
&= \frac{e^{x'\delta_s}}{1+e^{x'\gamma_s}+e^{x'\delta_s}}, \qquad \text{for } s=2,...,9, \\
&= \frac{e^{x'\delta_s}}{1+e^{x'\delta_s}}, \qquad \text{for } s=10.
\end{aligned}
$$

The vector of covariates include a constant, age, age squared, education, a dummy for marital status, and all these variables interacted with dummies for continent of birth. In addition, we inlcude years since migration, years since migration squared, continent of birth, dummies for entry year, and calendar year dummies. Of the multinomial logit model estimates, the coefficients of age, marriage variables, and education are significant for some $S_{t-1} = s$. These estimates are not directly interpretable, but give the signs of the impact of corresponding covariates on the probabilities of moving up and down.

Overall, age is negatively correlated with the probability of moving down, but is not a significant factor for the probability of moving up. Older individuals are less likely to move to lower deciles than younger ones. We also find that the foreign-native difference in the age coefficient estimates is not significant. The probabilities of moving up and moving down do not vary across immigrants with different years since migration, either. However, the coefficient estimates of age, age interacted with an immigrant dummy, and years since migration play a role when we evaluate the functions at different levels of age and years since migration. Note that individual coefficients may not be significant, but combinations of them may be significant.

In general, married individuals are more likely to improve than single ones, but this positive effect is not as strong among immigrants. We also find that lower decile group married individuals are less likely to move to lower deciles, but in middle and higher decile groups, marriage does not deter moving down.

The effects of education on the probabilities of moving up and moving down are interesting. For the sake of space, Table 3 reports the multinomial logit model estimates, $\widehat{\gamma}_s$ and $\widehat{\delta}_s$, for education interacted with dummies for continent of birth. For $S_{t-1} = 1$, the $\widehat{\gamma}_s$ estimate of education is positive (=0.148) and significant at the 1% significance level. In general, more educated individuals have a greater probability of moving up than less educated ones for all $S_{t-1} = s$. More educated individuals, however, also have a greater probability of moving down for $S_{t-1} = 4, 5, 6$. For example, for $S_{t-1} = 4$, the $\widehat{\delta}_s$ estimate of education is negative (=0.034) and significant at the 1% significance level. It means that the wages of more educated individuals in middle decile groups have larger variance than the wages of less educated ones. More educated individuals have a smaller probability of moving down for $S_{t-1} = 9, 10$. It implies that more educated individuals in top decile groups have a greater tendency of staying in higher deciles than less educated ones.

Immigrants with higher education levels also have a greater probability of moving up than less educated natives for all $S_{t-1} = s$. However, we also find that the effect of education on the probability of moving up for immigrants is not as great as the effect of education for natives because many of the $\widehat{\gamma}_s$ coefficients of education interacted with an immigrant dummy are negative and significant. The positive effect of education on the probability of moving up is especially low for immigrants from Central and South America. For instance, for $S_{t-1} = 1$, the $\widehat{\gamma}_s$ coefficient of education interacted with a dummy of Central and South America is negative (=–0.092) and significant at the 1% significance level. Therefore, the sum of $\widehat{\gamma}_s$ coefficients of education and education interacted with an immigrant dummy is 0.056 (=0.148–0.092) and is significant at the 1% significance level (not shown in the Table). In general, foreign-born individuals do not benefit from higher education in terms of the moving up probability than native-born individuals, but at the same time they have similar tendency of moving down as their native counterparts do.

Table 3. Multinomial Logit Model Estimates: $\widehat{\gamma}_s$ and $\widehat{\delta}_s$

$S_{i,t-1}$:	1	2	3	4	5	6	7	8	9	10
$\widehat{\gamma}_s$ (up)										
Educ	.148***	.143***	.150***	.174***	.188***	.191***	.161***	.198***	.165***	
	(.010)	(.011)	(.011)	(.011)	(.011)	(.011)	(.010)	(.011)	(.012)	
×C.S.A.	–.092***	–.064***	–.074***	–.072**	–.109***	–.133***	–.027	–.162***	–.056	
	(.015)	(.019)	(.025)	(.028)	(.038)	(.041)	(.058)	(.055)	(.067)	
×Europe	–.031	.006	.148	–.123**	.063	–.161**	.047	–.018	–.017	
	(.061)	(.066)	(.111)	(.062)	(.091)	(.064)	(.086)	(.069)	(.076)	
×Asia	–.041	–.088**	.114*	.178**	.078	–.068	.063	.081	–.046	
	(.033)	(.042)	(.066)	(.083)	(.076)	(.079)	(.090)	(.082)	(.084)	
$\widehat{\delta}_s$ (down)										
Educ		.021	.009	.034***	.030**	.023**	–.004	–.008	–.071***	–.194***
		(.016)	(.014)	(.012)	(.012)	(.011)	(.010)	(.010)	(.010)	(.012)
×C.S.A.		–.016	–.040	–.039	–.080***	–.040	–.030	–.037	–.051	–.222**
		(.022)	(.023)	(.026)	(.029)	(.035)	(.040)	(.041)	(.053)	(.092)
×Europe		–.177*	.178*	–.095	.045	–.094	–.007	.011	.071	.039
		(.091)	(.097)	(.081)	(.094)	(.074)	(.061)	(.056)	(.070)	(.063)
×Asia		–.062	.022	–.174**	–.121**	–.032	–.100	–.094	–.038	–.127*
		(.040)	(.054)	(.073)	(.062)	(.071)	(.077)	(.084)	(.079)	(.074)
# of Obs.	13061	13224	12973	13058	13081	13220	13309	13408	13725	12628

Standard errors are reported in parentheses. Confidence levels: 99% (***), 95% (**), 90% (*). # of Obs.: Sample Size.

Educ: the coefficients for education (for natives).

×C.S.A.: education interacted with an indicator of Central and South America. Other variables are defined similarly.

Other (not reorted) covariates are a constant, age, age squared, a dummy for marital status,

all these variables interacted with dummies for continent of birth,

years since migration, years since migration squared, dummies for entry year, and calendar year dummies.

5.3 Evaluation of the Estimated Transition Probability Functions

We evaluate the probabilities of moving to higher/lower deciles for selected values of covariates. We consider hypothetical immigrants from Central and South America, Europe, and Asia entering the United States at age 20. Hence, we compare a 24 year old immigrant who has 4 years of U.S. experience with a 24 year old native, a 36 year old immigrant who has 16 years of U.S. experience with a 36 year old native, a 48 year old immigrant who has 28 years of U.S. experience with a 48 year old native. Education is set to 8 when $S_{t-1} = 1, 2, 3$, to 12 when $S_{t-1} = 4, 5, 6, 7$, and to 16 when $S_{t-1} = 8, 9, 10$. We assume that all these individuals are married, since more people are married.

Tables 4A-4B present the foreign-native difference between the probabilities of moving up and moving down. In Table 4A, the first row of the first column corresponds to the difference in the probabilities of moving up between two individuals in the first decile group, $S_{t-1} = 1$. The first individual is a 24 year old person from Central and South America with 4 years of U.S. experience and the other is a 24 year old native person. The estimate $-.108$ implies that a foreign-born individual is less likely to move to higher deciles in the following year than a native-born individual in the same decile group by 10.8% points. It is significant at 1% level. According to the first entry in Table 4B, the foreign-native difference for immigrants from Central and South America, 0.221, is significant at 1% level. The positive value implies that immigrants from Central and South America in the lowest decile group are more likely to move to lower deciles than natives in the same decile group.

Similarly, the third row of the first column in Table 4A compares the difference in the probabilities of moving up between a 48 year old individual from Central and South America with 28 years of U.S. experience and a 48 year old native person in the first decile group. The estimates suggest that an immigrant person have a higher chance of moving up than a native person by 13.3% points. The third row of the first column in Table 4B compares the difference in the probabilities of moving down. An immigrant person from Central and South America are more likely to move down a native person by 17.1% points. Overall, the results in Tables 4A-4B suggests that for all $S_{t-1} = s$, immigrants from Central and South America have smaller chances of moving to higher deciles and greater chances of moving to lower deciles than their native counterparts. This is because the coefficients for education interacted with the dummy of Central and South America in the probability of moving up is negative and large in absolute sense.

The results for immigrants from Europe are mostly insignificant, meaning that they are not very different from natives. There are several exceptions where Europeans have a smaller probability of moving down than their native counterparts. For example, $S_{t-1} = 2$ in Table 4B shows that a foreign-born person from Europe at age 24 and 4 years of U.S. experience is less likely to move to lower deciles than observationally equivalent natives by 15.5% points. Overall, immigrants from Europe are similar to natives and, in some cases, they have a smaller probability of moving down.

The wage distribution for Asian immigrants diverge as compared to that for others. Asians who are located in the below-median decile groups have lower chances of moving to higher deciles and higher chances of moving to lower deciles than natives. For example, an Asian immigrant in $S_{t-1} = 3$ at age 36 and 16 years of U.S. experience has a lower chance of moving up by 11.2% points and higher chance of moving down by 16.8% points than natives. The results are persistent across below-median individuals. Asians located in the above-median decile groups, however, have lower chances of moving down than natives. For $S_{t-1} = 9$, a 24 year old Asian immigrant with 4 years of U.S. experience is less likely to move to lower deciles by 16.1% points than observationally equivalent natives. The signs of these estimates support the hypothesis, although other estimates are not very significant.

Table 4A. Foreign-Native Difference in the Probabilities of Moving Up

The estimates below are $\widehat{p}_{s,up}(x; imm) - \widehat{p}_{s,up}(x; nat)$, where

$\widehat{p}_{s,up}(x; imm) = \widehat{p}_{s,up}(age, ysm, educ, birth\_country, married)$

$\widehat{p}_{s,up}(x; nat) = \widehat{p}_{s,up}(age, educ, married)$

$educ = 8$ when $S_{i,t-1} = 1, 2, 3$. $educ = 12$ when $S_{i,t-1} = 4, 5, 6, 7$. $educ = 16$ when $S_{i,t-1} = 8, 9, 10$.

$S_{i,t-1}$:	1	2	3	4	5	6	7	8	9
C.S.America									
age=24, ysm=4	–.108***	–.075*	–.040	–.079	–.028	.092	.176	–.186	.084
	(.036)	(.044)	(.070)	(.089)	(.114)	(.138)	(.152)	(.136)	(.184)
age=36, ysm=16	.021	.002	–.012	–.138***	–.099*	–.009	.119	–.131**	–.013
	(.035)	(.038)	(.048)	(.043)	(.055)	(.065)	(.089)	(.064)	(.067)
age=48, ysm=28	.133**	.066	.002	–.192***	.033	–.026	.145	–.107	–.017
	(.066)	(.067)	(.066)	(.031)	(.110)	(.092)	(.133)	(.096)	(.092)
Europe									
age=24, ysm=4	–.115	–.165*	–.037	–.051	.051	.065	–.100	.017	.281*
	(.113)	(.085)	(.151)	(.140)	(.188)	(.177)	(.102)	(.153)	(.168)
age=36, ysm=16	.119	.087	–.029	–.062	.036	.146	.014	–.029	.136
	(.113)	(.098)	(.109)	(.073)	(.094)	(.101)	(.097)	(.080)	(.085)
age=48, ysm=28	.272**	.117	–.056	–.137**	.141	.205	.036	–.065	.039
	(.128)	(.119)	(.085)	(.058)	(.145)	(.143)	(.119)	(.103)	(.106)
Asia									
age=24, ysm=4	–.081	–.015	–.154***	–.165	–.219***	–.020	.256	–.014	.216
	(.075)	(.093)	(.055)	(.104)	(.066)	(.144)	(.211)	(.128)	(.151)
age=36, ysm=16	–.041	–.005	–.112**	–.222***	–.076	.004	–.011	.119	.064
	(.051)	(.063)	(.048)	(.029)	(.073)	(.086)	(.089)	(.091)	(.069)
age=48, ysm=28	.061	.035	–.054	–.217***	.022	.051	–.042	.111	.015
	(.079)	(.084)	(.068)	(.024)	(.119)	(.118)	(.088)	(.132)	(.092)

Standard errors are reported in parentheses. Confidence levels: 99% (***), 95% (**), 90% (*).

Table 4B. Foreign-Native Difference in the Probabilities of Moving Down

The estimates below are $\widehat{p}_{s,down}(x; imm) - \widehat{p}_{s,down}(x; nat)$, where

$\widehat{p}_{s,down}(x; imm) = \widehat{p}_{s,down}(age, ysm, educ, birth\_country; married)$

$\widehat{p}_{s,down}(x; nat) = \widehat{p}_{s,down}(age, educ; married)$

$educ = 8$ when $S_{i,t-1} = 1, 2, 3$. $educ = 12$ when $S_{i,t-1} = 4, 5, 6, 7$. $educ = 16$ when $S_{i,t-1} = 8, 9, 10$.

$S_{i,t-1}$:	2	3	4	5	6	7	8	9	10
C.S.America									
age=24, ysm=4	.221***	.299***	.062	.053	.114	–.065	.376**	.142	.223
	(.064)	(.094)	(.095)	(.109)	(.140)	(.124)	(.167)	(.209)	(.251)
age=36, ysm=16	.166***	.269***	.211***	.097	.204**	–.090	.219**	–.014	.183
	(.044)	(.064)	(.071)	(.071)	(.084)	(.079)	(.094)	(.076)	(.097)
age=48, ysm=28	.171**	.314***	.269**	.074	.229*	–.124	.159	–.021	.100
	(.080)	(.096)	(.114)	(.106)	(.124)	(.086)	(.137)	(.102)	(.118)
Europe									
age=24, ysm=4	–.155***	.149	.235	–.104	–.015	.037	.037	–.242***	–.107
	(.028)	(.219)	(.184)	(.101)	(.168)	(.208)	(.156)	(.051)	(.126)
age=36, ysm=16	–.097*	–.055	.172*	–.013	–.034	–.167**	.062	–.092	.009
	(.051)	(.093)	(.102)	(.077)	(.077)	(.065)	(.080)	(.057)	(.062)
age=48, ysm=28	.085	.019	.227	–.024	.084	–.208***	.086	–.026	–.005
	(.138)	(.120)	(.140)	(.098)	(.128)	(.054)	(.124)	(.097)	(.082)
Asia									
age=24, ysm=4	.063	–.000	.031	–.081	–.016	–.080	.416	–.161**	.136
	(.109)	(.135)	(.160)	(.111)	(.191)	(.165)	(.144)	(.081)	(.151)
age=36, ysm=16	.232***	.168*	.205**	.020	.081	–.122	–.020	–.102**	.031
	(.074)	(.093)	(.093)	(.075)	(.101)	(.088)	(.066)	(.048)	(.064)
age=48, ysm=28	.226**	.209	.289**	.041	.127	–.163**	–.012	–.094	.056
	(.108)	(.127)	(.130)	(.112)	(.135)	(.082)	(.099)	(.069)	(.283)

Standard errors are reported in parentheses. Confidence levels: 99% (***), 95% (**), 90% (*).

Overall, foreign-born Central and South American immigrants have smaller chances of moving to higher deciles and greater chances of moving to lower deciles than their native counterparts. These results are persistent across different age and decile groups, although there are a few exceptions. European immigrants, however, are not very different from natives in terms of wage mobility. The wage mobility of Asian immigrants are rather state dependent. Asians who are located in the below-median decile groups have lower chances of moving to higher deciles and higher chances of moving to lower deciles than natives. Asians who are located in the above-median decile groups have lower chances of moving to lower deciles than natives and similar chances of moving to higher deciles.

5.4 Heterogeneity within Decile Groups

The objective of this section is to understand why natives and immigrants in the same decile groups have different education coefficients. We specifically focus on why education is not sensitive to the proabability of moving up for immigrants from Central and South America compared at the top tail of the wage distribution to others in similar decile groups. We find that, in all decile groups, immigrants from Central and South America have on average lower education levels than their native and other immigrant counterparts. According to Table 5, among individuals in the eighth decile group, immigrants from Central and South America have 13.3 years of education, while natives and other immigrants have 14.7-16.1 years of education. Similarly, in the tenth decile group, the education level for immigrants from Central and South America is lower than that for natives and other immigrants by 0.8-1.7 years. These facts imply that immigrants from Central and South America in top decile groups would experience slower wage growth than natives and other immigrants due to their lower levels of education.

Table 5. Average Years of Education by Wage Decile Group and Continent of Origin

Decile Groups	Native	C.S.America	Europe	Asia	Total
1	12.9	8.7	12.9	12.4	11.9
2	13.1	9.4	12.6	12.8	12.5
3	13.2	10.0	12.8	13.4	12.9
4	13.4	10.7	12.8	14.0	13.2
5	13.6	11.2	13.7	14.7	13.5
6	13.9	11.6	14.0	14.9	13.9
7	14.2	12.7	14.3	15.6	14.2
8	14.7	13.3	15.1	16.1	14.7
9	15.3	14.3	15.7	16.8	15.4
10	16.3	15.5	16.5	17.2	16.3
Total	14.1	10.0	14.5	14.9	13.9

Next, we explore whether occupation distribution and mobility for natives and immigrants from different continents can explain the wage mobility results. Occupations are classified into five job zones based on the Occupational Information Network database (O*Net).[9] Job zone 1 occupations require 3 months of training or less, whereas job zone 5 occupations expect at least 4 years of training. Table 6 tabulates the distribution of job zones for immigrants and natives. The table is presented for two time periods because the composition of job zones are different in each of the periods due to the changes in the standard occupational classification (SOC) system. The CPS uses the 1980 SOC system for the years 1996-2002 and uses the 2000 SOC system for the years 2000-2008. The most significant pattern found in Table 6 is that immigrants from Central and South America are concentrated in low-skilled occupations. Immigrant workers from Europe are slightly more clustered in high-skill jobs than native workers. The occupation distribution of Asian immigrants has fatter tails than that of natives.

[9] There are alternative ways of measuring occupational status, such as the International Socio-Economic Index. This index is useful for international comparisons. See Akresh (2008) for details.

Table 6. 1st Year Job Zone Shares by Continent of Origin

Job Zone	Native	C.S.America	Europe	Asia	Total
1996-2002 Sample (based on the 1980 occupation codes)					
1	0.24	0.52	0.23	0.28	0.37
2	0.20	0.17	0.17	0.13	0.16
3	0.22	0.20	0.23	0.19	0.19
4	0.29	0.10	0.30	0.34	0.21
5	0.05	0.01	0.08	0.06	0.06
Total	1.00	1.00	1.00	1.00	1.00
2000-2008 Sample (based on the 2000 occupation codes)					
1	0.04	0.21	0.05	0.07	0.11
2	0.29	0.48	0.24	0.26	0.36
3	0.32	0.23	0.27	0.20	0.25
4	0.26	0.06	0.30	0.32	0.16
5	0.10	0.02	0.15	0.15	0.11
Total	1.00	1.00	1.00	1.00	1.00

Given that there are differences in occupation distributions, we move on to the question of whether immigrants from Central and South America are concentrated in low-skilled occupations conditional on decile groups. The six figures in Figure 8 show occupation distributions for top, middle, and bottom decile groups. The top two figures correspond to top decile groups, the middle two to middle decile groups, and bottom two to bottom decile groups. The figures in the left column use the 1996-2002 sample (based on the 1980 occupation codes) and those in the right column use the 2000-2008 sample (based on the 2000 occupation codes).

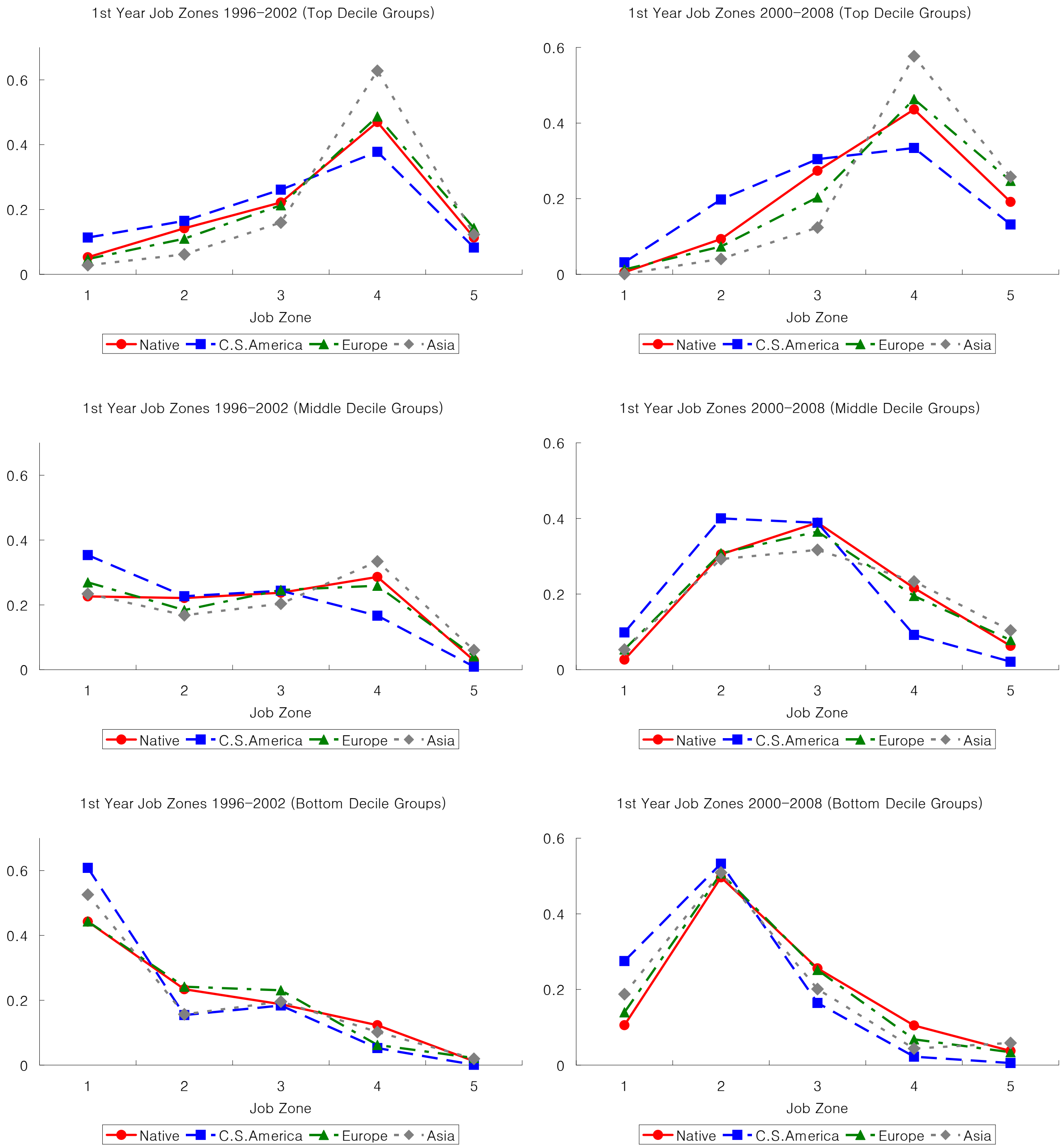

Figure 8: Occupation Distribution by Wage-Decile Groups

Figure 8 reveals that Central and South American immigrant workers are overrepresented in low-skilled jobs even after controlling for wage decile groups. For example, in the bottom left figure, 61% of bottom decile Central and South American immigrant workers have job zone

1 occupations, whereas 44% of bottom decile native workers have job zone 1 occupations. In the bottom right figure, these fractions are estimated as 28% and 11%, respectively. These patterns are similar for top decile group Central and South American immigrant workers. In bottom decile groups, Asian immigrant workers are also more likely to be employed in job zone 1 occupations than natives, although the results are not as dramatic as those for Central and South American immigrant workers.

Among the workers in top decile groups, we find that Asian immigrant workers are over-represented in job zone 4 occupations and possibly in job zone 5 occupations as compared to natives. For example, 63% and 12% of top decile Asian immigrant workers have job zone 4 and 5 occupations during 1996-2002, whereas 47% and 11% of top decile native workers have job zone 4 and 5 occupations. For the 2000-2008 period, 58% and 26% of top decile Asian immigrant workers have job zone 4 and 5 occupations, whereas 44% and 19% of top decile native workers have job zone 4 and 5 occupations. These findings are consistent with the evidence that the distribution effects for Asian immigrants exhibit clear divergence from those for other groups.

We next consider mobility across job zones. Figure 9 shows that, conditional on job zones, Central and South American immigrants have a higher probability of moving to lower deciles. The top two figures depict the probability of moving to higher deciles and the bottom two the probability of moving to lower deciles. These figures show that immigrant workers from Central and South America are systematically more likely to move to lower deciles and less likely to move to higher deciles regardless of their initial location on the occupation distribution. The occupation mobility results for European and Asian workers reveal that especially those who are in job zone 4 and 5 occupations are more likely to stay in the same job zones than natives. Overall, immigrants from Central and South America do worse than natives and other immigrants in terms of occupation mobility. Again, the reason is because, for any given job zone, immigrants from Central and South America have lower education levels than others.[10]

[10] We have examined detailed occupation codes rather than job zones, and have found a fair amount of heterogeneity in the distribution of occupations. For example, among European immigrants there are many chief executives and non-retail first-line supervisors; among Asian immigrants, the share of those who are computer software engineers, electrical engineers, civil engineers is significantly larger than for other immigrants. For immigrants from Central and South America, there are many construction managers, education administrators, and elementary school teachers. However, we do not find systematic differences in occupation mobility across

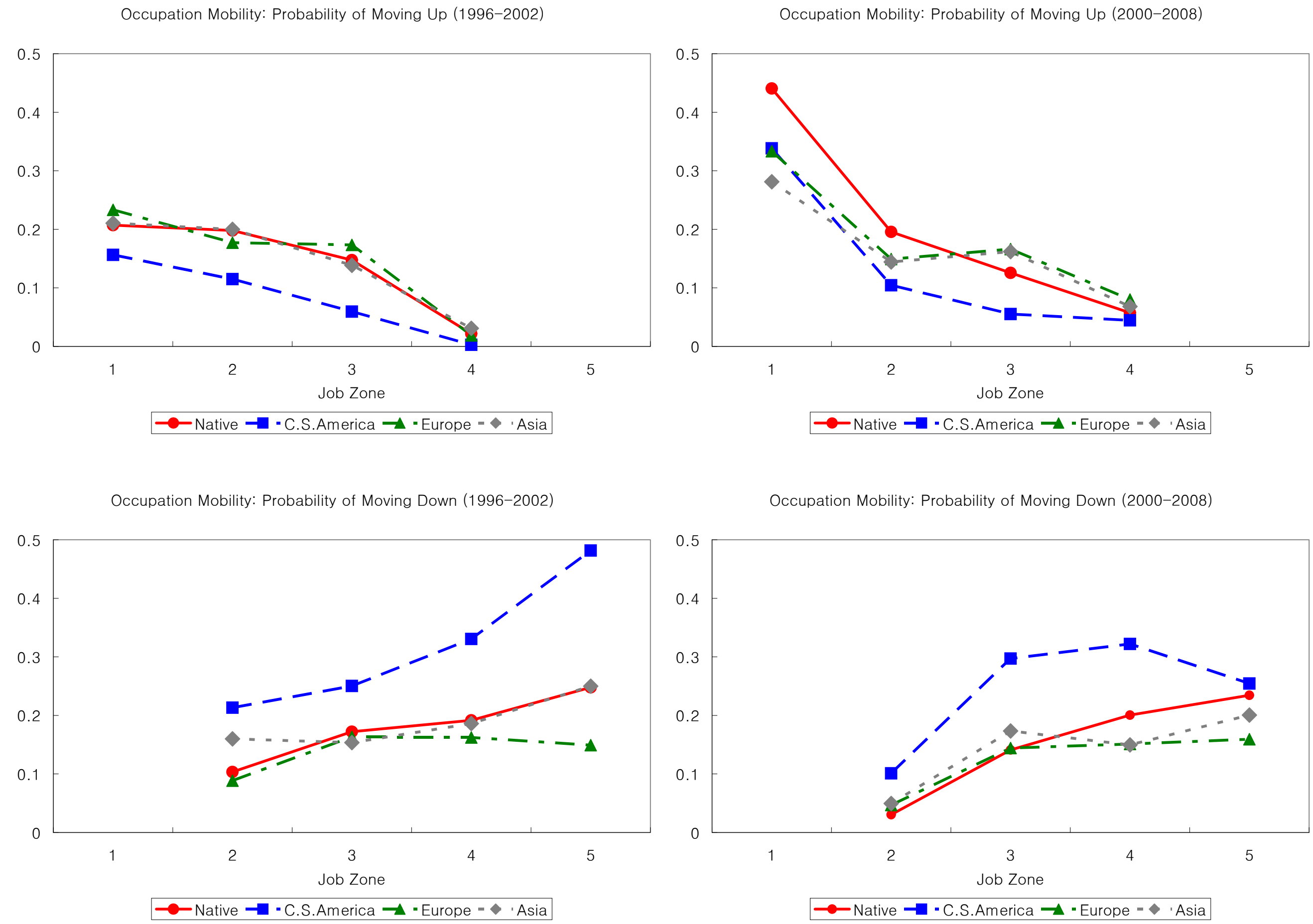

Figure 9: Occupation Mobility

6 Concluding Remarks

This study investigates economic assimilation of foreign-born individuals using a novel research design. It assigns foreign-born and native-born individuals into ten decile groups and estimates the probabilities of moving up, moving down, and staying based on a standard first-order Markov-switching model. The empirical findings from the CPS 1996-2008 suggest that age, marital status, and education are important in explaining wage mobility and the foreign-native gap in wage mobility. Older individuals are less likely to move to lower deciles. Married individuals are more likely to improve. High-educated individuals in top decile groups are more likely to move

different occupations. These results are available upon request.

to higher deciles and less likely to move to lower deciles. High-educated individuals in middle decile groups earn wages with greater variance.

Most foreign-born workers fail to assimilate. Immigrants in bottom decile groups, who are the majority of immigrants, are trapped in bottom decile groups. Immigrants in middle decile groups are more mobile than natives, but they have a higher chance of moving down than natives. Immigrants in top decile groups outperform natives, but they are a small fraction of all foreign-born individuals. The widening foreign-native gap in mean wages with the time spent in the United States found in the literature of economic assimilation for mid-1990's and 2000's is mostly driven by middle and bottom decile group immigrants.

7 References

Akresh, Ilana R. (2006): "Occupational Mobility Among Legal Immigrants to the United States," *International Migration Review*, 40(4), 854-885.

Akresh, Ilana R. (2008): "Occupational Trajectories of Legal US Immigrants: Downgrading and Recovery," *Population and Development Review*, 34(3), 435-456.

Bhattacharya, Debopam (2008): "Inference in Panel Data Models under Attrition Caused by Unobservables," *Journal of Econometrics*, 144 (2), 430-446.

Borjas, George J. (1985): "Assimilation, Changes in Cohort Quality and the Earnings of Immigrants," *Journal of Labor Economics*, 3(4), 463-489.

Borjas, George J. (1995): "Assimilation and Changes in Cohort Quality Revisited: What happened to Immigrant Earnings in the 1980s?" *Journal of Labor Economics*, 13(2), 201-245.

Borjas, George J. (1999): "The Economic Analysis of Immigration," in Ashenfelter, Orley C. and David Card, eds., *Handbook of Labor Economics*, Vol 2A, Ch28.

Bratsberg, Bernt, Erling Barth, and Oddbjorn Raaum (2006): "Local Unemployment and the Relative Wages of Immigrants: Evidence from the Current Population Surveys," *Review of Economics and Statistics*, 88(2), 243-263.

Buchinsky, Moshe and Jennifer Hunt (1999): "Wage Mobility in the United States," *Review of*

Economics and Statistics, 81(3), 351-368.

Butcher, Kristin F. and John DiNardo (2002): "The Immigrant and Native-Born Wage Distributions: Evidence from United States Censuses," *Industrial and Labor Relations Review*, 56(1), 97-121.

Chiswick, Barry R. (1978): "The Effect of Americanization on the Earnings of Foreign-Born Men," *Journal of Political Economy*, 86(5), 897-922.

Duleep, Harriet O. and Mark C. Regets (1997): "Measuring Immigrant Wage Growth using Matched CPS Files," *Demography*, 34(2), 239-249.

Hirano, Keisuke, Guido W. Imbens, Geert Ridder, and Donald B. Rubin (2001): "Combining Panel Data Sets with Attrition and Refreshment Samples," *Econometrica*, 69, 1645-1659.

Gittleman, Maury and Mary Joyce (1996): "Earnings Mobility and Long-Run Inequality: An Analysis using Matched CPS Data," *Industrial Relations*, 35(2), 180-196.

Jasso, Guillermina and Mark R. Rosenzweig (1982): "Estimating the Emigration Rates of Legal Immigrants using Administrative and Survey Data: The 1971 Cohort of Immigrants to the United States," *Demography*, 19(3), 279-290.

Jasso, Guillermina and Mark R. Rosenzweig (1988): "How Well do U.S. Immigrants do? Vintage Effects, Emigration Selectivity, and Occupational Mobility," in T. Paul Schultz, ed., *Research in Population Economics*, Vol 6. 229-253.

Kim, Seik (2010a): "Sample Attrition in the presence of Population Attrition," Working Paper.

Kim, Seik (2010b): "Economic Assimilation of Foreign-Born Workers in the United States: An Overlapping Rotating Panel Analysis," Working Paper.

LaLonde, Robert J. and Robert H. Topel (1997): "Economic Impact of International Migration and The Economic Performance of Migrants," in Mark R. Rosenzweig and Oded Stark, eds., *Handbook of Population and Family Economics*, Vol 3B, Ch 14.

Lemieux, Thomas (2006): "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *American Economic Review*, 96(3), 461-498.

Lubotsky, Darren H. (2007): "Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings," *Journal of Political Economy*, 115(5), 820-867.

8 Appendix

8.1 Variables used in the Analysis

This section explains in detail how the CPS MORG are processed to generate the sample used in the analysis. The wage measure used in the analysis is the hourly rate of pay. The wage measure is the hourly wage for the hourly workers and the weekly payments divided by the usual weekly hours of work for non-hourly workers. We clean the wage measure by following steps which are similar to those in Lemieux (2006). Workers with extreme wages (less than $2 and more than $200 in 1994 dollars) are trimmed. In addition, the sample drops persons with negative potential experience. These trimmed samples are used throughout the paper unless otherwise indicated.

The year of arrival information provided by the CPS MORG lets us identify those who arrived in the United States before 1950, 1950-1959, 1960-1964, 1965-1969, 1970-1974, 1975-1979, 1980-1981, 1982-1983, and so on. The most recent entrants, however, are coded in an inconsistent way. For instance, the arrival year code 18 in the 2004 sample includes the 2002-2004 arrivals, the code 18 in the 2005 sample includes the 2002-2005 arrivals, and the code 18 in the 2006 sample and afterwards include the 2002-2003 arrivals. Therefore foreign-born persons who arrived in the United States in 2002-2003 and are in the 2004-2005 or the 2005-2006 panels cannot be matched. As a consequence, we drop immigrants with the arrival year code 18 in the 2004-2005 and the 2005-2006 panels. So, the most recent immigrants in the 2004-2005 and the 2005-2006 panels are those who entered the U.S. in 2000-2001 with the arrival year code 17. Accordingly in other panels we keep immigrants with the arrival year code numbers of the followings:

1996-1997 and 1997-1998 panels: codes 1-13 (1992-1993)

1998-1999 and 1999-2000 panels: codes 1-14 (1994-1995)

2000-2001 and 2001-2002 panels: codes 1-15 (1996-1997)

2002-2003 and 2003-2004 panels: codes 1-16 (1998-1999)

2004-2005 and 2005-2006 panels: codes 1-17 (2000-2001)

2006-2007 and 2007-2008 panels: codes 1-18 (2002-2003)

where the years in the parentheses indicate the entry years of the most recent immigrants. Arrival years are given by intervals. In the analysis, the arrival year variable is defined by the mid-point of each period. Immigrants who arrived in the United States before 1950 are coded as 1940.

8.2 Matching Rates

Matching is directly related to residential mobility and outmigration as the housing units in the sample are kept fixed over the interview periods, provided that the non-interview rate is low.[11]

[11] The average yearly non-interview rates for the CPS in the early 1990's are as low as 4-7%. This non-interview rate is comparable with the initial non-response rate of the National Longitudinal Survey of Youth 1979 (NLSY79), which is 10%. The Census Bureau classifies the noninterviews into three types. Type A noninterviews are for household members that refuse, are absent during the interviewing period, or are unavailable for other reasons. Type B noninterviews include a vacant housing unit (either for sale or rent), a unit occupied entirely by individuals who are not eligible for a CPS labor force interview, or other reasons why a housing unit is temporarily not occupied. Type C noninterviews are for addresses that may have been converted to a permanent business, condemned or demolished, or fall outside the boundaries of the segment for which it was selected.

Table A1. Matching Rates (One minus Attrition Rates)

	Native Sample		Immigrant Sample	
	Matching Rate	Sample Size	Matching Rate	Sample Size
1996-1997	0.803	17142	0.713	2252
1997-1998	0.796	17150	0.709	2328
1998-1999	0.797	16896	0.713	2474
1999-2000	0.796	16172	0.730	2282
2000-2001	0.805	14955	0.723	2625
2001-2002	0.808	15983	0.728	2447
2002-2003	0.796	17485	0.713	2889
2003-2004	0.743	16453	0.669	2776
2004-2005	0.742	14767	0.681	2508
2005-2006	0.805	16510	0.707	2895
2006-2007	0.806	16169	0.709	3200
2007-2008	0.817	16249	0.722	3043
Total	0.793	195931	0.710	31719

Sample Size indicates the 1st Year Sample Size.

8.3 Sample Attrition in the Presence of (Unobserved) Population Attrition

Denote $D_S = 1$ when an individual is in the sample (or responds) in the second year and $D_S = 0$ when an individual is not in the sample (or does not respond) in the second year. Denote $D_P = 1$ when an individual is in the population (or stays in the United States) in the second period and $D_P = 0$ when an individual is not in the population (or leaves the United States) in the second period. It is possible to construct a balanced longitudinal sample by collecting all the individuals with $D_P = 1$ and $D_S = 1$. This sample is called the matched sample.[12]

[12] Similarly, if an individual stays in the U.S. but does not respond in the second period, it is denoted by $D_P = 1$ and $D_S = 0$. An individual who leaves the U.S. in the second period is denoted by $D_P = 0$. A combination of $D_P = 0$ and $D_S = 1$, where an individual leaves the country and responds in the second period, is not possible. As a result, being in the matched sample, $D_S = 1$, also implies residing in the U.S. at the same time, $D_P \cdot D_S = 1$.

Suppose that there is no population attrition. Assume that sample attrition is a function of u_1, u_2, and v, where u_1 and u_2 are vectors of time-varying variables in periods 1 and 2, respectively, and v is a vector of time invariant variables. For instance, u_1 (or u_2) is a vector of the endogenous variable and time-varying exogenous variables and is v is a vector of time-invariant exogenous variables. u_2 is observed because the second period cross-section is available. Specify one minus the sample attrition function by

$$\Pr\left(D_S = 1 | U_1 = u_1, U_2 = u_2, V = v\right) = g\left(v'\phi_0 + u_1'\phi_1 + u_2'\phi_2\right), \tag{5}$$

where v is a vector of a constant, age, education, and dummy variables (marital status, years in the United States, citizenship status, country of birth), u_1 and u_2 are vectors of logged hourly real dollar wages and indicators of "not usually working", and $g(r) = e^r / (1 + e^r)$. Since the $g(\cdot)$ function and $\Pr(D_S = 1)$ are estimable, one can construct the attrition-correcting weights by

$$C\left(u_1, u_2, v\right) = \frac{\Pr\left(D_S = 1\right)}{g\left(v'\phi_0 + u_1'\phi_1 + u_2'\phi_2\right)}. \tag{6}$$

Intuitively, this step is equivalent to weighting the individuals in the matched sample with the inverse of one minus the probability of sample attrition, $1/g\left(v'\phi_0 + u_1'\phi_1 + u_2'\phi_2\right)$.

In the presence of population attrition, one additional step is required prior to the above procedure. The population attrition function, $\Pr\left(D_P = 1 | u_2, v\right)$, can be nonparametrically identified when population attrition is solely determined by variables of known transition probability.[13] Suppose that the transition probability is given by $P\left(Z_2 = z_2 | Z_1 = z_1\right)$, where z is a vector of variables of known transition probability.[14] For instance, if z is year of entry, the transition probability is given by $P\left(z_2 | z_1\right) = 1\left(z_2 = z_1\right)$, where $1(\cdot)$ is the indicator function. If z is age, the transition probability is given by $P\left(z_2 | z_1\right) = 1\left(z_2 = z_1 + 1\right)$. Specify one minus the population

[13] This assumption is strong but necessary because we do not know who emigrated from the United States.
[14] The variables in z_2 must be included in (u_2, v).

attrition function by

$$\begin{aligned}\Pr\left(D_P = 1|u_2, v\right) &= \Pr\left(D_P = 1|z_2\right) \\ &\equiv k\left(z_2'\psi\right), \end{aligned} \tag{7}$$

where $k(r) = e^r$, and z_2 is a vector of age, years since migration, education (assuming that no additional schooling is obtained), country of origin, and year of entry.[15] Intuitively, weight the individuals in the population (or more precisely the cross-section) with the inverse of one minus the probability of population attrition, $1/k\left(z_2'\psi\right)$.

The weights in (6) can be estimated by the conditional moment restrictions given by

$$\begin{aligned} 1 &= E\left[\frac{D_S}{g\left(v'\phi_0 + u_1'\phi_1 + u_2'\phi_2\right)}|u_1, v\right] \quad \text{w.p.1}, \\ \frac{1}{k\left(z_2'\psi\right)} &= E\left[\frac{D_S}{g\left(v'\phi_0 + u_1'\phi_1 + u_2'\phi_2\right)}|u_2, v, D_P = 1\right] \quad \text{w.p.1}. \end{aligned} \tag{8}$$

In the first step, estimate $1/k\left(z_2\right)$, which is equivalent to weighting the individuals in the second year cross-section with the inverse of one minus the probability of population attrition. In the second step, estimate (8) and obtain (6). Finally, use (6) to weight individuals in the matched sample and estimate the main model of interest. Since the weights are assigned to individuals, the attrition-correcting method is robust to individual fixed effects.

[15] These variables have deterministic time paths and satisfy the known transition probability assumption. The assumption, however, is more restrictive than the sample selection model, for instance, because observable variables with unknown transition probability, such as the wage, cannot enter in the selection function. The assumption can be problematic as the transition probabilities of labor market performance variables are usually not known. Intuitively labor market performance will affect population attrition decision. If the assumption is indeed a serious problem in practice, it is required to develop an alternative way of handling population attrition.