Journal of Labor Research
https://doi.org/10.1007/s12122-020-09304-5

The Effect of Immigration on Labor Market Transitions of Native-Born Unemployed in the United States

Fernando Rios-Avila[1] · Gustavo Canavire-Bacarreza[2]

Published online: 17 July 2020

Abstract
Unemployed workers are the group most likely to be affected by the presence of immigrants in their local labor markets since they are actively competing for job opportunities. Yet, little is known about the effect of immigration on labor market opportunities of the unemployed. Using a sample of unemployed native-born citizens from the monthly Current Population Survey from 2001 to 2015 and state level immigration statistics, we employ a multinomial model in the framework of a discrete hazard model with competing risks to examine the effects of immigration on the transition out of unemployment. The results suggest that immigration does not affect attrition not the probabilities of native-born workers finding a job. Instead, we find that immigration is associated with smaller probabilities of remaining unemployed.

Keywords Immigration · Unemployment duration · Labor force transition

JEL Classifications J1 · J6

The views and opinions expressed in this paper are those of the authors and do not necessarily reflect the official policy or position of any other agency, organization, employer, or company. We would like to thank Catalina Amuedo-Dorantes, Klaus Zimmermann, anonymous referees, and the participants at the Bolivian Development Conference and the Latin American Meetings of the Econometric Society in for helpful comments and suggestions.

✉ Fernando Rios-Avila
friosavi@levy.org

✉ Gustavo Canavire-Bacarreza
gcanavire@gmail.com

1 Levy Economics Institute of Bard College, Annandale-on-Hudson, NY 12504-5000, USA

2 Universidad Privada Boliviana, La Paz, Bolivia

Introduction

The immigration debate in the United States has a longstanding history (Orrenius and Zavodny, 2012; Passel and Fix 1994). Over the last few decades, the share of immigrants in the country has increased rapidly. According to official data, the share of foreign-born individuals in the US increased from 7.9% in 1990 to almost 13.3% in 2014, representing about 41.3 million people. Furthermore, from the total immigrant population, in 2014, about 11.3 million immigrants were estimated to be unauthorized immigrants (Passel and Cohn, 2015). These trends have shaped the immigration policy in the US and motivated a large body of research focused on examining the economic impacts of immigration (Kerr and Kerr, 2011; Okkerse, 2008).

The majority of the immigration research has been focused on analyzing the effects that immigrants, particularly unauthorized immigrants, have on the wages and employment opportunities of native-born workers (Okkerse, 2008; Longhi, Nijikamp, and Poot, 2005, 2006, 2008, 2010; Borjas, 1999). However, while the literature on the effects of immigration on native-born workers has been broadly studied, little is known about the effects of immigration on the labor market opportunities of the unemployed.

Unemployed workers are the group most likely to be affected by the presence of immigrants in their local labor markets, either positively or negatively, as they are actively competing for jobs. Thus, the unemployed individual's opportunities to find a job, their decision to continue searching for jobs, or decide to exit the labor force are expected to be influenced by the impact immigration has on the labor market in terms of wages and job opportunities. Furthermore, even if immigration has no direct effect on labor market outcomes in the aggregate, the presence of immigrants may affect the expectations of wage trends and job opportunities in the labor market. The channel through which this effect may take place is added competition, which can also affect the transitions rates out of unemployment for native-born citizens (Ottaviano and Zavodny 2012; Mayda 2006; Scheve and Slaughter 2001).

We contribute to the literature by examining the effects of immigration on unemployed native-born workers in the US. Based on an area analysis approach, we exploit the differences in the changes in the immigrants-to-population ratio across states and time to identify the impact of immigration on native-born citizens' transitions out of unemployment. Using basic monthly Current Population Survey (CPS) data from 2001 from 2015, we match data for individuals who were interviewed for two consecutive months and identify workers' transitions out of unemployment. We employ a multinomial logit model in the framework of a discrete survival model with competing risks to estimate the impact immigration has on the probability that an unemployed native-born citizen will end their current unemployment spell by finding a job,[1] leaving the labor force, or due to attrition.

Our estimates suggest that the probabilities of a native-born citizen finding a job are not affected by the share of immigrants in their labor market. Instead, we find that high levels of immigration net-flows are associated with smaller probabilities of remaining

[1] Migration may influence unemployment spells since access to unemployment benefits (natives are more likely to have unemployment benefits and therefore, longer unemployment spells. I would expect a more significant effect on low skilled foreign-born non-citizens) or the degree of substitution/complementarity between natives and immigrants.

unemployed, contributing to shorter unemployment duration and marginally significant probabilities of leaving the labor force. We also find that immigration as a whole does not seem to be related to the probability of the native-born to migrate, but some evidence that likely unauthorized immigration may be positively associated with an outmigration effect.[2] These results suggest that immigration is not reducing employment opportunities for unemployed native-born citizens. The results are robust to different model specifications.

The rest of the paper is structured as follows. Section 2 presents a brief description of the literature. Sections 3 and 4 present a description of the data and the methodological approach. Section 5 discusses the findings of the paper, and section 6 concludes.

Literature Review: Immigration, Labor Market Outcomes, and Unemployment Duration

Immigration and Labor Market Outcomes of Natives

A large body of the literature has studied the economic impact of immigration on the labor market outcomes of native workers (Borjas, 1999; Okkerse, 2008; Kerr and Kerr, 2011), finding mixed results. According to the standard competitive model of supply and demand in a closed economy (see, for example, Borjas [1999]), immigration inflows may increase the labor supply in the local labor market. Simultaneously, competition for jobs would increase, putting downward pressures on wages, and displaces natives out of their jobs as they are potentially substituted by cheaper labor entering the labor market. On the other hand, the inflow of immigrants can also affect the demand side of the labor market by increasing the consumption of goods and services. Also, because the demographic composition of immigrants might be different from the one among natives, immigration may have a positive impact on wages, productivity, and employment due to task specialization and increased productivity (Peri, 2012; Peri and Sparber, 2009). Allowing for factor mobility further complicates the theoretical implications of immigration as capital and labor have the option to out migrate in response to the presence of immigration, weakening the observed effect of immigration (Borjas 1999; 2006; Card, 2005; Card and DiNardo, 2000).

The empirical research finds modest effects of immigration on the labor market outcomes of native-born workers. The large body of research finds that immigration has a negative and small, albeit statistically significant and consistent, impact on wages (Longhi, Nijikamp, and Poot, 2005, 2010; Kerr and Kerr, 2011). However, some authors have found a positive impact on productivity and wages (Hotchkiss, Quispe-Agnoli, and Rios-Avila, 2015; Peri, 2012; Peri and Sparber, 2009), with only a few studies showing evidence of more significant negative effects of immigration (Borjas 2003; Altonji and Card 1991), in particular when looking at the impact of less-educated and younger workers (Orrenius and Zacodny, 2007; Ottaviano and Peri, 2012;).

[2] We assume that if an individual was not followed in the CPS from one month to the next, it was because they have moved to a different location. Thus, while attrition may raise a concern, we run robustness tests that confirm that this is not an issue.

The evidence regarding job displacement, employment, and unemployment is also mixed. The meta-analysis study of Longhi, et al. (2006, 2010) suggests that immigration has a small effect on the native-born employment rate and employment probability. Most of the evidence also indicates that unemployment rates do not seem to be affected by immigration in the aggregate, even among young and minority workers (Islam 2007; Shan 1999; Winter-Ebmer and Zweimüller 1999; Pischke and Velling, 1997). Nevertheless, some of the literature (Card 2001; Frey 1996; Borjas 2003; Borjas et al. 2010; Smith, 2012; Glitz, 2012) states that immigration significantly reduces employment, increases unemployment, and increases native-born workers' outmigration. On the other hand, some findings suggest that the immigration of low-skilled workers may have had a positive impact on the native labor supply of high-skill workers (Cortés and Tessada 2011).

Immigration and Unemployment Duration: The Effect of the Native Unemployed

Unemployed natives may be affected by the presence of immigrants in the labor market conditional on the characteristics of the migrants. If migrants are perfect substitutes for native unemployed, they may have to compete with them to find jobs. On the contrary, if migrants are not perfect substitutes for native workers, the effect may be null or even positive if they build synergies to create new business. However, there has been very little attention paid to the impact immigration has on unemployed natives, their employment status prospects, and unemployment duration. Instead, most of the literature has concentrated on analyzing the aggregate effects of immigration on unemployment rates or job displacement.

To the extent of our knowledge, only Winter-Ebmer and Zweimüller (2000) explicitly study the impact of immigration on unemployment duration. Using data for Austria, they find that immigration increases the length of unemployment spells of natives but find no effect on the probability of becoming unemployed. A few other studies, however, have indirectly studied the impact of unemployment duration, providing some evidence of the relationship between immigration and transitions out of unemployment. Chapman and Cobb-Clark (1999), using data for Australia, finds that immigration has a positive impact on the employment opportunities of unemployed residents in the short run due to the additional consumption effect. The authors warn that the immigration effect may become negative in the long run as more immigrants enter the labor market. Cohen-Goldner and Paserman (2006) find that immigration has no effect on the probability of natives moving into a job but increases the probability of natives moving to non-employment in Israel. Venturini and Villosio (2006) indicate that immigration effect on transitions from unemployment to employment has changed through time, reducing the probability of transitioning from unemployment to employment in 1993, but finding either no effect or a positive effect in later years.

Most of the literature has focused on analyzing the impact of immigration on unemployment and the unemployment rate, with mixed conclusions. Papers such as Simon et al. (1993) for the U.S., Pischke, and Velling (1997) and Glitz (2012) for Germany, Withers, and Pope (1985) for Australia, Blanchflower and Schadforth (2009) for the U.K., Boubtane et al. (2013) for the OECD countries, and Del Carpio et al. (2015) for Malaysia, find, for the most part, no observed change in native unemployment due to an increase in immigration. On the other hand, Fromentin (2012) and Jean and Jimenez (2011), using aggregated panel data for OECD countries, find that immigration increases short-term unemployment but reduces long-term unemployment for native-born workers. Given the inflows of migrants across the country, along with the existing evidence for other countries, the US presents itself as an interesting setting to study the effect of immigration on unemployment. As was argued before, immigration in the US can increase unemployment duration given the size of the migration phenomenon and the fact that immigrants tend to locate in regions with high economic activity. In contrast, likely, immigration does not affect unemployment, given the characteristics of migrants. However, to the best of our knowledge, there is no research for the U.S. studying the impact of immigration on the labor market outcomes of the unemployed native-born.

Data and Summary Statistics

Data

The study uses the basic monthly data of the CPS from January 2001 to December 2018, obtained from the Integrated Public Use Microdata Series (IPUMS). The CPS is a monthly household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics and designed to be the primary source of labor force statistics in the U.S. Data for approximately 140,000 individuals living in 70,000 households is collected each month.

One feature of the CPS is its rotating panel design. Each household participating in the survey is interviewed for four consecutive months, excluded for eight months, and interviewed again for an additional four months. In any given month, approximately 75% of the households are interviewed for two consecutive months. Thanks to this feature, individuals can be followed to analyze their short-term labor force dynamics. For this paper, we use CPS-IPUMS constructed variable *CPSIDP* to link an individual's data from one month to the next. This variable is constructed following the methodology described in Drew, Flood, and Warren (2014), and Madrian and Lefgren (2000).

As described in the literature, linking CPS data across time is difficult, as the survey questions themselves might have changed, the individuals might have moved out of the household and are no longer followed, or they may have refused to participate in the survey. There can also be some level of data error that will prevent the accurate matching of data from one month to another which implies that individuals at any point in time can be classified into three different groups based on the matching success (i.e., individuals are accurately matched; they are incorrectly matched to a different individual in the following month, or no match is found due to attrition or data errors). For this paper, we exclude individuals interviewed in the fourth and eighth rounds because there is no match for them due to data design.

While the identification strategy described in Drew, Flood, and Warren (2014) to link individuals addresses most of the significant concerns regarding month-to-month matching when using the *CPSIDP* variable, further restrictions are imposed on the match to improve the quality of the data. Bad links are identified if an individual's sex, race, citizenship status, or country of birth differs across linked data, or if there is a difference larger than four years in the age from one month to the other.[3] Less than 1% of the data falls under the inaccurate mismatch classification, which is reclassified within the attrition group.

Since the purpose of this research is to estimate transition rates out of unemployment without considering the stability of such change, transitions are identified based on linked data for two consecutive months.[4] Also, the analysis concentrates on native-born U.S. citizens, excluding individuals born outside of the U.S., who are between 18 to 64 years of age, and those who declared to be unemployed at the time of the survey.

For the main explanatory variable in the paper, we use a state-level time-specific immigration-to-population ratio (IMM) based on data from the monthly CPS. This variable is defined as the ratio between people born outside of the U.S., who are noncitizens, to all individuals between 18 to 64 years of age living in the same state. While using monthly CPS data might allow us to have variation across time, the CPS data might not be enough to provide accurate estimations of the immigration-to-population ratio at the state level for each month. Furthermore, this may cause what is known as the "attenuation bias" problem (Aydemir and Borjas, 2011), which may create a downward bias on the estimations.

Given the volatility of this measure when using monthly data, especially in states with low levels of immigration, IMM is calculated using semiannual data. For instance, when estimating IMM for Georgia in February of 2013, we would pool the data from January to June of 2013. This procedure allows for a more accurate measure of the IMM for each state, preserving the long-run immigration trends, reducing the impact of attenuation bias, and allowing for variation across time.

Summary Statistics

After constraining the data, we end up with 489,471 observations, from which about 103 thousand are employed in the next month, 83 thousand leave the labor force, and 255 thousand remain unemployed. No match was found for about 36 thousand observations due to attrition or error. In fig. 1, we present the simple averages of the share of native-born citizens between 18 to 64 years of age who transition out of unemployment by finding a job, leaving the labor force, or due to attrition.

On average, 52.5% of all citizens in the sample who are currently unemployed remain unemployed for an additional month, 20.4% end their unemployment spell by becoming employed, 19.5% exit the labor force, and 7.5% fall into attrition. Looking at these transitions rates across time, we observe that the risk of attrition has shown little fluctuation through the period of analysis. The risk of individuals leaving the labor force shows a decline around the end of the Great Recession (June 2009), but showing a small upward trend since March of 2009 to the end of 2018. Similarly, while between January 2001 and August 2008, the average transition towards employment was about 23.8%, it shows a significant decline after the end of the Great Recession. Afterward, a small and steady improvement can be observed, although this transition remained

[3] For race, we use the aggregate classification of white, black, hispanic, or other. For country of birth we use a dual classification of U.S. born or born abroad.

[4] Later in the paper we use information for individuals interviewed for three or more consecutive months to assess the robustness of the results to spurious employment status changes, as in Rothstein (2011).

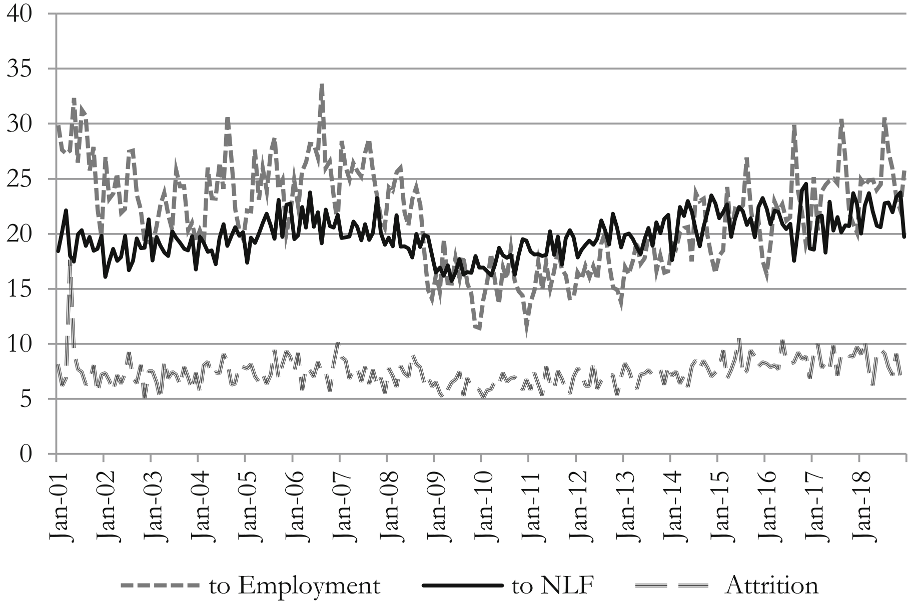

Fig. 1 Transitions rate out of unemployment

below the transition rate out of the labor force until the end of 2015. After 2016, however, the transition into the labor force is higher than the transition out of the labor force.

In terms of immigration, we observe that the share of non-citizen immigrants presented an upward trend until right before the Great Recession, showing an upward trend from 9.3% to just over 10% at the beginning of the recession (see Fig. 2). Afterward, a sharp decline in immigrants through the end of the recession was observed, with the share of immigrants remaining at around 9.5% until the end of 2015, with a small increase afterward, remaining stable just below 10% until the end of the period of analysis.

Table 1 presents the summary statistics of the variables included in the model by employment status, except for state, year, and month. In Appendix Table 10, we also present the proportion of individuals in each particular employment status for different demographic groups. The transition rates across different levels of the immigration rate show little variation compared to the overall average. However, the proportion of people transitioning to employment declines slightly in areas with a higher concentration of immigrants. In contrast, the proportion of individuals leaving the labor force and falling into attrition shows a small increase. If instead the data is classified using the change in the immigration-to-population ratio based on quartiles, we observe that the proportion of individuals transitioning into employment and leaving the sample is higher in areas with more significant changes in the immigration ratio. However, no clear trend regarding individuals leaving the labor force is observed.

There are more women among the people who exit the labor force, which translates into a higher proportion of unemployed women leaving the labor force compared to men. People who leave the labor force, followed by those who fall into attrition, are relatively younger compared to the overall average. In terms of education, natives with

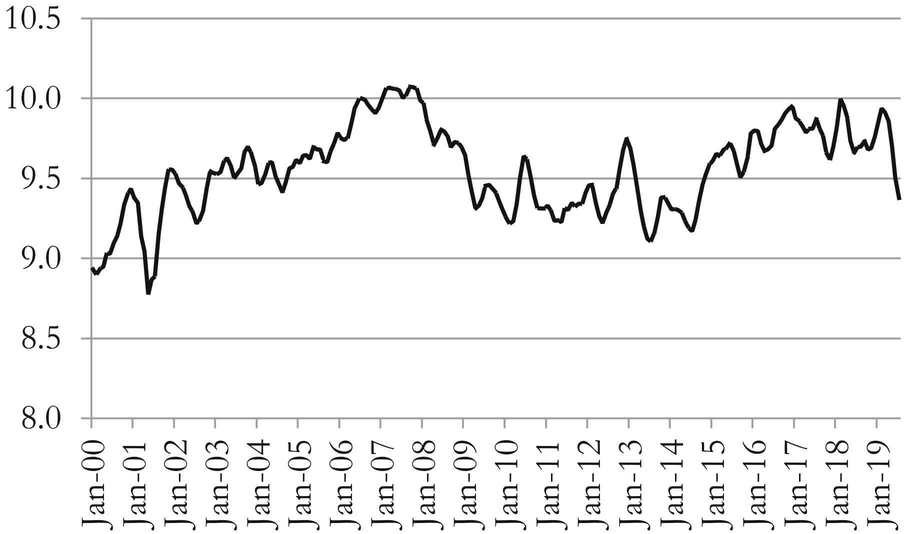

Fig. 2 Immigration-to-population ratio in the US

less-than-high-school education are more common among people who leave the labor force. In contrast, those with higher levels of education seem to be more likely to remain unemployed or transition into employment. There is a larger share of white people among those who move into a job or remain unemployed. At the same time, minorities are relatively more represented among those who leave the labor force or leave the sample.

In terms of household demographics, workers who have never been married (single) represent a larger share of the individuals who leave the labor force or are not matched. In the data, individuals who left the labor force are also characterized as living in larger households. It is not surprising that there are fewer homeowners among individuals in the attrition group, with a relatively more significant proportion among those who become employed.

Finally, when looking at labor market conditions, workers who remain unemployed live in states with lower growth rates and longer available weeks of unemployment insurance benefits. There are fewer job losers among those who leave the labor force, and fewer newly unemployed entrants and reentrants among those who remain unemployed or transition into employment. People who are currently going to school or are looking for a part-time job are the least common among those who remain unemployed and leave the sample. Lastly, people who become employed are more likely to have been unemployed for a shorter time. In contrast, those who leave the labor force have similar unemployment duration patterns as to the whole sample.

The Econometric Approach

The econometric approach employs a discrete hazard model, also known as a discrete-time transition model (Cameron Trivedi, 2001; Alisson, 2014), to analyze the factors affecting the probability of an unemployment spell to end from one month to the next.

Table 1 Summary Statistics

Status at t + 1				
Immigration ratio	E	NLF	A	U
0–5%	21.2	19.0	7.3	52.5
5–10%	20.5	19.0	7.5	53.0
10–15%	19.6	20.1	8.0	52.3
15 + %	19.6	20.5	7.5	52.4
Total	20.4	19.5	7.6	52.6
Immigration-ratio Change				
1st Quartile	19.7	19.5	7.5	53.4
2nd	19.9	18.9	7.3	54.0
3rd	20.8	19.7	7.4	52.1
4th Quartile	21.3	19.8	8.0	50.9
Demographics				
Immigration-to-population ratio	8.86	9.21	9.13	9.04
Sex				
Men	56.4%	49.0%	56.4%	55.5%
Women	43.6%	51.0%	43.6%	44.5%
Age				
18–24	30.7%	37.0%	35.5%	29.2%
25–39	34.0%	30.3%	38.3%	33.9%
40–54	25.6%	22.0%	20.4%	26.2%
54+	9.7%	10.7%	5.8%	10.8%
Education				
Less than high school	12.8%	19.8%	19.0%	15.7%
High school	37.1%	38.6%	40.4%	38.4%
Some college	31.7%	29.8%	27.7%	29.8%
College+	18.5%	11.9%	13.0%	16.1%
Race				
White	67.7%	56.1%	55.6%	61.6%
Black	17.0%	25.7%	26.2%	22.3%
Other	4.2%	5.3%	5.4%	4.6%
Hispanic	11.1%	12.9%	12.8%	11.4%
Household Demographics				
Civil status				
Single	49.41%	57.22%	59.60%	48.97%
Married	34.96%	27.79%	22.56%	32.63%
Separated/divorced/widowed	15.62%	15.00%	17.84%	18.40%
#Children 0–13	0.61	0.66	0.65	0.61
#Children 14–17	0.20	0.22	0.17	0.19
#Elderly in household	0.09	0.13	0.09	0.12
Household size	3.23	3.43	3.18	3.14
Homeownership	59.49%	55.28%	40.20%	56.50%

Table 1 (continued)

Status at t + 1				
Immigration ratio	E	NLF	A	U
Labor Market Conditions				
Log (min wage)	1.89	1.91	1.92	1.92
Log (# of max weeks of UI benefits)	3.63	3.69	3.66	3.78
% Potential UI beneficiaries	89%	78%	84%	80%
State GDP pc growth	0.80%	0.76%	0.73%	0.56%
Labor Market Experience				
Why unemployed?				
Laid off	59.0%	39.4%	51.2%	60.2%
Quit job	11.7%	9.5%	12.2%	9.8%
Entry/reentry	29.3%	51.1%	36.7%	30.0%
Goes to school or college	8.0%	11.7%	6.6%	4.7%
Looking for part-time job	15.4%	20.3%	10.3%	8.3%
Unemployment duration				
Less than 1 month	31.27%	18.10%	21.50%	13.87%
1 month	19.02%	15.33%	17.06%	14.42%
2 months	12.85%	11.95%	13.24%	12.03%
3–5 months	17.11%	17.44%	19.07%	20.97%
6–8 months	7.79%	10.75%	9.91%	11.94%
9–11 months	2.67%	4.09%	3.67%	5.22%
12–17 months	5.45%	11.55%	8.63%	11.49%
18–23 months	0.61%	1.14%	1.02%	1.64%
More than 24 months	3.22%	9.64%	5.90%	8.42%
Number of observations	103,988	93,702	36,529	255,252

Note: Averages were estimated using sample weights. E = employment, NLF = not in the labor force, A = attrition, U = unemployment

The identification of the impact of immigration is based on an area analysis approach that uses the variation in the changes in immigration concentration across states and time to identify the effect of immigration on labor market transitions and a Bartik-type instrument to address for potential endogeneity problems (Okkerse 2008; Altonji and Card, 1991; Cortés and Tessada, 2011). In the next section, we describe the basic set up of the econometric model, discuss the problem of potential endogeneity, and outline the identification strategy based on an instrumental variable approach. Lastly, we describe the model specification.

Discrete-Time Hazard Model

In the framework of a discrete-time hazard model (Alisson, 2014), the objective is to model the probability that a current unemployment spell of a native-born citizen ends in the current period, given that it has lasted at least for T periods, conditional on a set of individual and labor market characteristics (X):

$$h_i(T_i, X_i) = P_{i,t}(T_i = t | T_i \geq t, X_i) \quad (1)$$

Defining the variable δ_i as an indicator that takes the value of 1 if an individual leaves unemployment and zero if he remains unemployed, the likelihood function of the model may be written as:

$$L = \prod_{i=1}^{n} \left(h_i(T_i, X_i)^{\delta_i} \times (1 - h_i(T_i, X_i))^{1-\delta_i} \prod_{t=1}^{T_i - 1} (1 - h_i(t, X_i)) \right) \quad (2)$$

Where the first term indicates the probability that an unemployment spell ends exactly after T_i periods ($\delta_i = 1$), after having survived for at least T_i periods and the second is the probability that the unemployment spell would continue afterward ($\delta_i = 0$).

Since the structure of the CPS allows observing only a fraction of the unemployment history of individuals, the likelihood function needs to be adjusted to take into account that unemployment spells are not observed unless they have lasted for at least T_i periods. Under this assumption, the conditional likelihood function becomes:

$$L|_{T > T_0} = \prod_{i=1}^{n} h_i(T_i, X_i)^{\delta_i} (1 - h_i(T_i, X_i))^{1-\delta_i} \quad (3)$$

Reducing the model estimation to a standard binomial model. If an individual remains unemployed in the next period, its contribution to the likelihood function is given by 1 $- h_i(T_i, X_i)$, and if that individual transitions out of unemployment (for example exits the labor force) its contribution to the likelihood function is given by $h_i(T_i, X_i)$.

Discrete Competing Risks Model

Given that we can identify different reasons why individuals are no longer unemployed, the discrete hazard model can be extended to allow for a competing risk framework.[5] Similar to the framework used in Farber and Valletta (2015), transitioning to employment and out of the labor force is considered as competing events. Also, we identify attrition as a third competing event that might end the unemployment spell since the decision to move to a different location might be driven by the presence of immigrants in the region (Pedace, 1998; Card and Dinardo, 2000; Borjas, 2006).[6]

Following the nomenclature of Allison (2014), we differentiate the hazard rate for each of the four possible events that could cause the unemployment spell to end and define the overall hazard as the sum of each case-specific hazard:

$$h_{i,k}(T_i, X_i) = P_{i,k,t}(T_i = t, k_i = K | T_i \geq t, X_i) \; for \; k \in [E, N, A] \quad (4)$$

[5] These types of models have been proposed explicitly and implicitly in the literature when analyzing unemployment transitions in work by Farber and Valletta (2015), Allison (2014), and Baussola and Mussida (2014), among others.

[6] Nevertheless, as robustness checks, we also estimate models to test the sensitivity to including attrition as a competing event by excluding observations that fall in this category, adjusting sample weights after observations are excluded, and considering attrition as remaining unemployed.

$$h_i(T_i, X_i) = \sum_{k\in[E,N,A]} h_{i,k}(T_i, X_i) \tag{5}$$

where K indicates if the unemployment spell ended with the individual transitioning into employment (E), exit the labor force (N), or is no longer followed in the data (A). Substituting Eqs. 5 and 6 into the modified likelihood function shown in eq. 3, it can be shown that:

$$L|_{T>T_0} = \prod_{i=1}^{n} h_{i,E}(T_i, X_i)^{\delta_{i,E}} h_{i,N}(T_i, X_i)^{\delta_{i,N}} h_{i,A}(T_i, X_i)^{\delta_{i,A}} (1-h_i(T_i, X_i))^{1-\delta_{i,E}-\delta_{i,N}-\delta_{i,A}} \tag{7}$$

Under the assumption that the hazard risks are independent of each other (conditional on observed characteristics), and that there is no unobserved heterogeneity, we use a multinomial logit to estimate the above model for its tractable estimation and convergence properties. [7]Using the censored status (i.e., remaining unemployed) as the baseline category, the parametrization of each hazard rate becomes:

$$h_{i,k}(T_i, X_i, g(.), \alpha) = \frac{\exp(g_k(T_i) + \alpha_k X_i)}{1 + \sum_{j=E,N,A} \exp\left(g_j(T_i) + \alpha_j X_i\right)} \text{ for } k = E, N, A \tag{8}$$

where T_i is the unemployment spell length of individual i, X is a set of controls that affect the employment transitions probabilities of individual i, $g(.)$ is a set of flexible functions of the length of the current unemployment spell that would allow identifying the duration dependence of each specific hazard function, and α is the set of all parameters associated with the characteristics X.

Identification Strategy

In the model, we identify the effect immigration has on all-hazard functions by exploiting the variation in the changes in the immigration-to-population ratio across states and time. Initially, under the assumption that immigration flows are exogenous, and by controlling for all other factors that may affect individuals' propensity to end their unemployment spells, this strategy would allow us to identify the effects of immigration on the probability of unemployment spells ending (and indirectly on the duration of unemployment).

One drawback of this strategy is that even after controlling for observed characteristics, unobserved factors that affect the specific hazard rates at the regional level may also influence immigrants' decisions to relocate into a state, creating a potential endogeneity problem. For example, research shows that immigrants are more likely to be attracted to regions with high economic growth (Gurak and Kritz, 2000). If these

[7] As argued in Addison and Portugal (2003), decisions over the model specification are often done based on criteria of flexibility and tractability. For the purpose of our research, it is important to maintain a simple framework to address the potential problem of endogeneity on our main variable of interest, for which a model of independent competing risks was chosen. Nevertheless, based on the results from Addison and Portugal (2003), parametric corrections to unobserved heterogeneity does not yield substantial changes to the results that ignores unobserved heterogeneity.

regions are also characterized by having higher probabilities of finding a job, we may be more likely to find a positive impact of immigration on employment, even if immigration inflows deteriorate the labor market opportunities of natives.

To address this potential source of endogeneity, we follow the literature and use settlement patterns of previous immigrants to construct a Bartik-type instrumental variable (Bartik, 1991; Altonji and Card, 1991; Card and DiNardo, 2000; Cortés and Tessada, 2011; Card, 2001). This instrument is motivated by the fact that immigrants' location choice is profoundly affected by past immigration settlements (Bartel, 1989; Munshi 2003). New immigrants may have a preference for moving to areas with a more significant number of immigrants from their same nationality, culture, or language, as they expect these broader social and economic networks may facilitate their integration into society and the job market. Under the assumption that immigration settlements are uncorrelated with current economic performance, this instrument can be used to identify the impact of changes in immigrant concentration has on unemployment exit rates, which is generated by push factors.

Data from the Census 1980 is used to identify the settlement patterns of immigrants by region of origin[8] across states, in the U.S. These shares are then used to allocate immigration from the year 2001 to 2018 across states. For instance, if 10% of all Mexicans in 1980 were living in New York State, the instrument would allocate 10% of all Mexican immigrants from 2001 to 2018 to New York State. Finally, the instrumented immigration ratio would be defined as the sum of all "allocated" immigrants in a given state/year/month, divided by the total population in that year:

$$IMM_{IV,s,t} = \sum_r \left(\frac{\#immigrants_{r,s,1980}}{\#immigrants_{r,1980}} * \frac{\#immigrants_{r,t}}{\#pop_{s,t}} \right) \tag{9}$$

where $IMM_{IV,\,s,\,t}$ is the instrumental variable of the percentage of immigrants as a share of the population living in a specific state s in a given period t; $\frac{\#immigrants_{r,s,1980}}{\#immigrants_{r,1980}}$ is the percentage of immigrants from region r living in state s in 1980; $\#immigrants_{r,\,t}$ is the total number of immigrants from region r living in the U.S. in period t; and $\#pop_{s,\,t}$ is the total population count in state s and period t. For consistency, all components of eq. (9) are estimated using the population of immigrants between the ages of 18 to 64 years of age who are non-citizens, divided by the overall state population of the same age.

While Bartik/shift-share instrumental variables are commonly used in the migration literature, Jaeger et al. (2018) and Goldsmith-Pinkham et al. (2018) have recently argued that its use and validity requires further scrutiny. On the one hand, Goldsmith-Pinkham et al. (2018) indicate that the validity of this instrument holds if the initial shares, or its main contributors, are exogenous in the framework of the analysis. On the other hand, Jaeger et al. (2018) state that Bartik type instruments may be biased if local labor markets are slow to adjust to immigration shocks.

[8] We choose to use regions instead of countries, because even at the national level the identification of immigrants for certain countries is not accurately captured in the data. The broad regions used in the data are: other North American countries, Mexico, other Central American countries, the Caribbean, South America, Europe, East Asia, South Asia, India/Southwest Asia, Middle East/Minor Asia, Africa, and Oceania.

While, in principle, we agree with these authors, we argue that these limitations may be less relevant because of local labor market opportunities. In particular, out of unemployment transition rates, at the state level, may have already adjusted to the shocks that determined the initial immigration shares that are used to construct the instrumental variables. Furthermore, because we are using the change in immigration shares, instead of that the share in levels, we are also controlling for some of the dynamics of immigration in the model. Also, we argue that similar to the findings with regard to Card (2001), the use of immigrants region of origin is exogenous enough that it would be a reasonable instrument for the construction of the instrument variable and identification of the causal effect of immigration on employment opportunities, using national immigrant net flows as the source of variation that identifies effects of interest.

Implementation and Model Specification

The main control variable in the model is defined as the change in the state-level immigration ratio in the last 12 months ($\Delta\mathrm{IMM} = \mathrm{IMM_t} - \mathrm{IMM_{t-12}}$).[9] For the identification, we use the constructed Bartik-type instrument defined as the predicted annual change in the immigration-to-population ratio ($\Delta\mathrm{IMM_{iv}}$). As argued by Card and Peri (2016), these measures might capture a biased effect on labor market outcomes, because the change in the share of immigrants is affected not only by net-flows of immigrants but also by changes in the number of nonimmigrants in the area of residence. To address this concern, the main variable of interest is defined as follows:

$$\Delta\mathrm{IMM_t} = \frac{\#immigrants_{s,t} - \#immigrants_{s,t-12}}{\#pop_{s,t-12}} \tag{10}$$

With the instrumental variable being adjusted similarly following Basso and Peri (2015). Since the main model of interest is a non-linear model (Multinomial logit model), we implement a two-stage residual inclusion approach (2SRI), also known as control function approach, to account for the endogeneity problem (Terza, Basu, and Rathouz, 2008; Wooldridge, 2014; Petrin and Train, 2010). While this strategy may help to identify the short term impact of immigration on unemployment exit rates, recent research by Wan et al. (2018), have argued that 2SRI estimators may be inconsistent in the framework of survival models, because they do not account for the time dependence component. However, there is no indication of whether the introduced biased is better compared to a model that ignores endogeneity completely, especially when using short transition spells, as used here. In this regard, we believe that the bias of the proposed instrumental variable approach is less severe compared to ignoring that problem. Finally, to adjust for the fact that this is a two-stage procedure, standard errors are adjusted using a strategy similar to the one suggested in Wooldridge (2014) and implemented following Rios-Avila and Canavire-Bacarreza (2018), by estimating a simultaneous maximum likelihood model, explicitly allowing for the estimation errors of the first stage to be taken into account in the second stage estimation.

[9] When using the semi-annual pooled data, the change is defined as the difference in the immigration ratio of the current immigration ratio and the immigration ratio two semesters ago.

For the specification of the model, we follow the literature and use a specification similar to Meyer (1990), Valleta (2013), Addison and Portugal (2003), and Fabrizi and Mussida (2009), among others. As part of the explanatory variables, we include sex, age, education, and race to account for the differences in labor market opportunities that native citizens with different characteristics exhibit.

To capture individual job search preferences, and differences in the opportunity cost of longer unemployment spells, we include indicators for civil status (singe as a base category, married, and separated); the number of young children (0–13); the number of older children (14–17); the number of elderly (65+) in the household; and an indicator for homeownership. Moreover, to control for previous market experience, similar to Addison and Portugal (2003), we control for whether or not the individual is currently going to school (if an individual is younger than 24 years of age); if he or she is looking for part-time employment; and if he or she became unemployed because of job loss (base category), quit the job, or recently entered/re-entered the job market.

To control for the effect of the business cycles and local labor market health, we include the log of the minimum wage in the state (Wessels, 2005; Pedace and Rohn, 2011); the log of the maximum number of weeks of unemployment insurance (UI) available in a state in a given month and whether an individual unemployment spell is shorter than the maximum number of weeks of UI available in their state (Farber and Valletta, 2015; Meyer, 1990); and a measure for the growth in state-level GDP per capita (Bover, Arellano, and Bentolila, 2002; Gurak and Kritz, 2000). A full set of state, year, and month dummies are also included to control for unobserved factors that we are not able to control for otherwise.

Lastly, following the literature on duration models and survival analysis with discrete data (Cameron and Trivedi 2005; Allison, 2014), we account for the time dependence between the unemployment duration and the different hazard rates ($g_k(.)$) by including dummies that indicate how long an individual has been unemployed in the current spell.[10]

Results

Benchmark Model

Table 2 presents the relative risk ratios on the hazard of an unemployment spell ending due to employment, leaving the labor force or due to attrition based on the model described in section 4. These relative risk ratios represent the relationship between a variable X and the probability of an unemployed individual ending their current unemployment spell for a specific reason relative to the probability of remaining unemployed for an additional month. Given that the main reason why people would fall into attrition is that individuals or households moved from their current address (Madrian and Lefrge, 2000), we interpret attrition as weak evidence of unemployed natives migrating to a different location either within the same state or out of state.

[10] We use "less than one month" as the base category, identifying unemployment spells of one month, two months, between three to five months, six to eleven months, twelve to twenty-three months, and twenty-four months or more.

Nevertheless, it is imperative to acknowledge this is a loose interpretation, as this category also includes misclassified individuals or individuals who refuse to answer for idiosyncratic reasons.

For the benchmark model, we use the change in the semi-annual immigration ratio as the main explanatory variable and use the immigration settlements based on the Census data from 1980 for the construction of the instrumental variable. Since the variable IMM is constructed using pooled information, the results are clustered at the state and year/semester level. In addition to the variables presented in Table 1, the models control for the state of residence, year, and month fixed effects. The first-stage regression indicates an F-statistic of 25.8064, indicating a strong instrument.[11]

The estimations of the baseline model suggest that, on average, living in a state with a positive net-flow of immigrants reduces the likelihood of a worker remaining unemployed for an additional month. We observe this because the relative risk ratios associated with the change in the immigration ratio are larger than one for all potential exits. While the lower likelihood of remaining unemployed may translate into shorter unemployment spells.

According to the estimations, living in a state with a higher net-flow of immigrants does not affect the likelihood of an individual finding a job compared to remaining unemployed. Similarly, individuals show a small, positive (but not statistically significant) increase in the risk of leaving the sample due to attrition (1.013 rrr). Using the overall relative risk ratios, we estimate that a change in the immigration-to-population ratio of 1 pp. may increase the probability of leaving the labor force in 1.3%.[12] Putting things into perspective, the observed change in immigration in the period of analysis ranges from −0.85 pp. (10th percentile) to 1 pp. (90th percentile), with an average change of 0.09 pp., which implies that immigration net-flows may have a minimal effect on the probability of leaving the labor force. Two possible channels are explaining the effect of immigration on the probability of leaving the labor force. On the one hand, if immigration has a significant and negative effect on wages and employment, as suggested by Altonji and Card (1991), Card (2001) and Borjas (2003), native-born citizens will decide to leave the labor force in response to a decline in potential earnings and a decline in the availability of jobs in the local labor market caused by the net-flow of immigrants. On the other hand, even if wages are not strongly affected by immigration, as some of the literature suggests (Card, 2005; Pedace, 1998; Butcher and Dinardo 2002), unemployed native citizen's behavior might still be affected in the same way if they believe immigration will affect wages and the availability of jobs due to an increased competition effect.

When compared with the probability of remaining unemployed, there is little evidence to suggest that living in an area with a higher net flow of immigrants affects the employment opportunities of native-born unemployed workers. In other words, any two unemployed native-born individuals from different states have the same relative

[11] Results for the first-stage regression can be found in appendix Table 11.

[12] This estimation is obtained by calculating the change in the average relative risk ratios caused by an increase in the change of immigration-to-population of 1 percentage point. The new relative risk ratios are then used to estimate the new out of unemployment transition probabilities. These estimates of marginal effects are practically identical to the marginal effect obtained from estimating a multinomial probit model. These results are presented in appendix Table 13.

Table 2 Discrete Hazard Model: Relative Risk Ratios

	E		NLF		A	
	rrr	*se*	*rrr*	*se*	*rrr*	*se*
ΔIMM	1	(0.0443)	1.087*	(0.0485)	1.013	(0.0859)
Age Group (Base:18–24)						
25–39	0.904***	(0.0132)	0.917***	(0.0133)	0.852***	(0.0167)
40–54	0.801***	(0.0132)	0.910***	(0.0156)	0.627***	(0.0159)
55–64	0.700***	(0.0145)	1.097***	(0.0228)	0.451***	(0.0157)
Sex(Base: male)						
Female	0.979**	(0.0098)	1.275***	(0.0128)	0.984	(0.0132)
Race:(Base: white)						
Black	0.786***	(0.0112)	1.134***	(0.0160)	1.052**	(0.0224)
Other	0.880***	(0.0199)	1.152***	(0.0284)	1.093***	(0.0343)
Hispanic	0.927***	(0.0153)	1.092***	(0.0209)	0.983	(0.0244)
Education(Base: less than HS)						
High school	1.155***	(0.0172)	0.889***	(0.0124)	0.919***	(0.0179)
Some college	1.241***	(0.0190)	0.805***	(0.0115)	0.850***	(0.0197)
College degree+	1.315***	(0.0229)	0.643***	(0.0115)	0.799***	(0.0208)
Marital Status(Base: single)						
Married	1.160***	(0.0149)	0.982	(0.0136)	0.862***	(0.0175)
Sep/div/widow	1.052***	(0.0156)	0.961**	(0.0150)	1.154***	(0.0254)
#Children 0–13	0.979***	(0.0046)	1.022***	(0.0052)	0.969***	(0.0073)
#Children 14–17	1.016	(0.0102)	1.031***	(0.0112)	0.913***	(0.0146)
#Adult	1.086***	(0.0084)	1.168***	(0.0096)	1.021*	(0.0117)
#Elderly in household	0.953***	(0.0124)	1.193***	(0.0154)	0.913***	(0.0211)
Homeowner	1.045***	(0.0111)	0.977**	(0.0106)	0.594***	(0.0102)
Log (min Wage)	0.973	(0.0434)	1.05	(0.0538)	1.153	(0.1150)
Log (# of max weeks of UI benefits)	0.860***	(0.0288)	0.897***	(0.0304)	0.962	(0.0654)
Is eligible for UI	0.968	(0.0244)	1.008	(0.0208)	1.074**	(0.0332)
LM Experience (Base: laid off)						
Quit job	1.002	(0.0156)	1.350***	(0.0228)	1.169***	(0.0262)
Entry/reentry	0.903***	(0.0108)	1.998***	(0.0218)	1.173***	(0.0191)
Goes to school or college	1.165***	(0.0243)	1.247***	(0.0259)	0.929**	(0.0310)
Job Search (Base: looking for full-time job)						
Looking for part-time job	1.470***	(0.0216)	2.036***	(0.0286)	1.096***	(0.0260)
State GDP pc growth	4.532***	(1.6110)	3.035***	(1.1750)	0.719	(0.4900)
Unemployment duration (Base: less than 1 month)						
1 months	1		1		1	
2 months	0.615***	(0.0081)	0.837***	(0.0132)	0.764***	(0.0178)
3–5 months	0.512***	(0.0075)	0.803***	(0.0135)	0.724***	(0.0168)
6–8 months	0.409***	(0.0057)	0.719***	(0.0114)	0.633***	(0.0140)
9–11 months	0.341***	(0.0070)	0.787***	(0.0153)	0.609***	(0.0171)
12–17 months	0.278***	(0.0088)	0.758***	(0.0197)	0.562***	(0.0230)

Table 2 (continued)

	E		NLF		A	
	rrr	*se*	*rrr*	*se*	*rrr*	*se*
18–23 months	0.265***	(0.0068)	0.892***	(0.0191)	0.582***	(0.0198)
More than 24 months	0.210***	(0.0108)	0.745***	(0.0349)	0.583***	(0.0403)
Constant	0.214***	(0.0082)	0.994	(0.0318)	0.584***	(0.0283)
N	489,471					
IV F-stats (First Stage)	25.8064					

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered Standard errors at state and semester level in parenthesis. The model also includes state, year, and month dummies. ΔIMM: change in the immigration-to-population ratio; E: employed; NLF: not in the labor force; A: attrition

probability of transitioning into a job compared to remaining unemployed, regardless of how many immigrants moved into their state in the last year.[13]

The estimates also suggest that no evidence living in a state with a higher net-flow of immigrants changes the relative probability of an unemployed native-born citizen falling into attrition compared to remaining unemployed. Since the main reason why people would fall into attrition is that households moved from their current address (Madrian and Lefrge, 2000), this could be taken as evidence that unemployed native-born do not necessarily migrate as a response to the net-flow of immigrants, which is consistent with the findings of Card and Dinaro (2000) and Kritz and Gurak (2001). This does not necessarily contradict the findings on outmigration in Borjas (2003, 2006) and Frey (1996), as these results do not rule out the possibility that immigration net-flows affect the labor market decisions of native-born citizens who are employed or out of the labor force.

Regarding the rest of the variables, they follow patterns like those observed elsewhere in the literature (Valleta, 2013; Addison and Portugal, 2003; Fabrizi and Mussida, 2009; Meyer, 1990). As can be seen in Table 2, compared to the youngest cohort (18–24) all other individuals are less likely to end their unemployment spell for any reason, and only individuals 55–64 years of age have a higher risk (rrr = 1.097) of leaving the labor force relative to remaining unemployed. This can be related to a discouraged worker effect that older individuals face, facing the decision of early retirement (Coile and Levine, 2007). The estimates also indicate that the older an individual is, the less likely they are to find a job or fall into attrition.

In terms of gender and race, there is evidence of heterogeneity in the relative risks of ending their unemployment spells, as expected from the literature (Dawkins, Shen, and Sanchez, 2005). Being a man or a white native accelerates the exit out of unemployment and into a job for native-born citizens and reduces the odds of leaving the labor

[13] Estimations ignoring the possible endogeneity problem of immigration suggest that native workers living in areas with larger net-flows of immigrants are more likely to transition into employment. This can be explained because immigrants may be more likely to be attracted to areas with higher economic activity, which would also be related to higher transitions towards employment. Appendix Table 13 provides the relative risk ratios for models ignoring the possible endogeneity problems. Also, this, however, does not imply that immigration has no effects on the availability of jobs or job displacement of native-born citizens in the local market who are currently employed or not in the labor force.

force compared to their counterparts. Nonwhite natives are more likely to fall into attrition compared to whites and less likely to find a job in the next period. Among nonwhites, blacks have the lowest relative risk of finding a job (0.79 rrr) and highest of leaving the labor force (1.134 rrr) (see Table 2). We also find evidence that education plays a vital role in terms of job opportunities and the opportunity cost of unemployed natives. Higher levels of education increase the likelihood of finding a job and reduce the likelihood of leaving the labor force or falling into attrition, akin to the findings in Riddell and Song (2011).

Heterogeneity of Immigration Effects

Most of the literature on the economic impact of immigration suggests that the impact of immigrants may have on native-born workers depends on the degree of substitutability or complementarity between citizens and immigrants in the labor market (Peri, 2011; Ottaviano and Peri, 2012; Borjas et al. 2010). This implies that there could be some heterogeneity in the effects of immigration depending on the characteristics of the native-born population and how similar they are to the immigrant population. We explore this possibility by estimating the baseline specification using subsamples based on sex, age, and education. The coefficients can be interpreted as a demographic-specific effect of immigration on the relative risk of ending the unemployment duration spell. These estimates are presented in Table 3.

We find some evidence that the impact of immigration net-flows is somewhat larger for women compared to men, which may be explained by the somewhat weaker attachment women have on the labor market. Overall, we observe that changes in the net-flow of immigrants have a small and non-statistically significant impact on the transitions into employment or attrition, regardless of the age of the native-born. We observe a minimal and marginally significant relative risk to leave the labor force for native-born between 24 and 39 years of age-. As described by Ottaviano and Peri (2012) and Peri and Sparber (2009), this can be explained because natives and immigrants with same levels of education may not be competing for the same jobs and because native-born workers, in particular young native-born workers, may have an advantage in accessing jobs that require communication skills.

The closest measure of skill in our data is the workers' education level. In terms of wages, most of the literature has found that immigration has the most significant negative impacts on low-skilled native-born workers, as they represent the closest substitutes (Altonji and Card, 1991; Card, 2001). There is also evidence suggesting that the presence of highly skilled immigrants slightly reduce the wages of highly skilled native-born workers (Borjas, 2005; Borjas, Grogger et al. 2010), although others show that immigration has a positive impact on high-skilled native-born workers' wages and labor supply (Ottaviano and Peri, 2012; Cortés and Tessada 2011). Overall, and consistent with the main results, the education-specific estimation suggests that immigration has no impact on the probability of finding a job or of attrition, but that it increases the relative probability of leaving the labor force, particularly for native-born citizens with a high school degree, and to a lesser degree for natives with some college education. On average, this translates into a lower probability of remaining unemployed for an additional month. The results also suggest that the effects of immigration are small for native-born citizens with a college degree.

Table 3 Discrete Hazard Model: Heterogeneity by Sex, Age, and Education

	E	NLF	A	1st stage F-stat	N
ΔIMM	1.000	1.087*	1.013	25.81	489,471
	(0.041)	(0.051)	(0.091)		
By sex					
ΔIMM*men	1.000	1.055	0.953	26.66	267,897
	(0.051)	(0.051)	(0.091)		
ΔIMM*women	1.006	1.117*	1.102	24.54	221,574
	(0.071)	(0.071)	(0.111)		
By age group					
ΔIMM*(18–24)	1.052	1.100	1.111	24.88	132,383
	(0.091)	(0.081)	(0.121)		
ΔIMM*(25–39)	0.962	1.110*	0.913	26.36	161,592
	(0.061)	(0.061)	(0.101)		
ΔIMM*(40–54)	0.981	1.068	1.104	27.34	137,127
	(0.061)	(0.071)	(0.131)		
ΔIMM*(55–64)	1.039	1.055	0.981	21.40	58,369
	(0.111)	(0.131)	(0.231)		
By education					
ΔIMM*Less than HS	0.949	1.085	1.004	21.95	74,841
	(0.091)	(0.111)	(0.151)		
ΔIMM*High school	0.930	1.157*	1.015	26.90	189,671
	(0.061)	(0.081)	(0.111)		
ΔIMM*Some college	1.100	1.136*	1.132	26.29	145,350
	(0.091)	(0.081)	(0.141)		
ΔIMM*College	1.010	0.867	0.811	20.01	79,609
	(0.081)	(0.091)	(0.121)		

Note: * p<0.1, ** p<0.05, *** p<0.01. Clustered Standard errors at state and semester level in parenthesis. All models include state, year, and month dummies. ΔIMM=change in the immigration-to-population ratio; E: employed; NLF: not in the labor force; A: attrition.

These observed effects regarding education can be explained to the extent that a large proportion of immigrants tend to be low-skilled workers (Passel and Cohn, 2015). In this sense, the estimated effects among low-skilled native-born individuals can be explained by the new labor market competition with the highly substitutable labor (low-skilled immigrants). In contrast, workers with a college degree are the least affected because they are not expected to compete for the same jobs with immigrants (Ottaviano and Peri, 2012), they may benefit from the lower opportunity cost of participating in the labor market (Cortés and Tessada, 2011), or because of they benefit from the improvements in economic activity immigration can have on the local economy (Hunt and Gauthier-Loiselle, 2010). An interesting finding, however, is that positive net-flows of immigrants affect native workers with high school education and some college degree, suggesting that may still face the same difficulties in the labor market as less qualified workers when competing against immigrants.[14]

The Dual Nature of Immigration

A critical characteristic of immigrants, particularly in the U.S., is that they tend to be overrepresented at both the low and high end of the skill distribution (Freeman, 2006; Card, 2005; Altonji and Card, 1991). To analyze the role of this duality, we construct two measures of immigration-to-population ratio differentiating between low-skill immigrants (less than high school or high school education), and high-skill immigrants (some college, college or more). The new measures are defined as the ratios of low-(high) skilled immigrants divided by the total population with the same skill level in the state and period. The results are presented in Table 4.[15]

Our estimations suggest that only changes in the share of immigrants among the low-skilled population have a barely statistically significant effect increasing the relative risk of leaving the labor force. When the model is estimated separately for low-skilled and high-skilled native-born citizens (lower panels on Table 4), we observe weak evidence that increases in both high-skill and low-skill immigrants' net-flows increases the relative risk of leaving the labor force for the low-skilled natives. This is consistent with the results presented in Table 3 when considering the effect of overall levels of immigration. Among high-skilled native-born citizens, we observe that an increase in the net flow of immigrants may increase the likelihood of employment, with some evidence that it reduces the likelihood of attrition. This is consistent with the findings in Cortés and Tessada (2011), which suggests that low-skill immigration may have the effect of increasing the labor supply of highly skilled women.

Immigration Ties and Types of Immigrants

There are different channels through which immigration affects transition rates out of unemployment. One channel through the role of the expectations that unemployed native-born citizens have regarding the effect of immigration on wages and the availability of jobs. Native-born citizens may expect that a wave of immigrants may deter (or increase) their options to find a job or depress (or boost) their wages, in which case the results should be weaker (or stronger) for individuals with closer ties to immigrants (Orrenius and Zavodny, 2012; Mayda, 2006; Scheve and Slaughter, 2001)., another channel through which immigration affects the labor market is through competition, the impact of immigration should be unaffected by the ties natives have to immigrants.

To examine this hypothesis, we identify citizens with close ties to immigration: individuals with immigrant parents or who identify as being Hispanic (69,028 observations). These groups are expected to have a more neutral view on

[14] This could be explained by the changes in immigration mean education which decreased in the less than high school group but increased slightly in the high school and some college group.

[15] For this specification, the instrumental variables are also constructed using the skill-specific concentration of immigrants across states.

Table 4 Discrete Hazard Model: Low- vs. high-skill Immigration

	E	NLF	A	1st stage F-stat	N
ΔIMM low-skill	1.007	1.046*	1.061	13.792	489,471
	(0.021)	(0.021)	(0.051)		
ΔIMM high-skill	1.000	1.029	0.894		
	(0.041)	(0.041)	(0.081)		
By Native-born Skill Level					
Low-skill natives ΔIMM low-skill	0.966	1.061*	1.046	13.491	264,512
	(0.031)	(0.031)	(0.051)		
ΔIMM high-skill	0.993	1.049	0.929		
	(0.051)	(0.051)	(0.091)		
High-skill native					
ΔIMM low-skill	1.047*	1.031	1.082	13.596	224,959
	(0.031)	(0.021)	(0.061)		
ΔIMM high-skill	1.007	1.013	0.851*		
	(0.051)	(0.061)	(0.081)		

Note: * p<0.1, ** p<0.05, *** p<0.01. Clustered Standard errors at state and semester level in parenthesis. All models include state, year, and month dummies. ΔIMM high (Low) skill: change in the high- (low-) skill immigration-to-population ratio; E: employed; NLF: not in the labor force; A: attrition. The skill level defined based on education attainment.

immigration, and the impact immigrants have on the job market (Suro, 2005; Rouse, Wilkinson, and Garand, 2010). The results in Table 5 suggest there is little evidence of heterogeneity regarding the impact of immigration on unemployment exit risks and, if anything, the impact seems to be somewhat larger for native-born citizens without ties to immigration, but that difference is not statistically significant.

A different aspect to be considered when analyzing the impact of immigration in the labor market is the type of immigrants themselves. While there is a relative consensus that unauthorized/undocumented immigration has a detrimental impact on the economy, in particular for low-skill workers, there is less research regarding

Table 5 Discrete Hazard Model: Heterogeneity by Immigration Background

	E	NLF	A	1st stage F-stat	N
Immigration Ties					
Non-Hispanic with both Parents U.S.-born*ΔIMM	0.969	1.105*	0.963	13.080	420,443
	(0.045)	(0.057)	(0.092)		
At least one immigrant parent or Hispanic * ΔIMM	1.051	1.076	1.087	13.080	69,028
	(0.055)	(0.058)	(0.100)		

Note: * p<0.1, ** p<0.05, *** p<0.01. Clustered Standard errors at state and semester level in parenthesis. All models include state, year, and month dummies. E: employed; NLF: not in the labor force; A: attrition. ΔIMM: Change in the immigration-to-population ratio.

the impact of authorized immigrants specifically (Orrenius and Zavodny, 2007; Ottaviano and Peri, 2012). Nevertheless, since legally authorized and naturalized immigrants are more likely to have better human capital, earn higher wages, and are more likely to promote economic growth (Peri, 2012), one would expect that they have a more positive impact on wages and jobs in the labor market.[16] Even if native-born workers are not able to distinguish between types of immigrants, their behavior might still respond to the signals in the labor market in terms of changes in wages and the availability of jobs.

We test this hypothesis by distinguishing between two types of immigrants, based on their potential legal immigration status in the country: *likely* authorized immigrants and *likely* unauthorized immigrants. The correct identification of both types of immigrants is problematic because likely unauthorized immigrants would be less willing to participate in surveys such as the CPS. Based on Passel and Cohn (2015), *likely* unauthorized immigrants are identified as immigrants with at most a high-school diploma and of Hispanic origin. All other immigrants are classified as being *likely* authorized immigrants. The instrumental variables are modified accordingly. Alternatively, following Borjas (2017), we also identify what likely unauthorized or undocumented immigrants based on year of immigration, citizenship status, veteran status, if he/she works for the government, if the immigrant was born in Cuba or if he/she is married to a citizen.

In Table 6, we present the estimations of two different specifications that include the alternative measures of likely authorized and unauthorized immigration. In the first set of results, we observe that the changes in the concentration of likely authorized immigrants have no statistically significant effect on the relative probability of leaving the labor force or of transitioning to employment or out of the labor force. The point estimates of the impact of likely unauthorized immigration are consistent with the benchmark model but are not statistically significant. Interestingly, the results also suggest that positive net-flows of likely authorized immigrants reduce the relative risk of attrition. In contrast, net-flows of likely unauthorized immigrants increases the risk of attrition.

In the second set of results, which uses Borjas (2017) identification of authorized and unauthorized immigration, provide results that are qualitatively similar to the first set of estimations, but with effects that are statistically significant for the risk of leaving the labor force. The results suggest that changes in the share of unauthorized immigration are associated with a small increase in the relative risk of leaving the labor force. In contrast, changes in likely authorized immigration reduce the risk of leaving the labor force. Nevertheless, based on the lower F-statistic of the instruments, the estimates' effects may be less reliable.

The results from these two specifications suggest that positive net flows of immigrants have no direct effect on job opportunities of native-born citizens, net inflows of unauthorized immigrants may generate a small increase in the risk of leaving the labor force or move to a different location. In contrast, net inflows of authorized immigrants seem to reduce both risks.

[16] For alternative explanations on the labor market effects of immigration see Chassamboulli and Peri (2015) and Orozco-Aleman and Gonzalez-Lozano (2018)

Table 6 Discrete Hazard Model: Role of Immigrant Legal Status

	E	NLF	A	1st stage F-stat	N
By Immigrant type: Passel and Cohn (2015)					
ΔIMM Likely authorized	1.008	0.894	0.704*	9.042	489,471
	(0.066)	(0.077)	(0.291)		
ΔIMM Likely unauthorized	1.061	1.089	1.348*		
	(0.067)	(0.086)	(0.141)		
By Immigrant type: Borjas (2017)					
ΔIMM Likely authorized	1.102	0.657***	0.670	11.913	489,471
	(0.134)	(0.181)	(0.203)		
ΔIMM Likely unauthorized	1.020	1.137*	1.173		
	(0.050)	(0.081)	(0.143)		

Note: * p<0.1, ** p<0.05, *** p<0.01. Clustered Standard errors at state and semester level in parenthesis. All models include state, year, and month dummies. E: employed; NLF: not in the labor force; A: attrition. ΔIMM: Change in the immigration-to-population ratio by legal immigration status.

Robustness

Up to this point, we have shown that changes in the immigration-to-population ratio do not have an effect on unemployment and a barely significant small effect on the probability of a native-born citizen of end their unemployment spell by leaving the labor force. Because of attrition and identification of unemployment transitions, the model may be providing inconsistent estimates of the effect of immigration on labor market transitions. In this section, we provide additional specifications to test the robustness of the findings.

Attrition

As indicated in the data section, we control for the impact of attrition in the analysis by considering this state as an additional competing event in the analysis of unemployment duration. However, Farber and Valletta (2015) and Addison and Portugal (2003), and Portugal and Addison (2008) exclude individuals that fall into attrition from their analysis to improve the quality of the data matches and transition, with the implicit assumption that this is not an option for the unemployed.

In Table 7, we provide additional evidence that tests the sensitivity of the results to the treatment of attrition using three specifications. In the first row, we re-estimate the model, excluding all observations that were classified as falling into attrition. In the second row of Table 7, we provide estimates of the model after adjusting the sampling weights based on an inverse probability weighting approach (Seaman and White, 2011), so that the weighted sample maintains the same data structure as the one used in the baseline model. Finally, in the third row, we provide estimates of the model under the assumption that attrition should be considered as if those individuals remain unemployed. As can be observed, the general conclusions from the baseline model are robust across the three alternative specifications.

Table 7 Discrete Hazard Model: The Role of the "Attrition" Category

	E	NLF	1st stage F-stat	N
Excluding Attrition	1.000	1.093**	25.506	452,942
	(0.0442)	(0.049)		
Excluding Attrition w/weight adjustment	0.998	1.090**	25.675	452,942
	(0.0441)	(0.0487)		
Attrition as Censored	1.000	1.087**	25.842	489,471
	(0.0420)	(0.0480)		

Note: * p<0.1, ** p<0.05, *** p<0.01. Clustered Standard errors at state and semester level in parenthesis. All models include state, year, and month dummies. ΔIMM: change in the immigration-to-population ratio; E: employed; NLF: not in the labor force.

Spurious Transitions

Two aspects to consider for the validity of the analysis is the potential presence of spurious transitions out of unemployment (Farber and Valleta 2015; Rothstein 2011) and the decline in the quality of employment/unemployment status data across the household survey participation rounds (Krueger et al. 2017). Both potential problems can cause one to overestimate the probability of exit from unemployment, therefore biasing the results.

According to Krueger et al. (2017), households tend to provide better quality information regarding employment, unemployment, and unemployment duration during rounds one and five of their participation in the CPS. To reduce the risk of spurious transitions in the data, in the first row of Table 8, we estimate the benchmark model constraining the data to individuals who were interviewed during the first and fifth rounds of their survey participation (approximately 167,000 observations). Our estimates indicate that the overall conclusions do not change. However, the effect on the relative risk of leaving the labor force is somewhat smaller and non-significant, compared to the benchmark model.

The second strategy used in the analysis is the reclassification of potentially spurious transitions, similar to Farber and Valletta (2015) and Rothstein (2011). Using matched data for three consecutive months, individuals who are classified as unemployed in the first period, employed in the second, and unemployed again (UEU), are reclassified as if they never left unemployment (UUU), with a similar reclassification for individuals who left the labor force but return to unemployment (UNU- > UUU). This reclassification increases the average share of individuals who remain unemployed from 52.1% to 57.2%.[17] The estimates presented in Table 8 correspond to the spurious consistent estimation for the full dataset (rows 2 and 3). Because transitions between unemployment and leaving the force are more likely to happen for marginally attached individuals, we also estimate a

[17] Additional models were also estimated by restricting the sample to observations that remain in the sample for 3 consecutive periods, with similar results. These models are available upon request.

Table 8 Discrete Hazard Model: Robustness to Spurious Transitions

	E	NLF	NLF - U	A	1st stage F-stat	N
Restricted sample						
MIS1 & MIS5	0.986	1.059		1.930	26.981	166,947
	(0.0586)	(0.0561)		(0.101)		
Adjusting for spurious transitions						
Adjustment UEU→UUU	0.989	1.084*		1.010	25.842	
	(0.046)	(0.048)		(0.086)		
Adjustment UNU→UUU	0.987	1.092*		1.008	25.842	
	(0.045)	(0.047)		(0.086)		
NLF→ NLF-U	0.990	1.095*	1.036	1.010	25.842	
	(0.046)	(0.049)	(0.075)	(0.086)		

Note: * p<0.1, ** p<0.05, *** p<0.01. Clustered Standard errors at state and semester level in parenthesis. All models include state, year, and month dummies. E: employed, NLF: not in the labor force; NLF-U: NLF that was reclassified as unemployed; A: attrition. Estimates correspond to the rrr of ΔIMM.

model using this scenario (UNU) as an additional competing event (row 4). The results remain robust to the benchmark models.

Alternative Identification Strategies

While our main results are robust and the F-statistic shows that our instrument is strong, for most of the estimates, some recent literature argues that the use of Bartik instruments may lead to biased results (Jaeger et al. (2018) and Goldsmith-Pinkham et al. (2018)). As was explained before, the endogeneity between labor markets and immigration requires the use of instrumental variables (i.e., Bartik instrument). A source of

Table 9 Effects of Immigration using skill markets

	E	NLF	A	Avg U. Spell
Change in Immigration Share	0.194	0.282	−0.0405	−0.0604
	(0.542)	(0.363)	(0.128)	(0.123)
Avg U. Spell	-1.067^{***}	−0.193	−0.0550	
	(0.352)	(0.254)	(0.0728)	
_cons	128.9^{***}	67.36^{***}	17.50^{***}	27.27^{***}
	(9.617)	(6.941)	(1.987)	(0.0744)
N	250	250	250	250

Avg. U. Spell=Average Length of Unemployment spell. All regressions weighted by sample size and include year, education, and age fixed effects, as well as their interactions.

* $p < .1$, ** $p < 0.05$, *** $p < 0.01$

this endogeneity is the non-randomness location choice of the immigrant, as they may migrate to areas with better labor market conditions. Thus, to mitigate this bias, we follow Borjas (2003) in defining the labor market as a different skill market instead of by states, where the main independent variable is defined as the change in the share of immigrants within skill sub-groups across periods. Since it is harder for immigrants to move to another skill market than to move to another region, this approach should mitigate the bias in the endogeneity related to the location choice of immigrants. Overall, most effects are small and not statistically significant at conventional levels. Similar to our main results. However, positive net immigration increases have a small effect increasing the likelihood of leaving the labor force and finding a job, with a possible, reducing effect on unemployment duration.

Conclusion

In this paper, we have explored the effects that immigration has on the unemployment duration of native-born citizens in the US, using a discrete duration model with competing risks. We concentrated our interest in unemployed individuals, as they are the most likely to be affected by the presence of immigrants when searching for jobs in the labor market.

Based on our estimations, the evidence suggests that immigration does not affect the relative risk of a native-born unemployed citizen to transition into a job in the following month successfully. We also find that immigration as a whole does not affect the risk of attrition, but find some weak evidence that unauthorized immigration may increase the risk of attrition, which we associate with weak evidence that immigration has an outmigration effect on the unemployed as described in the literature. Also, we find a marginally significant and small risk of unemployed native-born citizens' leaving the labor force if they live in a state that experiences a significantly significant and positive net flow of immigrants. While the estimated effects are small across all groups, they suggest the effect may be more prevalent among relatively young unemployed women with a high school degree. These results are relevant for the unemployed population but cannot be generalized for other populations.

Acknowledgments We would like to thank Catalina Amuedo-Dorantes, Klaus Zimmermann, and the participants at the Bolivian Development Conference and the Latin American Meetings of the Econometric Society in for helpful comments and suggestions.

Authors' Contributions Both Authors (FRA and GJCB) contributed equally.

Compliance with Ethical Standards

Conflict of Interests The authors declare that they have no conflict of interests to disclose.

Availability of Data and Material The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Appendix

Table 10 Transition Rates by Selected Characteristics

Immigration rate	E	NLF	A	U
0–5%	21.22	18.97	7.29	52.52
5–10%	20.54	18.99	7.50	52.98
10–15%	19.61	20.14	8.01	52.25
15 + %	19.56	20.48	7.54	52.42
Total	**20.41**	**19.48**	**7.55**	**52.56**
Sex				
Male	20.76	17.21	7.67	54.36
Female	19.97	22.32	7.39	50.33
Age				
18–24	21.49	24.73	9.20	44.59
25–39	20.52	17.43	8.53	53.52
40–54	19.95	16.39	5.88	57.78
54+	18.27	19.25	4.06	58.41
Education				
Less than high school	16.62	24.52	9.11	49.75
High school	19.69	19.58	7.94	52.79
Some college	21.65	19.44	7.00	51.90
College+	23.52	14.40	6.10	55.98
Race				
White	22.43	17.75	6.82	53.00
Black	15.51	22.40	8.87	53.22
Other	18.64	22.38	8.74	50.24
Hispanic	19.80	21.94	8.44	49.83
Household demographics				
Civil status				
Single	19.59	21.66	8.74	50.01
Married	22.72	17.24	5.42	54.62
Separated/divorced/widowed	18.62	17.06	7.86	56.46
#Children 0–13				
None	20.59	18.91	7.44	53.06
1+	20.07	20.53	7.75	51.65
#Children 14–17				
None	20.32	19.02	7.72	52.94
1+	20.88	21.86	6.64	50.62
#Adults in household				
None	17.7	17.1	8.32	56.89
1	21.1	18.13	7.29	53.48
2+	21.22	22.91	7.4	48.47

Table 10 (continued)

Immigration rate	E	NLF	A	U
#Elderly in household				
None	20.76	19.11	7.72	52.4
1+	17.01	23.02	5.88	54.09
Home ownership				
Not homeowner	18.64	19.64	10.18	51.54
Homeowner	21.82	19.36	5.45	53.37
Unemployment insurance UI				
Not a potential UI beneficiary	11.94	23.55	6.66	57.85
Potential UI beneficiary	22.28	18.58	7.75	51.39
Labor market experience				
Why unemployed?				
Job loss	21.81	13.91	6.99	57.29
Quit job	23.15	18.01	8.92	49.91
Entry/reentry	17.35	28.86	8.03	45.77
Goes to school	23.73	33.07	7.18	36.02
Looking for FT job	19.67	17.70	7.72	54.91
Looking for PT job	25.70	32.26	6.31	35.73
Unemployment duration				
Less than 1 month	33.90	18.74	8.62	38.74
1–2 months	24.67	18.98	8.18	48.16
2–3 months	21.37	18.97	8.14	51.52
3–5 months	18.05	17.56	7.44	56.95
6–8 months	14.85	19.56	6.98	58.60
9–11 months	12.50	18.27	6.35	62.88
12–17 Months	11.07	22.38	6.48	60.07
18–23 Months	9.66	17.29	6.01	67.05
More than 24 months	8.86	25.37	6.01	59.76

Table 11 Discrete Duration Model: Coefficient Estimates and First Stage Results

	E		*NLF*		*A*		1st Stage	
	Coef	*se*	*Coef*	*se*	*Coef*	*se*	*Coef*	*se*
ΔIMM	0.000	(0.0443)	0.0836*	(0.0446)	0.0132	(0.0847)		
ΔIMM_{IV}							0.447***	(0.0880)
Age group (Base:18–24)								
25–39	−0.101***	(0.0146)	−0.0863***	(0.0145)	−0.160***	(0.0197)	−0.002	(0.0053)
40–54	−0.222***	(0.0164)	−0.0946***	(0.0171)	−0.466***	(0.0254)	0.002	(0.0064)
55–64	−0.357***	(0.0207)	0.0926***	(0.0208)	−0.796***	(0.0348)	−0.004	(0.0082)
Sex (Base: male)								
Female	−0.0210**	(0.0100)	0.243***	(0.0100)	−0.017	(0.0134)	0.001	(0.0033)
Race (Base: white)								
Black	−0.241***	(0.0142)	0.125***	(0.0141)	0.0509**	(0.0212)	−0.0200*	(0.0105)
Other	−0.128***	(0.0226)	0.141***	(0.0247)	0.0887***	(0.0314)	0.009	(0.0150)
Hispanic	−0.0759***	(0.0165)	0.0883***	(0.0191)	−0.017	(0.0249)	−0.0550***	(0.0189)
Education (Base: less than HS)								
High school	0.144***	(0.0149)	−0.118***	(0.0140)	−0.0849***	(0.0195)	−0.004	(0.0054)
Some college	0.216***	(0.0153)	−0.217***	(0.0143)	−0.163***	(0.0232)	−0.0112*	(0.0060)
College degree+	0.274***	(0.0174)	−0.441***	(0.0179)	−0.224***	(0.0260)	−0.0315***	(0.0090)
Marital status (Base: single)								
Married	0.148***	(0.0128)	−0.019	(0.0138)	−0.149***	(0.0203)	0.005	(0.0055)
Sep/div/widowed	0.0510***	(0.0148)	−0.0395**	(0.0156)	0.144***	(0.0220)	0.0107*	(0.0060)
#Children 0–13	−0.0212***	(0.0047)	0.0220***	(0.0051)	−0.0312***	(0.0075)	0.001	(0.0018)
#Children 14–17	0.016	(0.0100)	0.0301***	(0.0109)	−0.0911***	(0.0160)	0.000	(0.0037)
#Adult	0.0828***	(0.0077)	0.155***	(0.0082)	0.0211*	(0.0114)	−0.003	(0.0029)
#Elderly in household	−0.0483***	(0.0130)	0.177***	(0.0129)	−0.0909***	(0.0231)	−0.0124**	(0.0060)
Homeowner	0.0442***	(0.0106)	−0.0228**	(0.0108)	−0.521***	(0.0172)	0.0105**	(0.0049)

Table 11 (continued)

	E		*NLF*		*A*		1st Stage	
	Coef	*se*	*Coef*	*se*	*Coef*	*se*	*Coef*	*se*
Log (min wage)	−0.027	(0.0446)	0.049	(0.0513)	0.142	(0.0994)	0.028	(0.1950)
Log (# of max weeks of UI benefits)	−0.150***	(0.0335)	−0.109***	(0.0339)	−0.038	(0.0679)	0.005	(0.1370)
Is eligible for UI	−0.032	(0.0252)	0.008	(0.0207)	0.0711**	(0.0309)	−0.004	(0.0100)
LM Experience (Base: laid off)								
Quit job	0.002	(0.0156)	0.300***	(0.0169)	0.156***	(0.0224)	0.009	(0.0059)
Entry/reentry	−0.102***	(0.0119)	0.692***	(0.0109)	0.160***	(0.0163)	0.003	(0.0042)
Goes to school or college	0.153***	(0.0209)	0.221***	(0.0208)	−0.0742**	(0.0334)	−0.003	(0.0071)
Job Search (Base: Looking for full-time job)								
Looking for part-time job	0.386***	(0.0147)	0.711***	(0.0140)	0.0914***	(0.0238)	0.002	(0.0048)
State GDP pc growth	1.511***	(0.3560)	1.110***	(0.3870)	−0.330	(0.6820)	3.737**	(1.6170)
Unemployment duration (Base: less than 1 month)								
1 month	−0.487***	(0.0132)	−0.178***	(0.0158)	−0.269***	(0.0233)	−0.002	(0.0037)
2 months	−0.670***	(0.0147)	−0.219***	(0.0168)	−0.324***	(0.0232)	−0.00817*	(0.0049)
3–5 months	−0.894***	(0.0139)	−0.330***	(0.0158)	−0.457***	(0.0221)	−0.00998*	(0.0052)
6–8 months	−1.076***	(0.0206)	−0.239***	(0.0195)	−0.496***	(0.0281)	−0.0203***	(0.0073)
9–11 months	−1.280***	(0.0316)	−0.278***	(0.0260)	−0.577***	(0.0409)	−0.0346***	(0.0108)
12–17 months	−1.330***	(0.0256)	−0.115***	(0.0214)	−0.541***	(0.0340)	−0.011	(0.0097)
18–23 months	−1.563***	(0.0515)	−0.294***	(0.0468)	−0.539***	(0.0692)	0.000	(0.0164)
More than 24 months	−1.540***	(0.0381)	−0.006	(0.0320)	−0.539***	(0.0485)	−0.0246*	(0.0131)
Residual (1st stage)	0.019	(0.0447)	−0.086*	(0.0446)	0.010	(0.0846)		
Constant	0.301**	(0.1367)	−1.055***	(0.1419)	−1.176***	(0.2852)	0.168	(0.5828)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered Standard errors at state and semester level in parenthesis

Table 12 Discrete Duration Model: Marginal Effects Multinomial Probit

	U		*E*		*NLF*		*A*	
	Mgf	*se*	*Mgf*	*se*	*Mgf*	*se*	*Mgf*	*se*
ΔIMM	−0.009	(0.007)	−0.003	(0.005)	0.0120**	(0.005)	0.000	(0.004)
Age Group (Base:18–24)								
25–39	0.0262***	(0.003)	−0.0101***	(0.002)	−0.00671***	(0.002)	−0.00946***	(0.001)
40–54	0.0522***	(0.003)	−0.0241***	(0.002)	0.000	(0.002)	−0.0280***	(0.002)
55–64	0.0553***	(0.004)	−0.0487***	(0.003)	0.0384***	(0.003)	−0.0450***	(0.002)
Sex (Base: male)								
Female	−0.0226***	(0.002)	−0.0127***	(0.001)	0.0397***	(0.001)	−0.00442***	(0.001)
Race (Base: white)								
Black	0.00816***	(0.002)	−0.0415***	(0.002)	0.0278***	(0.002)	0.00546***	(0.001)
Other	−0.005	(0.004)	−0.0270***	(0.003)	0.0257***	(0.003)	0.00606***	(0.002)
Hispanic	0.000	(0.003)	−0.0147***	(0.002)	0.0164***	(0.002)	−0.001	(0.001)
Education (Base: less than HS)								
High school	0.003	(0.003)	0.0274***	(0.002)	−0.0247***	(0.002)	−0.00607***	(0.001)
Some college	0.00829***	(0.003)	0.0442***	(0.002)	−0.0415***	(0.002)	−0.0110***	(0.001)
College degree+	0.0236***	(0.003)	0.0637***	(0.002)	−0.0743***	(0.002)	−0.0131***	(0.002)
Marital Status (Base: single)								
Married	−0.00839***	(0.002)	0.0274***	(0.002)	−0.00765***	(0.002)	−0.0114***	(0.001)
Sep/div/widow	−0.00747***	(0.003)	0.00756***	(0.002)	−0.0103***	(0.002)	0.0102***	(0.002)
#Children 0–13	0.001	(0.001)	−0.00373***	(0.001)	0.00468***	(0.001)	−0.00209***	(0.000)
#Children 14–17	−0.002	(0.002)	0.00252*	(0.001)	0.00537***	(0.001)	−0.00638***	(0.001)
#Adult	−0.0257***	(0.001)	0.00678***	(0.001)	0.0209***	(0.001)	−0.00197***	(0.001)
#Elderly in household	−0.0103***	(0.002)	−0.0132***	(0.002)	0.0314***	(0.002)	−0.00783***	(0.001)

Table 12 (continued)

	U		*E*		*NLF*		*A*	
	Mgf	*se*	*Mgf*	*se*	*Mgf*	*se*	*Mgf*	*se*
Homeowner	0.0182***	(0.002)	0.0159***	(0.001)	0.002	(0.001)	−0.0363***	(0.001)
Log (min wage)	−0.008	(0.008)	−0.009	(0.006)	0.007	(0.006)	0.00943**	(0.004)
Log (# of max weeks of UI benefits)	0.0286***	(0.005)	−0.0196***	(0.004)	−0.0110***	(0.004)	0.002	(0.003)
Is eligible for UI	−0.001	(0.004)	−0.004	(0.003)	0.000	(0.003)	0.00502**	(0.002)
LM Experience (Base: laid off)								
Quit job	−0.0344***	(0.003)	−0.0124***	(0.002)	0.0395***	(0.002)	0.00729***	(0.001)
Entry/reentry	−0.0708***	(0.002)	−0.0434***	(0.002)	0.112***	(0.002)	0.00194*	(0.001)
Goes to school or college	−0.0354***	(0.004)	0.0144***	(0.003)	0.0321***	(0.003)	−0.0111***	(0.002)
Job Search (Base: Looking for full-time job)								
Looking for part-time job	−0.120***	(0.003)	0.0254***	(0.002)	0.107***	(0.002)	−0.0116***	(0.001)
State GDP pc growth	−0.261***	(0.057)	0.195***	(0.045)	0.127***	(0.046)	−0.0612**	(0.030)
Unemployment duration (Base: less than 1 month)								
1 month	0.0868***	(0.003)	−0.0839***	(0.002)	0.003	(0.002)	−0.00624***	(0.001)
2 months	0.114***	(0.003)	−0.114***	(0.003)	0.00625***	(0.002)	−0.00642***	(0.002)
3–5 months	0.154***	(0.003)	−0.143***	(0.002)	0.000	(0.002)	−0.0108***	(0.001)
6–8 months	0.163***	(0.003)	−0.171***	(0.003)	0.0197***	(0.003)	−0.0125***	(0.002)
9–11 months	0.188***	(0.005)	−0.193***	(0.004)	0.0205***	(0.004)	−0.0153***	(0.003)
12–17 months	0.170***	(0.004)	−0.202***	(0.003)	0.0476***	(0.003)	−0.0148***	(0.002)
18–23 months	0.209***	(0.008)	−0.222***	(0.005)	0.0232***	(0.007)	−0.0110**	(0.004)
More than 24 months	0.167***	(0.005)	−0.225***	(0.004)	0.0724***	(0.005)	−0.0149***	(0.003)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered Standard errors at state and semester level in parenthesis. All models use the same model specification as the baseline estimation. Unless otherwise stated ΔIMM_{IV} is measured as in the baseline model

Table 13 Discrete Hazard Model: Heterogeneity by Sex, Age, and Education without instruments for ΔIMM

	E	NLF	A
ΔIMM	1.019***	1.001	1.023
	(0.006)	(0.006)	(0.016)
By sex			
ΔIMM*men	1.022***	0.998	1.020
	(0.008)	(0.009)	(0.018)
ΔIMM*women	1.015*	1.002	1.027
	(0.009)	(0.009)	(0.018)
By age group			
ΔIMM*(18–24)	1.032**	0.989	1.002
	(0.013)	(0.011)	(0.011)
ΔIMM*(25–39)	1.019*	1.015	1.041**
	(0.011)	(0.012)	(0.018)
ΔIMM*(40–54)	1.005	0.982	1.022
	(0.012)	(0.012)	(0.024)
ΔIMM*(55–64)	1.014	1.031	1.039
	(0.019)	(0.019)	(0.035)
By education			
ΔIMM*Less than HS	1.041**	1.006	1.042
	(0.017)	(0.015)	(0.025)
ΔIMM*High school	1.020*	1.003	1.018
	(0.010)	(0.010)	(0.018)
ΔIMM*Some college	1.012	0.993	1.031
	(0.010)	(0.011)	(0.022)
ΔIMM*College	1.013	1.003	1.001
	(0.014)	(0.016)	(0.029)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered Standard errors at state and semester level in parenthesis. All models use the same model specification as the baseline estimation

References

Addison J, Portugal P (2003) Unemployment duration: competing and defective risks. J Hum Resour 38(1): 156–191

Altonji JG, Card D (1991) The effects of immigration on the labor market outcomes of less-skilled natives. In: Abowd JM, Freeman RB (eds) *Immigration, Trade, and the Labor Market*, National Bureau of economic research project report. University of Chicago Press, Chicago

Allison PD (2014) Event history and survival analysis, 2nd edn. Sage, Newbury Park, CA

Aydemir A, Borjas GJ (2011) Attenuation Bias in measuring the wage impact of immigration. J Labor Econ 29(1):69–112

Blanchflower DG, Shadforth C (2009) Fear, unemployment and migration. Econ J 119:F136–F182

Boubtane E, Coulibaly D, Rault C (2013) Immigration, growth, and unemployment: panel VAR evidence from OECD countries. Labour 27(4):399–420

Bartel AP (1989) Where do the new U.S. immigrants live? J Labor Econ 7(4):371–391

Bartik, T.J. (1991). Who benefits from state and local economic development policies?, in books from Upjohn press. W.E. Upjohn Institute for Employment Research
Basso, G., & G. Peri. (2015). The association between immigration and labor market outcomes in the United States. IZA discussion papers no 9436
Borjas GJ (1999) The economic analysis of immigration. In: Ashenfelter O, Card D (eds) Handbook of labor economics. North-Holland Elsevier Science, Amsterdam
Borjas GJ (2003) The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. Q J Econ 118(4):1335–1374
Borjas GJ (2005) The labor-market impact of high-skill immigration. Am Econ Rev 95(2):56–60
Borjas GJ (2006) Native internal migration and the labor market impact of immigration. J Hum Resour 41(2): 221–258
Borjas GJ (2017) The labor supply of undocumented immigrants. Labour Econ 46(2017):1–13
Borjas GJ, Grogger J, Hanson GH (2010) Immigration and the economic status of African-American men. Economica 77(306):255–282
Baussola M, Mussida C (2014) Transitions in the labour market: discouragement effect and individual characteristics. Labour 28(2):209–232
Bover O, Arellano M, Bentolila S (2002) Unemployment duration, benefit duration and the business cycle. Econ J 112(479):223–265
Butcher KF, Dinardo J (2002) The immigrant and native-born wage distributions: evidence from United States censuses. Ind Labor Relat Rev 56(1):97–121
Cameron AC, Trivedi PK (2005) Microeconometrics: methods and applications. Cambridge University Press, Cambridge
Card D (2001) Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. J Labor Econ 19(1):22–64
Card D (2005) Is the new immigration really so bad? Econ J 115(507):F300–F323
Card D, Peri G (2016) Immigration economics by George J. Borjas: a review essay. J Econ Lit 54(4):1333–1349
Card D, DiNardo J (2000) Do immigrant inflows Lead to native outflows? Am Econ Rev 90(2):360–367
Chapman B, Cobb-Clark D (1999) A comparative static model of the relationship between immigration and the short-run job prospects of unemployed residents. Economic Record 75(4):358–368
Chassamboulli A, Peri G (2015) The labor market effects of reducing the number of illegal immigrants. Rev Econ Dyn 18(4):792–821
Cohen-Goldner S, Paserman MD (2006) Mass migration to Israel and Natives' employment transitions. Ind Labor Relat Rev 59(4):630–652
Coile CC, Levine PB (2007) Labor market shocks and retirement: do government programs matter? J Public Econ 91(10):1902–1919
Cortés P, Tessada J (2011) Low-skilled immigration and the labor supply of highly skilled women. Am Econ J Appl Econ 3(3):88–123
Dawkins CJ, Shen Q, Sanchez TW (2005) Race, space, and unemployment duration. J Urban Econ 58(1):91–113
Del Carpio X, Özden Ç, Testaverde M, Wagner M (2015) Local labor supply responses to immigration. Scand J Econ 117:493–521
Drew J, Flood S, Warren JR (2014) Making full use of the longitudinal design of the current population survey: methods for linking records across 16 months. J Econ Soc Meas 39(3):121–144
Fabrizi E, Mussida C (2009) The determinants of labour market transitions, Giornale degli Economisti e Annali di Economia, 68(2):233–265
Farber H, Valletta R (2015) Do extended unemployment benefits lengthen unemployment spells? Evidence from recent cycles in the US labor market. J Hum Resour 50(4):873–909
Frey WH (1996) Immigration, domestic migration, and demographic balkanization in America: new evidence for the 1990s. Popul Dev Rev 22(4):741–763
Freeman RB (2006) People flows in globalization. J Econ Perspect 20(2):145–170
Fromentin V (2012) Migration and unemployment duration in OECD countries: a dynamic panel analysis. Econ Bull 32(2):1113–1124
Glitz A (2012) The Labor Market Impact of Immigration: A Quasi-Experiment Exploiting Immigrant Location Rules in Germany. J Labor Econ 30(1):175–213
Goldsmith-Pinkham P, Sorkin I, Swift H (2018) Bartik Instruments: What, When, Why, and How. NBER Working Paper 24408
Gurak DT, Kritz MM (2000) The interstate migration of U.S. immigrants: individual and contextual determinants. Social Forces 78(3):1017–1039

Hotchkiss JL, Quispe-Agnoli M, Rios-Avila F (2015) The wage impact of undocumented workers: evidence from administrative data. South Econ J 81(4):874–906
Hunt J, Gauthier-Loiselle M (2010) How much does immigration boost innovation? Am Econ J Macroecon 2(2):31–56
Islam A (2007) Immigration unemployment relationship: the evidence from Canada. Aust Econ Pap 46(1):52–66
Jaeger, D.,J. Ruist and J. Stuhler, (2018). "Shift-Share Instruments and the Impact of Immigration," *NBER Working Papers* 24285, National Bureau of Economic Research, Inc.
Jean S, Jiménez M (2011) The unemployment impact of immigration in OECD countries. Eur J Polit Econ 27(2):241–256
Kerr SP, Kerr WR (2011) Economic impacts of immigration: a survey. Finn Econ Pap 24(1):1–32
Kritz MM, Gurak DT (2001) The impact of immigration on the internal migration of natives and immigrants. Demography 38(1):133–145
Krueger BA, Mas A, Niu X (2017) The evolution of rotation group bias: will the real unemployment rate please stand up?. Rev Econ Stat 99(2):258–264
Longhi S, Nijkamp P, Poot J (2005) A meta-analytic assessment of the effect of immigration on wages. J Econ Surv 19(3):451–477
Longhi S, Nijkamp P, Poot J (2006) The fallacy of 'job robbing': a meta-analysis of estimates of the effect of immigration on employment. Journal of Migration and Refugee Issues 1(4):131–152
Longhi S, Nijkamp P, Poot J (2008) Meta-analysis of empirical evidence on the labour market impact of immigration. Région et Développement 27:161–191
Longhi S, Nijkamp P, Poot J (2010) Joint impacts of immigration on wages and employment: review and meta-analysis. J Geogr Syst 12(4):355–387
Madrian BC, Lefgren L (2000) An approach to longitudinally matching current population survey (CPS) respondents. J Econ Soc Meas 26(1):31–62
Mayda AM (2006) Who is against immigration? A cross-country investigation of individual attitudes toward immigrants. Rev Econ Stat 88(3):510–530
Meyer BD (1990) Unemployment insurance and unemployment spells. Econometrica 58(4):757–782
Munshi K (2003) Networks in the modern economy: Mexican migrants in the US labor market. Q J Econ 118(2):549–599
Okkerse L (2008) How to measure labour market effects of immigration: a review. J Econ Surv 22(1):1–30
Orozco-Aleman S, Gonzalez-Lozano H (2018) Labor market effects of immigration policies. J Lab Res 39(2): 150–177
Orrenius PM, Zavodny M (2007) Does immigration affect wages? A look at occupation-level evidence. Labour Econ 14(5):757–773
Orrenius PM, Zavodny M (2012) The economics of U.S. immigration policy. J of Policy Anal Manag 31(4): 948–956
Ottaviano GIP, Peri G (2012) Rethinking the effect of immigration on wages. J Eur Econ Assoc 10(1):152–197
Passel JS, Cohn D (2015) Unauthorized immigrant population stable for half a decade. Pew Research Center, Washington, DC
Passel JS, Fix M (1994). Myths about Immigrants, Foreign Policy, 95(1994): 151–160
Pedace R (1998) The impact of immigration on the labor market for native-born workers: incorporating the dynamics of internal migration. East Econ J 24(4):449–462
Pedace R, Rohn S (2011) The impact of minimum wages on unemployment duration: estimating the effects using the displaced worker survey. Industrial Relations: J Econ Soc 50(1):57–75
Peri G (2011) Rethinking the area approach: immigrants and the labor market in California. J Int Econ 84(1): 1–14
Peri G (2012) The effect of immigration on productivity: Evidence from US states. Rev Econ Stat 94(1):348–358
Peri G, Sparber C (2009) Task specialization, immigration, and wages. Am Econ J Appl Econ 1(3):135–169
Petrin A, Train K (2010) A control function approach to Endogeneity in consumer choice models. J Mark Res 47(1):3–13
Pischke J, Velling J (1997) Employment Effects of Immigration to Germany: An Analysis Based on Local Labor Markets. Rev Econ Stat 79(4):594–604
Portugal P, Addison JT (2008) Six ways to leave unemployment. Scottish J Political Econ 55(4):393–419
Riddell WC, Song X (2011) The impact of education on unemployment incidence and re-employment success: evidence from the U.S. labour market. Labour Econ 18(4):453–463

Rios-Avila F, Canavire-Bacarreza GJ (2018) Standard error correction in two-stage optimization models: a quasi-maximum likelihood estimation approach. Stata J 18(1):206–222

Rothstein, J. (2011). "Unemployment insurance and job search in the Great Recession," *Brookings Papers on Economic Activity* (Fall): 143–96

Rouse SM, Wilkinson BC, Garand JC (2010) Divided loyalties? Understanding variation in Latino attitudes toward immigration. Soc Sci Q 91(3):856–882

Scheve KF, Slaughter MJ (2001) Labor market competition and individual preferences over immigration policy. Rev Econ Stat 83(1):133–145

Seaman SR, White IR (2011) Review of inverse probability weighting for dealing with missing data. Stat Methods Med Res 22(3):278–295

Shan J (1999) Immigration and unemployment: new evidence from Australia and New Zealand. Int Rev Appl Econ 13(2):253–260

Simon JL, Moore S, Sullivan R (1993) The Effect of Immigration on Aggregate Native Unemployment: An Across-City Estimation. J Labor Res 14(Summer): 299–316

Smith C (2012) The impact of low-skilled immigration on the youth labor market. J Labor Econ 30(1):55–89

Suro R (2005) Attitudes toward immigrants and immigration policy: surveys among Latinos in the US and Mexico. Pew Hispanic Center, Washington, DC

Terza JV, Basu A, Rathouz PJ (2008) Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. J Health Econ 27(3):531–543

Valletta RG (2013) House lock and structural unemployment. Labour Econ 25:86–97

Venturini A, Villosio C (2006) Labour market effects of immigration into Italy: an empirical analysis. Int Labour Rev 145(1–2):91–118

Wan F, Small D, Mitra N (2018) A general approach to evaluating the bias of 2-stage instrumental variable estimators. Stat Med 37:1997–2015. https://doi.org/10.1002/sim.7636

Wessels WJ (2005) Does the minimum wage drive teenagers out of the labor force? J Lab Res 26(1):169–176

Winter-Ebmer R, Zweimüller J (1999) Do immigrants displace young native workers: the Austrian experience. J Popul Econ 12(2):327–340

Winter-Ebmer R, Zweimüller J (2000) Consequences of trade creation and increased immigration for the Austrian labour market. In: Landesmann M, Pichelmann K (eds) Unemployment in Europe. Macmillan, Basingstoke

Wooldridge JM (2014) Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. J Econ 182(1):226–234