Consequences of Immigrating During a Recession: Evidence from the US Refugee Resettlement Program

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5 December 2018

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Abstract

I examine long-term employment and wage consequences for refugees who migrate to the United States under poor business cycle conditions. It is difficult to credibly estimate the relationship between initial economic conditions and subsequent labor outcomes for immigrants as most can choose when to migrate. However, estimation is possible for refugees because their arrival dates are exogenously determined through the US Refugee Resettlement Program. For every one percentage point increase in the national unemployment rate at arrival, refugees experience a 3.45% reduction in wages after five years and a 3.65 percentage point reduction in employment after four years.

Keywords: Immigration, Labor Market Outcomes, Settlement Policies, Recession

JEL Codes: J15, J24, J31, J41, J61

*For their valuable guidance, I want to thank Darren Lubotsky, Benjamin Feigenberg, Ben Ost, Erik Hembre, Marcus Casey, Steve Rivkin, Jonathan Dingel, Jamin Speer, participants at the Spring 2018 UIC Economics Lunch seminar, and participants at the 48th Annual Illinois Economics Association meeting. I also want to sincerely thank Lori Beaman and Rami Arafah for their assistance with the ORR Annual Survey of Refugees data.

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1 Introduction

The timing of labor market entry matters. Several studies (Oyer 2006; Oyer 2008; Kahn 2010; Oreopoulus, von Wachter, and Heisz 2012) have shown that poor initial economic conditions faced by college graduates and post-graduates can be detrimental for long-term employment and wage outcomes. This phenomenon, known as "scarring," is an important area of research in labor economics because it provides context regarding the significance of early career decisions, job mobility, and human capital investment. In this study, I provide evidence that this phenomenon is also observed among refugees who migrate to the United States. This finding contributes both to existing scarring literature but also to migration literature. Migration economists have long looked at whether immigrant earnings differ from those of natives, why they differ, and how that gap changes over time (Chiswick 1978; Borjas 1985; LaLonde and Tobel 1992; Friedberg 1992; Borjas 1995; Hu 2000; Card 2005; Lubotsky 2007; Lubotsky 2011; Kim 2012; Abramitzky, Boustan and Eriksson 2014). Evidence of employment and wage scarring among immigrant groups like refugees, and how those effects compare with natives, helps to further explain the mechanisms that lead to wage differentials, *ceteris paribus*.

It is difficult to credibly estimate the impact of initial economic conditions on long-term assimilation outcomes for most immigrants as some may choose not to migrate to the US if economic conditions are not favorable. However, refugees do not have this choice. They are unable to stay in their country of origin due to political persecution, conflict, famine or general lack of security. But they also can not immediately migrate to the US as the US Refugee Resettlement program requires extensive background checks and screening that last 18-24 months before arrival. Additionally, refugees can not choose their initial resettlement location unless they have family in the US. These institutional features provide exogenous variation that make it possible to estimate how initial business cycle conditions affect assimilation outcomes over the long term.

Another important feature of this study is the use of a comprehensive, government-administered household survey called the Annual Survey of Refugees. To my knowledge, no other US-based refugee dataset tracks refugees for more than ninety days post-arrival. Researchers who study long-term assimilation outcomes for refugees have instead relied on imputation methods using the US Census (Capps, et. al. 2015; Evans and Fitzgerald 2017). These imputation methods likely suffer from contamination as some individuals imputed as refugees may not actually be refugees. The data used in this study, which have appeared only in a limited capacity in previous research (Beaman 2012; Arafah 2016), track refugees for five years and thus provide a breakthrough opportunity for research into long-term assimilation outcomes for refugees that resettle in the US.

Applying a fixed-effect model where the national unemployment rate at the time of arrival is interacted with potential experience, I find that for every one percentage point increase in the national unemployment rate at arrival, refugees on average experience a 3.45% reduction in wages five years later and a 3.65 percentage point reduction in employment four years later. In a separate regression, I substitute the arrival national unemployment rate with the arrival placement-state unemployment rate. These estimates are used understand how mobility across regions might mitigate scarring effects. Poor economic conditions in their state of placement could cause some refugees to move to states with more favorable economic conditions. I observe that for every one percentage point increase in the state of initial placement unemployment rate at arrival refugees on average experience a 1.36% reduction in wages up to three years later but observe no evidence of a reduction in employment. The wage results found using state unemployment rates are also less persistent than those found using the national unemployment rate.

Previous work on immigrant wage and employment scarring have looked at both immigrants in the US and refugees in Scandinavia. Chiswick, Cohen and Zach (1997) examine immigrant employment outcomes in the US and find no evidence of a long-term scarring effect.

Chiswick and Miller (2002) find some some evidence of wage scarring for immigrants in the US. However, these studies do not account for the fact that many immigrants may choose to migrate based on economic conditions. Given this concern for selective migration, Åslund and Rooth (2007) instead use refugees in Sweden to measure this effect. Similar to the US context, refugees in Sweden in the early 1990s were exogenously placed in a varied geographic settings at different points of time. They find that poor initial economic conditions can decrease wages for refugees for up 10 years after migration. Godøy (2017) also examines refugees in Norway and finds no evidence of a long-lasting wage scarring effect.

In this study, I examine employment and wage scarring effects for refugees who migrate to the US. There are several reasons why the US setting provides a valuable contribution. The US admits roughly half of the refugees that resettle to a third country. Refugee arrivals to the US range between 50,000 to 200,000 per year, whereas only a few thousand migrate to Scandinavian countries each year[1]. The US also has more geographic variation and ethnic diversity, which could make the employment choice set larger for refugees. The US Refugee Resettlement program, unlike resettlement programs in some countries, has also enjoyed relative stability since its inception in 1980. For example, in Sweden, as noted by Åslund and Rooth (2007), the formal refugee resettlement program was suspended in the early 1990s as resources were diverted to accommodate an influx of asylum-seekers at their border. The long-term stability of the US refugee resettlement program allows for examination of the program over multiple business cycles. Finally, it is likely that estimates found in other countries may not be applicable for the US setting. For example, refugees in Sweden are encouraged to defer entry into the labor market for 18 months post-arrival (Ibid.). In the US, refugees are encouraged to find work as soon as possible[2].

This study also contributes to literature that examines heterogeneity of scarring effects within the population. Hoynes, Miller and Schaller (2012) show that the impacts on labor market

[1] https://www.unhcr.org/statistical-yearbooks.html

[2] https://www.state.gov/j/prm/ra/receptionplacement/

outcomes from changes in business cycle conditions can differ greatly across gender, race, age and education. Differences have been found to arise within education groups based on field of study (Altonji, Kahn and Speer 2014) and across male workers with different years of education (Speer 2016). Schwandt and von Wachter (2018) find larger effects for non-whites and high school dropouts. In a separate analysis, I divide my sample across gender and educational attainment in country of origin. One key advantage to this study is that educational attainment is not endogenous to US economic conditions as refugees obtain these degrees prior to arrival. I observe more persistent decreases in employment for non-high-school-educated and high-school-educated males than for college-educated males. I also observe less persistence in wage scarring for college-educated males than non-college-educated males. However, for women, I observe more persistence and larger magnitude decreases in employment for those that are college-educated than those in less educated groups.

Finally, this study contributes to literature related to refugee labor supply shocks. This literature is based primarily on the Mariel Boatlift, a mass emigration event of Cubans to the US between April and October 1980. Exploiting the exogenous timing of these arrivals, economists have used this event to explore whether or not immigration hurts native wages and labor supply (Card 1990; Bodvarsson, Van der Berg and Lewer 2008; Peri and Yasenov 2015; Borjas 2017; Borjas and Monras 2017; Clemens and Hunt 2017). However, relatively little is known about how changes in native labor supply could affect immigrant groups like refugees. By focusing on labor outcomes for refugees, this study helps provide a better understanding how natives and refugees may compete with one another. For example, in comparison to studies that examine scarring for natives, notably Kahn (2010) which finds an increase in labor supply after five years in response to poorer initial national economic conditions, I find that refugees instead *decrease* their labor supply.

2 Refugee Resettlement Program

In most circumstances individuals or families seeking to resettle in the US as refugees must first go through the United Nations High Commission for Refugees (UNHCR). The UNHCR determines the need for permanent resettlement through seven criteria: "legal and/or physical protection needs, survivors of torture and/or violence, medical needs, women and girls at risk, family reunification, children and adolescents at risk and lack of foreseeable alternative duration solutions"[3]. The UNHCR makes a determination of where to send these individuals based on country refugee acceptance quotas, family presence and cultural affinities. If the individual or family is referred by the UNHCR to resettle in the United States, they must undergo a screening process through the US Department of Homeland Security. This screening process involves multiple interviews, submission of biometric information and background checks. On average, applicants must wait 18 to 24 months before being granted admission to the United States.

The State Department partners with nine non-profit voluntary resettlement agencies (VOLAGs) to determine placement once a refugee or family has been granted admission to the US. These organizations have 315 affiliates in 180 communities throughout the US. In Figure 1, each affiliate's office is mapped by its corresponding VOLAG. The State Department meets with these organizations weekly to review information on incoming refugees and assign them to a particular organization[4]. If an individual or family has family currently living in the US, every effort is made to resettle them with or near their family. Otherwise, a resettlement agency agrees to sponsor an individual or family based on available resources [5].

The nine VOLAGs are responsible for providing reception services for refugees during the first ninety days of arrival, including providing safe and affordable housing, furnishings, and services to acclimate them to their new environment. After ninety days, the Office

[3]http://www.unhcr.org/en-us/information-on-unhcr-resettlement.html
[4]https://fas.org/sgp/crs/misc/RL31269.pdf
[5]https://www.pbs.org/newshour/world/asked-refugees-referred-live-u-s

of Refugee Resettlement works with individual states and non-govermental organizations (NGOs) to provide longer-term services like medical assistance and social welfare benefits. Refugees are allowed freedom of movement, so they are not bound to stay in the state they were initially resettled. However, their financial assistance may in jeopardy if they move to a state that does not offer the same benefits as their initial state of resettlement[6].

There are exceptions to this resettlement process. Some individuals who eventually resettle in the United States as refugees are referred through a US embassy or a human rights group. Nevertheless, these individuals must still undergo the same screening process as refugees referred by UNHCR. There are also individuals who request asylum at the US border, or cross the border through illegal means and request asylum afterward. The asylum process is significantly different than the formal refugee resettlement process. These individuals must undergo court proceedings to gain asylum and are not afforded the same benefits and support. For the purposes of this study, the term "refugee" will refer to individuals who undergo the formalized refugee resettlement process. This distinction is important because my identification strategy will rely on the fact that refugees who undergo this formalized process cannot choose when or where they migrate within the United States.

3 Theory on Employment and Wage Scarring

The term "scarring" was first coined by David Ellwood (1982) to describe long-term negative consequences of entering the job market in a bad economy that persist well beyond the transitory period. This phenomenon has been observed primarily with college graduates. Oreopoulos, von Wachter, and Heisz (2012) and Kahn (2010) find large and persistent negative wage effects lasting 10 and 20 years for college graduates, respectively. It has also been observed with individuals re-entering the job market after displacement. Ruhm (1991) finds that such displaced workers experience a 10-13% drop in wages less than five years after

[6]https://www.state.gov/j/prm/ra/receptionplacement/

displacement.

One potential theoretical explanation for this phenomenon is labor market friction. If employment and wages are determined by labor market conditions in a spot labor market, where wages are determined by current supply and demand, then we would expect to not observe any differences between similar individuals who enter the economy during different business cycle conditions once economic conditions are similar. This is because productivity between these individuals should not differ apart from slight experience disparities. If the relationship between current employment and wages is influenced by labor market conditions in a contract model, where future wages are pre-determined based on agreements with employers made in prior periods, then persistence of depressed wages and employment could be explained by mobility. An individual that cannot easily move between firms once labor market conditions improve could see persistent effects. Beaudry and Dinardo (1991) examine how wages are affected by market conditions and find that a contract model with costless mobility fits this relationship better than a traditional spot labor market.

Another potential explanation is human capital accumulation. If an individual enters the job market when opportunities are scarce, they might be forced to spend more time in a bad match. As noted in Kahn (2010), if human capital accumulation is important, particularly in the first few years of an individual's career, then an individual's inability to switch jobs and find a better match could yield persistent, long-term detrimental outcomes. As the labor market improves, individuals are able to switch jobs and gain human capital but they would have lost the opportunity in earlier years. Therefore, controlling for experience, there would be a disparity in human capital between individuals who entered the labor market under difference economic conditions.

4 Data

The data set I use in my analysis is the Annual Survey of Refugees. This survey was started in 1975 as a way for refugee resettlement groups to assess assimilation outcomes for Asian refugees, particularly those from Vietnam. In 1980, with the passage of the Refugee Act, the survey became an important tool for the newly-created Office of Refugee Resettlement (ORR) in the production of an annual report to Congress on refugee outcomes as required by the new law. In 1993, the survey was expanded to include all refugee groups[7]. I use the 1993 through 2004 versions of these data to conduct my analysis. These data were previously used in Beaman (2012) to provide intuition on the magnitude of her results derived from another data set. More recent versions of the Annual Survey of Refugees data were provided by ORR through Freedom of Information Act requests (Arafah 2016), but do not contain information on the initial state of resettlement or country of origin for individuals in the data.

The survey in its current form is a five-year rolling panel, whereby 1000-2000 refugee households are contacted in their initial year of resettlement and followed for a period of five years. Each year an additional cohort is added and the cohort entering its sixth year is dropped. The survey is broken down into two parts: an individual family member portion that is given to all individuals in the household that are over the age of 16, and a household level portion. The individual portion asks basic demographic information including gender, age, years of education prior to arrival, degree attainment prior to arrival, disability, fluency in English upon arrival, marital status, parental status, family size, country of birth, month and year of entry, and original state of resettlement. The remainder of the individual survey includes questions about current employment and hourly wages[8]. The household portion of the survey includes questions on utilization of means-tested welfare programs like the

[7]https://archive.acf.hhs.gov/programs/orr/data/04arc8.htm8

[8]The survey is conducted over a period of several years. In my analysis wages are inflation-adjusted to constant 2000 US dollars to allow for comparison across years.

Supplemental Nutrition Assistance Program (SNAP), the Temporary Assistance for Needy Families program (TANF)[9], Supplemental Security Income (SSI), and General Assistance (GA).

In order to create a sample that is best suited for my analysis, I limit to individuals who go through the formalized refugee resettlement process. The Office of Refugee Resettlement is responsible for both Cuban and Haitian asylees as well as refugees[10]. The data do not distinguish whether Cubans and Haitians in the data are asylees or refugees, so I drop these individuals. I also drop individuals that did not arrive to the US during the target period of zero to five years prior to being surveyed. Since the survey participants are determined on a household basis instead of an individual basis, some individuals appear in the data that did not arrive during the target period. Finally, I limit the sample to individuals between the ages of 16 to 65 in order to analyze individuals of working age in the US. The final sample used in my analysis contains 39,026 observations of 18,710 individuals[11] who resettled in the US between May 1988 and May 2004.

Table 1 contains summary statistics of the sample broken down by intervals of year of arrival. As expected, the composition of refugees by region of origin changes over time. In the late-1980s and early-1990s, a large portion of refugees resettled in the US came from Asia. In the mid-1990s, following the breakup of Yugoslavia, the majority of refugees came from Europe. In the early-2000s, the composition of origin-regions is fairly evenly split between Africa, Asia and Europe. Despite big differences in origin-region composition, the composition of refugees by demographic characteristics appears fairly consistent. The most noticeable difference is that refugees in the early-2000s are much more fluent in English than in previous

[9]The Temporary Assistance for Needy Families (TANF) program replaced the Aid to Families with Dependent Children (AFDC) program following the passage of the Personal Responsibility and Work Opportunity Reconciliation (PRWORA) Act in 1996. The data make no distinction between the two programs.

[10]https://www.acf.hhs.gov/orr/resource/who-we-serve-cuban-haitian-entrants

[11]The original individual indicator variable in the data (f1id) has inconsistencies in terms of gender, country of origin and date of birth. This is likely because numbers are recycled after an individual's five year survey period ends. I construct a new individual indicator variable that groups individual records by the dataset's original indicator variable and fixed demographic characteristics to account for this problem.

years. There is also a decrease over time in the percentage of refugees who are married when they arrive. Empirical tests outlined in Section 7.3 suggest that these differences don't correlate much with the timing of arrival once I control for country of origin.

5 Empirical Strategy

My empirical strategy is based on two plausibly exogenous features of the refugee resettlement program: month and year of arrival and, for refugees who don't already have family living in the US, initial state of placement. I use seasonally-adjusted civilian unemployment rates for both the nation and placement-state as measures of initial economic conditions. The national unemployment rate at date of arrival is used to measure the general effect that initial economic conditions may have on long-term assimilation outcomes. The placement-state unemployment rate is used to introduce a mobility element into the analysis. If a refugee migrates to the US during a recession, moving to a different state will not change their exposure to national labor market conditions. However, if a refugee is placed in a state with poorer economic conditions than neighboring states, they could move and potentially experience better long-term labor outcomes than they would otherwise. Wozniak (2010) finds that for highly educated workers, economic improvement in a particular state can have large effects on whether the worker decides to relocate there. Given that refugees may not have particularly strong ties to the state they were initially resettled, it could be the case that they are also motivated to move in order to find better opportunities.[12]

Borrowing from Kahn (2010) and Godøy (2017)[13], I rely on an interaction between unemployment rate at arrival and years since migration to measure how initial economic conditions

[12] Unfortunately, the Annual Survey of Refugees data do not offer a credible way to test actual mobility. There is no information on a refugee's current state of residence. There is a question about whether a refugee lived in the same state in the previous year, but a large portion (>40%) of the observations are missing.

[13] Godøy (2017) uses immigrant employment rates instead of unemployment rates because Norway measures unemployment based on the number of registered jobseekers. Refugees in Norway have little incentive to register as jobseekers. This is not a concern in the US context because unemployment rates are derived from randomized sampling of the entire population.

affect assimilation outcomes over time. The specification using the national unemployment rate at date of arrival treatment is:

$$y_{it} = \alpha + \beta_{0k}(ue_0 \times \Phi_k) + \delta X_i + \Phi_c + \Phi_k + \gamma ue_{st} + \varepsilon_{ictsk}$$

The identifying assumption in this specification is that the date of arrival, and by extension the initial economic conditions a refugee faces, is as good as random conditional on country of origin. y_{it} can represent a variety of assimilation outcomes. This study focuses primarily on current employment and log wages, but I also show the effect of initial economic conditions on welfare utilization. The subscript i denotes variation across individuals, t denotes variation across survey years, c denotes variation across countries of origin, s denotes variation across states of placement, and k denotes variation across years since moving to the US (analogous to experience). β_{0k} represents an interaction between the national unemployment rate at the month and year of arrival and k years since the refugee migrated to the US. This interaction measures how the unemployment rate at arrival affects assimilation outcomes as the refugee gains experience in the US. The national unemployment variable, ue_0, is the national unemployment for the month and year of arrival for each refugee. The years since migration fixed effect variable, Φ_k, divides the number of days since migration into intervals. The earliest a refugee appears in the Annual Survey of Refugees data is six months post-arrival. Therefore, a value of 0 for k would represent a refugee who has been in the US between six months and one year. A value of 5 for k represents a refugee who has been in the US between five years and 2,175 days, the longest-tenured refugee in the sample. To allow for full flexibility, I do not make any linearity assumptions regarding the interaction between years since migration and the initial unemployment rate.

National and state unemployment rates at the time of arrival never change for a refugee, so it is not possible to measure a scarring effect by comparing an individual across time. Therefore, I control for individual characteristics to create comparisons between individuals with similar characteristics. X_i contains a vector of controls that includes years of education prior to arrival, gender, age, age^2, English ability at arrival, disability status, marital status, family size, and parental status. Disability status, marital status, family size, and parental status are asked in the context of the period being surveyed, so I use only the initial answer given when the refugee first appears in the dataset[14]. I control for country of origin fixed effects, Φc, to ensure that only individuals from the same country are being compared to one another. Given that push factors (where a conflict starts) and pull factors (possible discrimination on who is admitted based on country of origin) determine how many refugees from a certain country are admitted each year, it is especially important to include this control. I also control for years since migration fixed effects, Φ_k, in order to separate pure potential experience from the interaction of initial economic conditions with experience. Finally, I control for the contemporaneous state of placement unemployment rate, ue_{st}, in order to account for persistence of economic conditions[15]. It is expected that poor initial economic conditions would persist over the next few years as the economy is recovering. By controlling for the contemporaneous state of placement unemployment rate and years since migration fixed effects, the effect measured from the interaction between initial unemployment rate and years since migration fixed effects represents only those effects that are unexplained by persistence of economic conditions or experience. This measure is the best representation of "scarring" as consistent with the literature[16].

The specification using the state unemployment rate at date of arrival treatment is:

[14]Given that refugees are not surveyed until at least six months after entry, these controls could still be endogenous. However, differences between columns 5 and 6 on Appendix Tables A.1-A.4 provide evidence that these endogeneity concerns do not seem to drive results.

[15]Ideally I would like to control for the unemployment rate of the state that the refugee is currently residing. Unfortunately, this information is not available. The contemporaneous state of placement unemployment rate is a better substitute than the contemporaneous national unemployment rate because it provides more variation. However, results using the contemporaneous national unemployment rate yield qualitatively similar (in most cases statistically indistinguishable) results.

[16]Some papers in the scarring literature also control for contemporaneous year fixed effects. This is likely a bad control when using the Annual Survey of Refugees data. My treatment, unemployment rate at arrival, is based on the date of arrival. Date of arrival determines when a refugee is first surveyed and whether they appear in the survey one to five years later. Therefore, the treatment is highly correlated and deterministic of the contemporaneous survey year. This is not the case with contemporaneous unemployment rate because initial economic conditions do a poor job of predicting future economic conditions.

$$y_{it} = \alpha + \beta_{s0k}(ue_{s0} \times \Phi_k) + \delta X_i + \Phi_c + \Phi_k + \gamma ue_{st} + \Phi_0 + \Phi_s + \varepsilon_{icstk}$$

The identifying assumption in this specification is that the initial economic conditions of the state a refugee is placed is as good as random, conditional on country of origin, date of arrival and state of placement. This specification is similar to the specification using the national unemployment rate with the exception of two additional controls. Date of arrival fixed effects, Φ_0, control for national economic trends at time of arrival. State fixed effects, Φ_s, control for general differences between states. With these controls, the interaction between state unemployment rate at arrival and years since migration should be interpreted as the effect of initial state labor market conditions deviating from the national average that is unexplained by the persistence of economic conditions, experience, or idosyncratic differences between states.

Unfortunately, there is no information in the data about whether a refugee already has family living in the country, so the estimates using placement-state unemployment at arrival could be biased upward or downward. Empirical tests outlined in Sections 7.1 and 7.2 suggest they are likely biased downward. For this reason, I rely solely on results using national unemployment rate at arrival to provide unbiased estimates of scarring. Nevertheless, I believe estimates using placement-state unemployment are still informative as this potential bias would only apply to those individuals who already have family in the country.[17]

6 Results

6.1 Employment and Wages

Table 2 shows the main results of my analysis. The table is split into two parts. The first two columns represent estimates found using the national unemployment rate at arrival in-

[17] Unfortunately, there is no published information on how many of these individuals have family already living in the country. My discussions with former employees of various VOLAGS suggest it could be as high as 50% of refugees.

teracted with years since migration. The third and fourth columns model estimates found using the state unemployment rate at arrival interacted with years since migration. The first and third columns model current employment at the time the refugee was surveyed and should be interpreted as percentage point changes. The second and fourth columns model log wages[18] of employed individuals at the time the refugee was surveyed and should be interpreted as (approximate) percentage changes. The first row represents individuals who have been in the United States between six months and one year. The final row represents individuals who have been in the United States for over five years with the longest-tenured refugees in the sample having been in the country for 2,175 days.

In Table 2, Column 1, I observe that refugees who have been in the country between four and five years experience a 3.65 percentage point decrease in current employment for every one percentage point increase in the national unemployment rate in the month and year of their arrival. Given that I control for both contemporaneous state of placement unemployment rate and years since migration, these estimates represent the effect of labor market conditions at arrival that is unexplained by the persistence of economic conditions or experience. Standard errors are clustered at the month by year level and remain statistically significant at the 0.1% level until year five. In Appendix Table A.1, I provide detailed information about the estimates found in Table 2, Column 1. Columns 1-6 in Appendix Table A.1 show changes to the estimates as covariates are added.

In Table 2, Column 2, I find that after five years in the United States, refugees experience a 3.45% decrease in wages for every one percentage point increase in the national unemployment rate in the month and year of their arrival. The estimates are still significant after a refugee has been in the country over five years. This provides evidence that initial national economic conditions have a long-term persistent effect on wages. Appendix Table A.2 pro-

[18]The log wage estimates are based only on those individuals who are employed at the time they are surveyed. This is a classic selection bias issue. In order to verify results, I estimate the effect of initial economic conditions on hourly wages (with those currently unemployed reporting zero dollars in wages) using a Poisson QMLE model and find results that have the same sign but are larger in magnitude, as expected.

vides detailed information about the estimates found in Table 2, Column 2.

In Table 2, Column 3, I find evidence of a slightly positive relationship between the state unemployment rate in the month and year of arrival and current employment for refugees who have been in the country between four and five years. This specification controls for both national economic trends in the year and month of arrival and state fixed effects, so the interpretation is that refugees who have been in the country for four to five years experience a 1.36 percentage point increase in current employment for every one percentage point difference in the state of arrival unemployment rate from the national unemployment rate. This could be the result of mobility. As refugees are placed in states with tighter labor market conditions than neighboring states, they could be incentivized to move and experience better long term employment outcomes than they would otherwise. Appendix Table A.3 provides detailed information about the estimates found in Table 2, Column 3.

In Table 2, Column 4, I find that refugees experience a 1-2% decrease in wages for up to three years after migration for every one percentage point increase in the difference from the state unemployment rate and the national unemployment rate in the month and year of arrival. As predicted, the estimates dissipate faster than what I observe using the national unemployment rate at arrival because refugees are able to move out of states that are experiencing tighter labor market conditions. However, even with the option of moving to better labor market conditions, the wages for refugees who experience tighter labor market conditions at arrival are still lower for up to three years after arrival. Appendix Table A.4 provides detailed information about the estimates found in Table 2, Column 4.

6.2 Welfare Utilization

In Table 3, I show how national and state unemployment rates at arrival affect utilization of means-tested social welfare programs for refugees. Unlike most immigrants, refugees are an exempt group that are allowed to participate in means-tested social welfare programs during their first five years in the country[19]. This is an important outcome to investigate because empirical evidence has shown that increasing access to welfare programs for refugees can lead to increases in wages (LoPalo 2018). Finding evidence of a positive relationship between welfare utilization and unemployment at arrival suggests that some of the wage scarring effects for refugees may have been mitigated. Since non-refugee immigrants are not allowed to participate in these programs for their first five years post-arrival, this provides suggestive evidence that the wage scarring effects may be much larger for non-refugee immigrant groups.

I look at four different programs: Aid to Families with Dependent Children (AFDC) (now Temporary Assistance for Needy Families [TANF]), General Assistance (GA), Supplemental Nutrition Assistance Program (SNAP) and Supplemental Security Income (SSI). AFDC (now TANF) is cash grant program for families with children[20]. GA is a state program that works similarly to AFDC for individuals who do have children[21]. I group GA with AFDC/TANF into a single outcome variable that is 1 if either program is used and 0 if neither program is used. SNAP is a food nutrition program that provides vouchers and/or debit cards to purchase food[22]. SSI is a federal income supplement program that provides cash assistance to aged, blind and disabled people[23].

It is important to note that the AFDC/GA, SNAP and SSI variables do not represent whether or not an individual refugee participated in each of these programs. The Annual Survey of Refugees questionnaire asks the head of household in each survey period whether or not someone within the family unit received benefits from each of these programs in the last 12 months. Therefore, the correct interpretation of the estimates found in Table 3 should be whether a percentage point increase in the national or state unemployment rate at arrival

[19]https://aspe.hhs.gov/basic-report/overview-immigrants-eligibility-snap-tanf-medicaid-and-chip

[20]https://aspe.hhs.gov/aid-families-dependent-children-afdc-and-temporary-assistance-needy-families-tanf-overview-0

[21]https://www.cbpp.org/research/family-income-support/state-general-assistance-programs-are-weakening-despite-increased

[22]https://www.fns.usda.gov/snap/supplemental-nutrition-assistance-program-snap

[23]https://www.ssa.gov/ssi/

increased the percentage likelihood that at least one person within one's family collected one of these benefits in the past 12 months.

In Table 3, column 1, I find that a one percentage point increase in the national unemployment rate at arrival increased the likelihood that at least one family member received either AFDC/TANF or GA in the past year by 2.89% after five years. I find similar results with SNAP in Table 3, column 2. A one percentage point increase in the national unemployment at arrival increases the likelihood that at least one family member received SNAP benefits in the past years by 3.58% up to five years later. Interestingly, I find a negative relationship between arrival national unemployment rate and SSI utilization. A one percentage point increase in the national unemployment rate at arrival decreases the likelihood that at least one family member received SSI benefits in the past year by 1.82% up to four years later. This could be because SSI eligibility is tied to other income streams so an increase in AFDC/TANF benefits could offset the ability for families to also obtain this benefit[24].

Similar to estimates found using the national unemployment rate at arrival, in Table 3, columns 4 and 5, I find an increase in both AFDC/GA and SNAP utilization within families as a result of an increase in the state unemployment rate at arrival. However, as found in the state estimates in Table 2, these effects dissipate within the first two to three years. In Table 3, column 6, I find that an increase in the state unemployment does have a persistent negative effect on SSI utilization within families. A one percentage point increase in the state unemployment rate at arrival decreases the likelihood that at least one family collected on SSI within the last year by 2.47% after five years.

6.3 Heterogeneity Within Employment and Wage Estimates

In Tables 4 and 5, I split the employment and log wage estimates from the Main Results table, Table 2, into groups by gender and educational attainment in the origin country. Ed-

[24]https://www.ssa.gov/policy/docs/ssb/v66n4/v66n4p21.html

ucational attainment is classified as "No High School" for refugees with no secondary school, college diploma or medical school diploma from their country of origin. I classify refugees who report having completed secondary school but not college or medical school in their country of origin as "High School." Lastly, I classify refugees who completed college and/or medical school in their country of origin as "College."

In Table 4, I examine heterogeneity across employment estimates found in Table 2. Using the national unemployment rate at arrival as the treatment, I observe that college-educated males experience less persistence in employment scarring than non-high-school-educated and high-school-educated males. College-educated males experience a 2.82 percentage point decrease in employment up to 3 years later while non-high-school-educated males experience a 5.58 percentage point decrease up to 4 years later. High-school-educated males experience a 4.72 percentage point decrease in employment up to 5 years later. For females, the effect is persistent across all education groups and larger in magnitude for college-educated-females than estimates found for non-high-school-educated females and high-school-educated females. For every percentage point increase in the national unemployment rate at arrival, college-educated females experience a 9.59 percentage point reduction in employment after five years. High-school-educated females experience a 6.09 percentage point reduction in employment after five years and non-high-school educated females experience a 4.79 percentage point reduction in employment up to five years. Estimates using the state unemployment rate as treatment show no statistically significant estimates of employment scarring across groups. However, the positive relationship between state unemployment rate at arrival and employment outcomes found in Table 2 between the fourth and fifth year seem to be driven entirely by college-educated males. When I isolate the sample to only this group, I observe a 4.79 percentage point increase in employment after 4 years. However, this is the only time period that I observe a statistically significant effect.

In Table 5, I examine heterogeneity across wage estimates found in Table 2. Again I find a less persistent effect for college-educated males using the national unemployment rate at arrival as treatment, but the magnitudes are similar to those found in non-high-school-educated males and high-school-educated males. The effect is the most persistent and largest in magnitude for high-school-educated males. For every one percentage point increase in the national unemployment rate at arrival, high-school-educated males experience a 5.67% decrease in wages after five years. For females, I find similar results in magnitude and persistence for non-high-school-educated females and high-school-educated females. I do not observe statistically significant results for college-educated-females but the magnitudes are similar to those found in the other age groups suggesting that the results might be similar but I lack statistical power for this group. Using the state unemployment rate at arrival as treatment, I only observe statistically significant estimates of wage scarring for high-school-educated males. However, the magnitudes in estimates for college-educated-males and college-educated-females are larger but lack of statistical power to assess whether these estimates are statistically indistinguishable from zero.

7 Threats to Internal Validity

7.1 Treatment Endogeneity

One way my estimates could be biased is if there is endogenous sorting of refugees either in timing of their arrival or in the states where they are placed. The national unemployment rate at arrival depends on the assumption that the number of refugees coming to the US is not systematically related to national economic conditions. In order to test the validity of this assumption, I use fiscal year refugee arrival totals found in Zong J. et. al (2017) for the 1980-2015 time period. These data cover the entire period of the refugee resettlement program. I compare these data to annual new immigrant arrival totals calculated using IPUMS American Community Survey data (Ruggles et. al 2017) for the 1980-2015 time period. I convert both sets of totals to logs to ease interpretation (immigrant totals are in millions while refugee totals are in tens of thousands) and plot them across average national unemployment rates for the time periods that the totals were reported. In Figure 2, we can see that while total immigration is systematically related to national economic conditions, refugee immigration is not. Total immigration decreases at a statistically significant rate of 9.85% for every one percentage point increase in the national unemployment rate, while refugee totals show a statistically insignificant increase of 3.46% with a standard error of 3.10%.

The placement-state unemployment rate at arrival treatment relies on stronger assumptions. For this treatment to be exogenous, refugee arrivals must also not be systematically related the economic conditions of the state where they are placed. In Table 6, I provide a test of exogeneity in the state placement process. The Refugee Processing Center collects monthly data on refugee arrivals by state and country of origin[25]. Unfortunately, data are only available after 2002 so I am only able to look at the 2002-2016 period. I run three separate regressions in order to look at the level difference of refugee placement on state unemployment rate changes, the percentage difference and the percentage difference accounting for state-month pairs where no refugees were placed. In columns 1, 3, and 5 of Table 2, I regress monthly placement totals on the monthly state unemployment rate controlling for individual state fixed effects. These estimates represent the changes in refugee placement as the state unemployment rate increases. Using a Poisson QMLE model to account for state-month pairs where no refugees were placed, I find a slightly positive response of 3.22% in refugee placements as the state unemployment rate rises one percentage point. In columns 2, 4, and 6 of Table 2, I also control for year by month fixed effects. These estimates represent the changes in refugee placement in response to deviations from the national unemployment rate. Therefore, the estimates found in columns 2, 4, and 6 more accurately characterize whether refugee placements are systematically related to states with better or worse economic conditions. In column 6, I find a negative response of 3.27% as the state unemployment rises

[25]These data are provided through an online portal called WRAPSNet, http://ireports.wrapsnet.org

one percentage point above the national unemployment rate. However, in terms of levels, I find in column 2 that this change constitutes a statistically insignificant response of 1.714 less refugees from a baseline of 97.39. Nevertheless, the evidence for exogeneity in state placement is less certain so I rely more on my estimates using the national unemployment at arrival to provide an unbiased estimate of employment and wage scarring for refugees.

7.2 Non-Random Sorting

In Section 2, I outline how volunteer agencies (VOLAGS) make every effort to place refugees who have family already living in the country near or with them. This presents a potential problem of non-random sorting. Unfortunately, I do not have information in my data on whether a refugee has family already living in the country or how many refugees are being placed with families. Therefore, the model using the state unemployment rate at arrival treatment could be biased downward or upward. If more refugees are being placed with family members in states with worse initial economic conditions, it may appear that the state of placement is responsible for better assimilation outcomes when it is actually the added benefits of having family already living in the country. Conversely, if more refugees are being placed with family members in states with better initial economic conditions, the added benefit of having family already living in the country could increase the differences found in good states and bad states. This potential for bias does not exist for the specification using the national unemployment rate because familial ties do not determine when a refugee will arrive. All refugees must still undertake a 18-24 month screening process prior to arrival.

In order to assess how this potential problem of non-random sorting might affect my estimates I turn to another dataset on refugees. In Beaman (2012), the primary dataset used in her analysis are administrative records from the International Rescue Committee (IRC), one of the VOLAGs mentioned in Section 2. These data comprise over 1700 males who arrive between 2001 and 2005. Given that there is information on whether a refugee is placed with or near their family, the sample is limited to those individuals who do not have any familial ties prior to arrival. Unfortunately, the data only measure outcomes after ninety days and arrival dates are only reported in years. Therefore I can not estimate employment or wage scarring using these data. However, I can use these data to assess how initial economic conditions might affect initial employment and wage outcomes in the absence of family placement.

I use the following regression for columns 1 and 2 in Table 8: $y_i = \alpha + \beta ue_0 + \delta X_i + \Phi_c + \varepsilon_{ict}$. In this regression, I look at the effect of the national unemployment rate at arrival (as measured by the annual average in the year of arrival) on employment and wage outcomes 90 days post-arrival. I control for country of origin fixed effects, Φ_c, and a vector of covariates, X_i. Covariates include age, age^2, disability, english ability, years of education, marital status and family size. For Table 8, columns 3 and 4, I use the following regression: $y_i = \alpha + \beta ue_{s0} + \delta X_i + \Phi_c + \Phi_0 + \Phi_s + \varepsilon_{icst}$. This regression is the same as the regression used in the first two columns with the exception of added controls for year of arrival fixed effects, Φ_0, and state of placement fixed effects, Φ_s.

In Table 8, I find that initial national and state economic conditions do have a substantial impact on both initial employment and log wage outcomes. The estimates are also larger in magnitude than initial six months to one year estimates found Table 2, but these effects are also measured much earlier. The main point of this exercise is to assess the effect on employment and log wage outcomes using the state unemployment at arrival treatment in the absence of family placement. For every one percentage point increase in the state unemployment rate from the national unemployment rate, I find a very large negative effect of 12.4 percentage points on initial employment and large negative effect of 4.33% on initial log wages. This result suggests that either the negative effect of a high state unemployment at arrival dissipates very quickly or my results found in columns 3 and 4 of Table 2 might be biased downward from non-random placement near family for some refugees in my dataset.

7.3 Sample Selection

In Figure 1 and Table 6, I test whether the total refugee arriving population is systematically related to national and state economic conditions, respectively. However, given that I am working with only a sample of these refugees, I also need to assess whether the national unemployment at arrival and state unemployment at arrival treatments are systematically related to any of my covariates. It is understood that country of origin will be systematically related to the timing of arrival for refugees because of both push and pull factors. Push factors, including the break out of conflict in a particular country at a particular time, partially determine how many refugees from a particular country are applying to the UNHCR and US Refugee Resettlement program. Pull factors, including differential arrival quotas of refugees by region[26], partially determine how many refugees from a particular country are allowed to enter the US at a particular time. Luckily, I have information on country of origin for each refugee in my data so I am able to control for this.

In Table 7, I test whether any other covariates might be systematically related to the national unemployment rate at arrival or state unemployment rate at arrival treatments after controlling for country of origin. For Table 7, column 1, I use the following specification, $ue_0 = \alpha + \delta X_i + \Phi_c + \varepsilon_{ict}$. This regression tests whether any of the covariates, X_i, are related to the national unemployment rate at arrival after controlling for country of origin fixed effects, Φ_c. In the second column, I use the specification, $ue_{s0} = \alpha + \delta X_i + \Phi_c + \Phi_0 + \varepsilon_{ict}$. In this regression, I test whether any of the covariates, X_i, are related to state unemployment rate at arrival controlling for country of origin fixed effects, Φ_c, and year by month of arrival fixed effects, Φ_0. Year by month of arrival fixed effects are used to demean state unemployment rates from the national unemployment rate so I can test whether covariates are related to states with better or worse economic conditions. In Table 7, column 1, I find that years of education and gender are both positively related to the national unemployment rate at arrival. This suggests that, within my sample, those arriving to the US under worse economic

[26] https://www.state.gov/j/prm/releases/docsforcongress/261956.htm

conditions are slightly more educated and female. It's unclear whether these differences bias my estimates as more education is related to better labor outcomes while being female may be linked to worse labor outcomes. In Table 7, column 2, I find that marriage is positively related to the state unemployment rate at arrival. This means that states with worse economic conditions than the rest of the country are receiving more married individuals. This could potentially bias my state estimates downward as marriage may be linked to better labor outcomes and those individuals are being placed in states with worse initial economic conditions. Overall, however, the sample appears to be fairly balanced after controlling for country of origin.

7.4 Attrition

Another potential concern is attrition bias. Fewer than 10% of individual refugees in the sample are surveyed all five years. One problem is that the Annual Survey of Refugees targets families, not individuals, so there are some individuals who appear in the data in some years and not in others, even though the family itself may be included in all five years. This could bias estimates upwards if individuals are more likely to participate in the survey if they are unemployed. If refugees are more likely to be employed under better initial economic conditions, and those who are employed are less likely to participate in the survey, then comparisons between similar refugees entering the US under different economic conditions would reflect differences predominantly between the unemployed individuals of each group.

Attrition may also occur in the data because families move and thus become harder to find for subsequent surveys. If individuals who have a harder time finding a job are more likely to move, then this could bias results downwards. It may be the case that refugees who immigrate to the US under poorer economic conditions are more likely to move in their first few years and achieve better assimilation outcomes as a result. However, given that these individuals are less likely to participate in the survey given that they have moved, my estimates would reflect differences among refugees who enter the US under better economic conditions and only those refugees who could not afford to move would be reflected in the group who entered the US under worse economic conditions.

In order to test if attrition is problematic for my results, I first regress current employment and log wages on fixed characteristics of the individuals: gender, age, age^2, disability status at arrival, English at arrival, years of education at arrival, marital status at arrival, family size at arrival, whether or not an individual has children at arrival. I then take the predicted values of this regression and plug them into my original specifications. For example, I take the predicted values of current employment on covariates and regress those predicted values on an interaction between the national unemployment rate at month and year of arrival and years since migration, controlling for country of origin, years since migration, and contemporaneous placement-state unemployment rate. If the interaction between the national unemployment rate at the month and year of arrival and years since migration show any significant effects on the predicted values, I would be concerned that characteristics of individuals in later years are changing and that attrition may be driving my results.

Table 9 shows the results of this analysis. Using the state unemployment rate specification, the results are all statistically indistinguishable from zero with the exception of a marginally significant but small estimate for employment in the first 6 months to 1 year of arrival. This provides evidence that there are no changes in the characteristics of individuals over different years in the interaction between the state unemployment rate at the year and month of arrival and years since migration. Thus, attrition is likely not driving the results for the state unemployment rate specification for either the employment or log wage outcomes. Using the national unemployment rate specification, there is some evidence of changes in characteristics of the individuals for those refugees who have been in the US between six months to one year and those who have been in the US for 1 to 2 years for employment estimates. However, there is no evidence that the employment results found in later years is driven by changes in the general makeup of individuals. For log wage estimates using the national unemployment rate treatment, I find only small statistically significant differences in 6 months to one year and 2 to 3 years estimates. Given that overall, the national and state unemployment specifications in Table 9 do not predict the outcomes from the main specifications, I am confident that attrition is not driving my results.

8 Conclusion

In this study, I find evidence of both wage and employment scarring among refugees who migrate to the US. On average, refugees experience a 3.45% decrease in wages after five years and a 3.65 percentage point decrease in employment after four years for every one percentage point increase in the national unemployment rate at arrival. Attempts were also made to understand how across-region mobility might mitigate these effects. Using placement-state unemployment rate at arrival, I find no evidence of employment scarring effect and a less persistent wage scarring effect. However, empirical tests show that estimates using the state of placement unemployment rate may be biased downward due to an unknown number of refugees being placed near their families. Therefore, I rely only on the national unemployment rate of arrival treatment to provide unbiased estimates of employment and wage scarring for refugees.

I also find evidence that initial economic conditions have a long-term effect on utilization of means-tested welfare programs. For every one percentage point increase in the national unemployment rate at arrival, I observe a 2.89% increased likelihood that at least one member of a refugee's family is collecting AFDC/TANF or GA benefits after five years. I also observe a 3.58% increased likelihood that at least one member of their family is collecting SNAP benefits up after four years. Empirical evidence from LoPalo (2018) suggests that increased access to these programs increases wages for refugees, so it is possible that these wage scarring effects have been somewhat mitigated. If so, wage scarring for non-refugee immigrants could be larger in magnitude as these groups are barred from accessing such programs.

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Figures

Figure 1: Resettlement Sites by Volunteer Agency[27]

[27]Source: `https://www.acf.hhs.gov/orr/resource/fy2014-reception-and-placement-rp-network-affiliates-map`

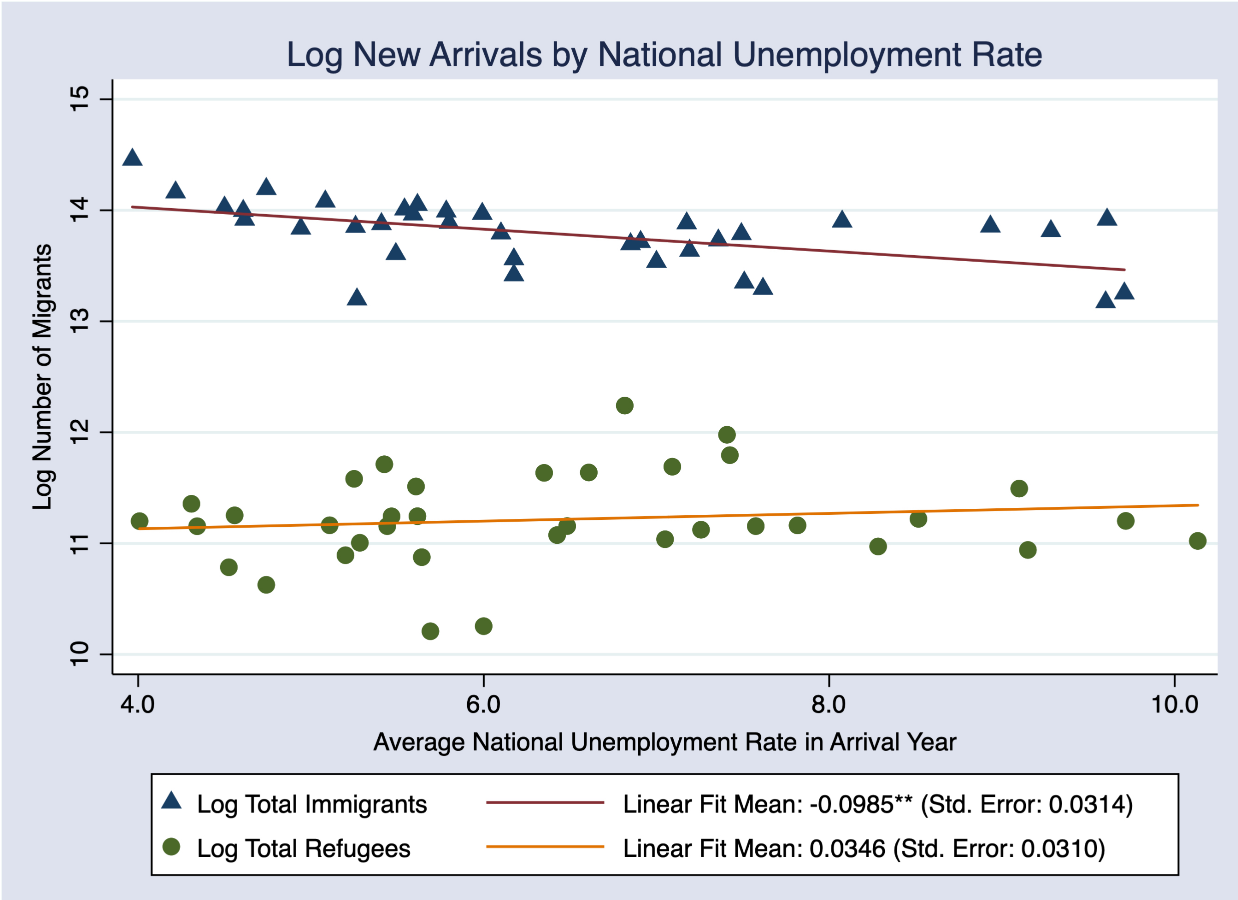

Figure 2: Log New Arrivals by National Unemployment Rate (1980-2015)[28]

Note: Standard errors are clustered at year of arrival level.

[28]Log new arrival totals for all immigrants are based on author estimates using IPUMS American Community Survey data for 2011-2016 (Ruggles et. al 2017). Log new arrival totals for refugees are based on reported estimates from the Migration Policy Institute (Zong J. et. al 2017). The average national unemployment rate is the average for the calendar year for the immigrant estimates as those totals are reported in calendar years. The average national unemployment rate is the average for the fiscal year (October of the previous year to September of the current year) for the refugee estimates as those totals are reported in fiscal years.

Tables

Table 1: **Summary Statistics by Year of Arrival**

Demographics	**1988-1991**	**1992-1995**	**1996-1999**	**2000-2004**	**All Years**
Years Of Education	10.25	10.42	10.74	9.94	**10.36**
% Female	50.63	51.34	49.74	43.46	**49.45**
Age at Arrival	31.51	32.98	32.13	30.49	**32.11**
% Fluent in English	9.21	7.47	10.68	20.18	**10.35**
% Disabled	10.70	13.21	8.35	8.84	**11.11**
% Married	61.26	54.40	58.40	49.17	**55.29**
Family Size	4.98	5.00	4.62	4.97	**4.93**
% Have Children	55.01	56.49	61.24	57.52	**57.20**
% from Africa	1.62	5.14	10.21	31.15	**10.32**
% from Asia	86.42	79.06	43.39	38.34	**66.71**
% from Europe	11.96	15.78	45.79	29.45	**22.66**
% from S. America	0	0	0.62	1.06	**0.31**
Individuals	3336	8712	3086	3576	**18710**

Table 2: **Main Results**

	National Unemployment Rate		State Unemployment Rate	
	(1) Employment	(2) Log Wages	(3) Employment	(4) Log Wages
6 mos to 1 year, ue_0	-0.0129	-0.0171+	0.0084	-0.0117+
	(0.0115)	(0.0095)	(0.0109)	(0.0069)
1 to 2 years, ue_0	-0.0452***	-0.0314***	-0.0056	-0.0164*
	(0.0070)	(0.0058)	(0.0076)	(0.0064)
2 to 3 years, ue_0	-0.0553***	-0.0397***	-0.0024	-0.0136+
	(0.0066)	(0.0055)	(0.0071)	(0.0069)
3 to 4 years, ue_0	-0.0488***	-0.0251*	0.0074	-0.0067
	(0.0106)	(0.0097)	(0.0070)	(0.0068)
4 to 5 years, ue_0	-0.0365***	-0.0437***	0.0136*	-0.0092
	(0.0100)	(0.0079)	(0.0065)	(0.0065)
Over 5 years, ue_0	-0.0201	-0.0345***	0.0101	-0.0018
	(0.0168)	(0.0090)	(0.0095)	(0.0066)
Observations	32278	14100	32278	14100
Adj. R^2	0.265	0.255	0.289	0.285

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month by year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month by year of arrival level for state unemployment rate estimates.

Table 3: **Estimates on Welfare Utilization**

	National Unemployment Rate			State Unemployment Rate		
	(1) AFDC/GA	(2) SNAP	(3) SSI	(4) AFDC/GA	(5) SNAP	(6) SSI
1 to 2 years, ue_0	-0.0292*	0.0392**	-0.0148	0.0025	-0.0038	-0.0347***
	(0.0135)	(0.0119)	(0.0109)	(0.0115)	(0.0103)	(0.0086)
2 to 3 years, ue_0	0.0363***	0.0659***	0.0029	0.0248*	0.0181+	-0.0228*
	(0.0095)	(0.0131)	(0.0087)	(0.0108)	(0.0107)	(0.0095)
3 to 4 years, ue_0	0.0315**	0.0380**	-0.0182*	0.0142	0.0062	-0.0237**
	(0.0104)	(0.0114)	(0.0071)	(0.0102)	(0.0104)	(0.0084)
4 to 5 years, ue_0	0.0515***	0.0358**	0.0082	0.0142	0.0053	-0.0088
	(0.0087)	(0.0114)	(0.0101)	(0.0098)	(0.0104)	(0.0084)
Over 5 years, ue_0	0.0289**	-0.0107	-0.0197	0.0024	-0.0094	-0.0247*
	(0.0106)	(0.0147)	(0.0133)	(0.0114)	(0.0147)	(0.0100)
Observations	32123	32226	32217	32123	32226	32217
Adj. R^2	0.225	0.285	0.151	0.277	0.322	0.182

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month by year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month by year of arrival level for state unemployment rate estimates.

Table 4: **Heterogeneity within Employment Estimates**

National Unemployment Rate

	(1) No HS Males	(2) HS Males	(3) College Males	(4) No HS Females	(5) HS Females	(6) College Females
6 mos to 1 year, ue_0	-0.0168	-0.0414+	-0.0546	0.0185	0.0197	-0.0755*
	(0.0221)	(0.0223)	(0.0354)	(0.0267)	(0.0164)	(0.0347)
1 to 2 years, ue_0	-0.0564**	-0.0537***	-0.0543**	-0.0172	-0.0420**	-0.0528*
	(0.0159)	(0.0121)	(0.0174)	(0.0133)	(0.0141)	(0.0245)
2 to 3 years, ue_0	-0.0576***	-0.0653***	-0.0282+	-0.0648***	-0.0441***	-0.0244
	(0.0151)	(0.0116)	(0.0152)	(0.0151)	(0.0089)	(0.0240)
3 to 4 years, ue_0	-0.0558**	-0.0562***	-0.0158	-0.0607***	-0.0563**	-0.0380
	(0.0178)	(0.0104)	(0.0212)	(0.0166)	(0.0164)	(0.0266)
4 to 5 years, ue_0	0.0057	-0.0472***	-0.0015	-0.0479*	-0.0556**	-0.0717**
	(0.0208)	(0.0113)	(0.0206)	(0.0187)	(0.0173)	(0.0225)
Over 5 years, ue_0	-0.0014	-0.0112	0.0020	0.0087	-0.0609***	-0.0959***
	(0.0285)	(0.0255)	(0.0233)	(0.0336)	(0.0170)	(0.0265)
Observations	4532	8522	2718	5561	7687	2473
Adj. R^2	0.290	0.233	0.299	0.236	0.235	0.278

State Unemployment Rate

	(1) No HS Males	(2) HS Males	(3) College Males	(4) No HS Females	(5) HS Females	(6) College Females
6 mos to 1 year, ue_0	0.0064	-0.0150	-0.0160	0.0228	0.0184	-0.0423
	(0.0174)	(0.0186)	(0.0296)	(0.0151)	(0.0177)	(0.0261)
1 to 2 years, ue_0	-0.0012	-0.0128	-0.0222	0.0097	-0.0180	-0.0256
	(0.0139)	(0.0147)	(0.0201)	(0.0132)	(0.0126)	(0.0247)
2 to 3 years, ue_0	-0.0102	-0.0057	0.0126	-0.0018	-0.0082	-0.0209
	(0.0141)	(0.0148)	(0.0156)	(0.0131)	(0.0136)	(0.0227)
3 to 4 years, ue_0	-0.0160	0.0080	0.0173	-0.0026	0.0081	-0.0250
	(0.0117)	(0.0123)	(0.0164)	(0.0138)	(0.0136)	(0.0230)
4 to 5 years, ue_0	0.0039	0.0078	0.0479**	-0.0035	0.0060	-0.0122
	(0.0129)	(0.0120)	(0.0171)	(0.0131)	(0.0126)	(0.0233)
Over 5 years, ue_0	-0.0151	0.0086	0.0130	0.0108	-0.0031	-0.0205
	(0.0165)	(0.0133)	(0.0175)	(0.0150)	(0.0161)	(0.0263)
Observations	4532	8522	2718	5561	7687	2473
Adj. R^2	0.333	0.266	0.353	0.284	0.264	0.324

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month and year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month and year of arrival level for state unemployment rate estimates.

Table 5: **Heterogeneity within Log Wage Estimates**

National Unemployment Rate

	(1) No HS Males	(2) HS Males	(3) College Males	(4) No HS Females	(5) HS Females	(6) College Females
6 mos to 1 year, ue_0	-0.0407**	-0.0200	-0.0176	-0.0247	-0.0019	-0.0597
	(0.0123)	(0.0225)	(0.0360)	(0.0184)	(0.0204)	(0.0520)
1 to 2 years, ue_0	-0.0448***	-0.0313**	-0.0433*	-0.0318**	-0.0300**	-0.0160
	(0.0105)	(0.0091)	(0.0160)	(0.0104)	(0.0107)	(0.0205)
2 to 3 years, ue_0	-0.0278*	-0.0510***	-0.0445+	-0.0705***	-0.0360***	-0.0419
	(0.0108)	(0.0071)	(0.0247)	(0.0110)	(0.0090)	(0.0249)
3 to 4 years, ue_0	-0.0303+	-0.0146	-0.0448+	-0.0550**	-0.0390***	-0.0114
	(0.0172)	(0.0109)	(0.0254)	(0.0188)	(0.0105)	(0.0260)
4 to 5 years, ue_0	-0.0333*	-0.0650***	-0.0158	-0.0573**	-0.0292*	-0.0558
	(0.0133)	(0.0102)	(0.0244)	(0.0168)	(0.0125)	(0.0358)
Over 5 years, ue_0	-0.0282	-0.0567***	0.0085	-0.0335*	-0.0469**	0.0190
	(0.0255)	(0.0113)	(0.0318)	(0.0149)	(0.0148)	(0.0519)
Observations	1825	4578	1266	1813	3399	922
Adj. R^2	0.173	0.223	0.266	0.251	0.164	0.199

State Unemployment Rate

	(1) No HS Males	(2) HS Males	(3) College Males	(4) No HS Females	(5) HS Females	(6) College Females
6 mos to 1 year, ue_0	0.0028	-0.0138	-0.0362	0.0083	-0.0062	-0.0449
	(0.0177)	(0.0111)	(0.0403)	(0.0138)	(0.0127)	(0.0606)
1 to 2 years, ue_0	-0.0184	-0.0252*	-0.0392	0.0113	-0.0162	-0.0266
	(0.0164)	(0.0108)	(0.0323)	(0.0137)	(0.0122)	(0.0359)
2 to 3 years, ue_0	-0.0035	-0.0233*	-0.0357	-0.0013	-0.0103	-0.0251
	(0.0168)	(0.0101)	(0.0306)	(0.0144)	(0.0131)	(0.0349)
3 to 4 years, ue_0	0.0001	-0.0117	-0.0532	0.0163	-0.0025	-0.0270
	(0.0152)	(0.0099)	(0.0334)	(0.0141)	(0.0094)	(0.0335)
4 to 5 years, ue_0	-0.0015	-0.0186+	-0.0486	0.0137	0.0021	-0.0329
	(0.0152)	(0.0100)	(0.0323)	(0.0131)	(0.0097)	(0.0313)
Over 5 years, ue_0	0.0047	-0.0147	-0.0270	0.0167	-0.0013	0.0282
	(0.0156)	(0.0105)	(0.0353)	(0.0137)	(0.0108)	(0.0396)
Observations	1825	4578	1266	1813	3399	922
Adj. R^2	0.264	0.277	0.309	0.330	0.216	0.293

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month and year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month and year of arrival level for state unemployment rate estimates.

Table 6: **Refugee Placements by State Unemployment Rate (2002-2016)**[29]

	(1) Refugee Placements	(2) Refugee Placements	(3) Log Refugee Placements	(4) Log Refugee Placements	(5) Refugee Placements	(6) Refugee Placements
State Unemployment Rate	3.937***	-1.714	0.0590***	-0.0582***	0.0322***	-0.0327**
	(0.715)	(1.232)	(0.00592)	(0.0125)	(0.00575)	(0.0108)
State FE	*	*	*	*	*	*
Year by Month FE		*		*		*
Model	OLS		OLS		Poisson QMLE	
Baseline	97.39	97.39	3.92	3.92	97.39	97.39
Observations	9180	9180	7908	7908	9180	9180
Adj. R^2	0.638	0.725	0.716	0.838		
Pseudo R^2					0.746	0.871

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at state by month by year level.

[29]Monthly Refugee Placement data comes from the Refugee Processing Center WRAPSNet website. http://ireports.wrapsnet.org

Table 7: **Test of Balance for Continuous Treatments**

	(1) National Unemp. Rate	(2) State Unemp. Rate
Age	-0.0005	-0.0010
	(0.0015)	(0.0013)
English Fluency	0.0037	-0.0010
	(0.0467)	(0.0476)
Years Of Education	0.0075*	0.0005
	(0.0036)	(0.0048)
Gender	0.0286*	0.0019
	(0.0112)	(0.0159)
Disability	0.0351	0.0422
	(0.0377)	(0.0468)
Married	-0.0057	0.0670+
	(0.0335)	(0.0356)
Family Size	0.0110	-0.0059
	(0.0088)	(0.0098)
Any Children	0.0116	0.0081
	(0.0271)	(0.0460)
Observations	15780	15780
Adj. R^2	0.257	0.543

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Sample is restricted to first observation of each refugee in the data. Standard errors are clustered at month by year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month by year of arrival level for state unemployment rate estimates.

Table 8: **Estimates On Employment and Log Wages using IRC Data**[30]

	National Unemployment Rate		State Unemployment Rate	
	(1)	(2)	(3)	(4)
	Employment	Log Wages	Employment	Log Wages
Unemp. Rate at Arrival	-0.0619*	-0.0210+	-0.124**	-0.0433*
	(0.0252)	(0.0112)	(0.0439)	(0.0185)
Observations	1606	1033	1606	1033
Adj. R^2	0.116	0.075	0.180	0.237

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are heteroskedastic robust.

[30]The International Rescue Committee refugee data used in Beaman 2012 come from supplemental data provided on the Review of Economic Studies website, https://academic.oup.com/restud/article/79/1/128/1562775#supplementary-data.

Table 9: **Test for Attrition Bias**

	National Unemployment Rate		State Unemployment Rate	
	(1) Predicted Employment	(2) Predicted Log Wages	(3) Predicted Employment	(4) Predicted Log Wages
6 mos to 1 year, ue_0	-0.0308***	-0.0062*	-0.0073+	-0.0020
	(0.0043)	(0.0030)	(0.0043)	(0.0024)
1 to 2 years, ue_0	-0.0115**	0.0017	-0.0042	-0.0008
	(0.0038)	(0.0021)	(0.0038)	(0.0022)
2 to 3 years, ue_0	-0.0054	0.0034+	-0.0013	-0.0011
	(0.0039)	(0.0019)	(0.0036)	(0.0024)
3 to 4 years, ue_0	-0.0026	0.0025	-0.0006	-0.0006
	(0.0039)	(0.0022)	(0.0041)	(0.0025)
4 to 5 years, ue_0	-0.0006	0.0016	-0.0014	-0.0009
	(0.0044)	(0.0024)	(0.0038)	(0.0025)
Over 5 years, ue_0	0.0097	0.0046	0.0005	0.0011
	(0.0075)	(0.0031)	(0.0045)	(0.0027)
Observations	32438	32438	32438	32438
Adj. R^2	0.058	0.178	0.079	0.205

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month by year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month by year of arrival level for state unemployment rate estimates.

Appendix

Table A.1: **Employment Estimates - National Unemployment Rate Treatment** (Robustness Table for Results Found in Table 2, Column 1)

	(1)	(2)	(3)	(4)	(5)	**(6)**
6 mos to 1 year, ue_0	-0.0391**	-0.0298*	-0.0297*	-0.0262*	-0.0261*	**-0.0129**
	(0.0116)	(0.0124)	(0.0123)	(0.0121)	(0.0124)	**(0.0115)**
1 to 2 years, ue_0	-0.0532***	-0.0526***	-0.0523***	-0.0503***	-0.0503***	**-0.0452*** **
	(0.0065)	(0.0069)	(0.0070)	(0.0068)	(0.0069)	**(0.0070)**
2 to 3 years, ue_0	-0.0581***	-0.0577***	-0.0571***	-0.0563***	-0.0567***	**-0.0553*** **
	(0.0083)	(0.0075)	(0.0075)	(0.0071)	(0.0068)	**(0.0066)**
3 to 4 years, ue_0	-0.0493***	-0.0538***	-0.0536***	-0.0525***	-0.0517***	**-0.0488*** **
	(0.0116)	(0.0113)	(0.0114)	(0.0118)	(0.0116)	**(0.0106)**
4 to 5 years, ue_0	-0.0359**	-0.0446***	-0.0432***	-0.0372**	-0.0363**	**-0.0365*** **
	(0.0123)	(0.0116)	(0.0115)	(0.0111)	(0.0110)	**(0.0100)**
Over 5 years, ue_0	-0.0099	-0.0232	-0.0233	-0.0192	-0.0184	**-0.0201**
	(0.0170)	(0.0155)	(0.0153)	(0.0165)	(0.0163)	**(0.0168)**
Country of Origin	*	*	*	*	*	*****
Years Of Education		*	*	*	*	*****
Gender			*	*	*	*****
Age/Age^2				*	*	*****
English At Arrival					*	*****
Other Covariates						*****
Years Since Migration FE	*	*	*	*	*	*****
Contemp. State Unemp Rate	-0.0565***	-0.0553***	-0.0557***	-0.0584***	-0.0588***	**-0.0580*** **
	(0.0041)	(0.0037)	(0.0037)	(0.0039)	(0.0040)	**(0.0041)**
Observations	32278	32278	32278	32278	32278	**32278**
Adj. R^2	0.110	0.156	0.166	0.242	0.244	**0.265**

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month and year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month and year of arrival level for state unemployment rate estimates.

Table A.2: **Log Wage Estimates - National Unemployment Rate Treatment** (Robustness Table for Results Found in Table 2, Column 2)

	(1)	(2)	(3)	(4)	(5)	**(6)**
6 mos to 1 year, ue_0	-0.0305**	-0.0263**	-0.0246**	-0.0225*	-0.0216*	**-0.0171+**
	(0.0089)	(0.0092)	(0.0089)	(0.0091)	(0.0092)	**(0.0095)**
1 to 2 years, ue_0	-0.0317***	-0.0358***	-0.0351***	-0.0339***	-0.0341***	**-0.0314*** **
	(0.0059)	(0.0061)	(0.0059)	(0.0057)	(0.0056)	**(0.0058)**
2 to 3 years, ue_0	-0.0351***	-0.0415***	-0.0406***	-0.0406***	-0.0409***	**-0.0397*** **
	(0.0065)	(0.0057)	(0.0058)	(0.0058)	(0.0056)	**(0.0055)**
3 to 4 years, ue_0	-0.0224*	-0.0275**	-0.0280**	-0.0276**	-0.0268**	**-0.0251***
	(0.0100)	(0.0093)	(0.0092)	(0.0094)	(0.0096)	**(0.0097)**
4 to 5 years, ue_0	-0.0416***	-0.0445***	-0.0452***	-0.0441***	-0.0438***	**-0.0437*** **
	(0.0083)	(0.0078)	(0.0078)	(0.0081)	(0.0079)	**(0.0079)**
Over 5 years, ue_0	-0.0252*	-0.0320**	-0.0335**	-0.0326**	-0.0323**	**-0.0345*** **
	(0.0108)	(0.0098)	(0.0099)	(0.0096)	(0.0096)	**(0.0090)**
Country of Origin	*	*	*	*	*	*
Years Of Education		*	*	*	*	*
Gender			*	*	*	*
Age/Age^2				*	*	*
English At Arrival					*	*
Other Covariates						*
Years Since Migration FE	*	*	*	*	*	*
Contemp. State Unemp Rate	-0.0208***	-0.0213***	-0.0227***	-0.0234***	-0.0239***	**-0.0240*** **
	(0.0038)	(0.0039)	(0.0039)	(0.0038)	(0.0039)	**(0.0040)**
Observations	14100	14100	14100	14100	14100	**14100**
Adj. R^2	0.167	0.209	0.230	0.247	0.251	**0.255**

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month and year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month and year of arrival level for state unemployment rate estimates.

Table A.3: **Employment Estimates - State Unemployment Rate Treatment**
(Robustness Table for Results Found in Table 2, Column 3)

	(1)	(2)	(3)	(4)	(5)	**(6)**
6 mos to 1 year, ue_0	0.0014	0.0014	0.0014	0.0079	0.0079	**0.0085**
	(0.0121)	(0.0119)	(0.0118)	(0.0113)	(0.0113)	**(0.0109)**
1 to 2 years, ue_0	-0.0092	-0.0108	-0.0106	-0.0043	-0.0042	**-0.0056**
	(0.0092)	(0.0086)	(0.0086)	(0.0086)	(0.0085)	**(0.0076)**
2 to 3 years, ue_0	-0.0040	-0.0062	-0.0060	-0.0001	0.0001	**-0.0024**
	(0.0085)	(0.0080)	(0.0080)	(0.0074)	(0.0074)	**(0.0071)**
3 to 4 years, ue_0	0.0065	0.0024	0.0024	0.0092	0.0094	**0.0074**
	(0.0087)	(0.0080)	(0.0079)	(0.0073)	(0.0072)	**(0.0070)**
4 to 5 years, ue_0	0.0120	0.0077	0.0082	0.0160*	0.0164*	**0.0136***
	(0.0080)	(0.0075)	(0.0074)	(0.0067)	(0.0067)	**(0.0065)**
Over 5 years, ue_0	0.0107	0.0063	0.0065	0.0131	0.0129	**0.0101**
	(0.0116)	(0.0113)	(0.0111)	(0.0100)	(0.0101)	**(0.0095)**
Country of Origin	*	*	*	*	*	*****
Years Of Education		*	*	*	*	*****
Gender			*	*	*	*****
Age/Age^2				*	*	*****
English At Arrival					*	*****
Other Covariates						*****
Years Since Migration FE	*	*	*	*	*	*****
Year by Month of Arrival FE	*	*	*	*	*	*****
State of Placement FE	*	*	*	*	*	*****
Contemp. State Unemp Rate	-0.0337***	-0.0330***	-0.0330***	-0.0331***	-0.0332***	**-0.0318*****
	(0.0060)	(0.0061)	(0.0061)	(0.0058)	(0.0058)	**(0.0057)**
Observations	32278	32278	32278	32278	32278	**32278**
Adj. R^2	0.137	0.181	0.190	0.267	0.268	**0.289**

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month and year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month and year of arrival level for state unemployment rate estimates.

Table A.4: **Log Wage Estimates - State Unemployment Rate Treatment**
(Robustness Table for Results Found in Table 2, Column 4)

	(1)	(2)	(3)	(4)	(5)	**(6)**
6 mos to 1 year, ue_0	-0.0118	-0.0123+	-0.0120+	-0.0110	-0.0109	**-0.0117+**
	(0.0072)	(0.0072)	(0.0070)	(0.0069)	(0.0068)	**(0.0069)**
1 to 2 years, ue_0	-0.0152*	-0.0172*	-0.0176**	-0.0166*	-0.0166*	**-0.0164***
	(0.0068)	(0.0066)	(0.0065)	(0.0065)	(0.0064)	**(0.0064)**
2 to 3 years, ue_0	-0.0129+	-0.0143*	-0.0144*	-0.0138+	-0.0137+	**-0.0136+**
	(0.0070)	(0.0070)	(0.0069)	(0.0070)	(0.0069)	**(0.0069)**
3 to 4 years, ue_0	-0.0062	-0.0084	-0.0082	-0.0074	-0.0071	**-0.0067**
	(0.0070)	(0.0069)	(0.0068)	(0.0068)	(0.0067)	**(0.0068)**
4 to 5 years, ue_0	-0.0098	-0.0111+	-0.0110+	-0.0093	-0.0090	**-0.0092**
	(0.0065)	(0.0066)	(0.0064)	(0.0063)	(0.0063)	**(0.0065)**
Over 5 years, ue_0	-0.0009	-0.0033	-0.0027	-0.0007	-0.0010	**-0.0018**
	(0.0071)	(0.0069)	(0.0069)	(0.0067)	(0.0067)	**(0.0066)**
Country of Origin	*	*	*	*	*	*****
Years Of Education		*	*	*	*	*****
Gender			*	*	*	*****
Age/Age^2				*	*	*****
English At Arrival					*	*****
Other Covariates						*****
Years Since Migration FE	*	*	*	*	*	*****
Year by Month of Arrival FE	*	*	*	*	*	*****
State of Placement FE	*	*	*	*	*	*****
Contemp. State Unemp Rate	-0.0264***	-0.0265***	-0.0264***	-0.0252***	-0.0254***	**-0.0240*****
	(0.0052)	(0.0049)	(0.0050)	(0.0050)	(0.0050)	**(0.0050)**
Observations	14100	14100	14100	14100	14100	**14100**
Adj. R^2	0.202	0.241	0.262	0.278	0.282	**0.285**

+ 0.1, * 0.05, ** 0.01, *** 0.001

Note: Standard errors are clustered at month and year of arrival level for national unemployment rate estimates. Standard errors are clustered at state of arrival by month and year of arrival level for state unemployment rate estimates.