Immigrant Birth-country Networks and Unemployment Duration around the Great Recession: a Repeated Cross-Sectional Analysis

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ABSTRACT

This paper examines the role of birth-country networks on immigrants' unemployment duration around the Great Recession using monthly Current Population Survey data from 2001 – 2013. and finds that immigrant birth-country networks have an important role in lowering unemployment duration, particularly during the economic crisis. We use Guell-Hu (2006) model for repeated cross-sectional data with uncompleted unemployment spells and analyze unemployment duration at an individual level. In the absence of panel data analyzing unemployment using repeated cross sectional methods is very crucial. We find that birth-country networks measured at the state level significantly lower unemployment duration for all immigrants, particularly during the economic crisis and longer the immigrant is unemployed, less effective are her social networks in job search. Varying the effect of networks over duration categories the authors show that networks are more effective in lowering duration for immigrants unemployed for 1-2 months than for immigrants who are unemployed for longer periods and this effect is stronger during the post-recession period than the pre-recession period. The findings are robust to different specifications and measures of networks including those measured at the local MSA level.

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1. Introduction

The recent Great Recession was characterized by an increase in delayed retirement (McFall, 2011) and a decline in home ownership rates (Allen 2011; Mundra 2013). Even those who remained employed experienced a decline in earnings due to lower real wages (Rios-Avila and Hotchkiss, 2013) and fewer work hours (Aguiar et al. 2013). In terms of the labor market U.S. lost over 7.5 million jobs, with an unemployment rate that surpassed the 10 % mark, and a rapid increase in unemployment duration (Farber and Valletta, 2015; Grusky et al. 2011). These increases in unemployment duration in combination with extended unemployment benefits have generated a burden on the economy. According to the Congressional Budget Office, federal budget spending on unemployment insurance benefits increased almost five times from 33 billion in 2004 to 155 billion in 2011.[1] For households, increased unemployment not only lowered their income and hence their standard of living, but also reduced their chance of reintegrating back into the labor market.

There is substantial evidence indicating that social networks improve ethnic minorities and migrants' labor market outcomes mostly through job referrals, facilitating their transition into employment (Granovetter 1995; Munshi 2003; Mouw 2003; Patel and Vella 2013 to name a few), but little is known regarding how social networks affect immigrant unemployment duration. Nevertheless, a few studies have focused on this particular link between networks and unemployment duration for the population in general (for example Cingano and Rosolia 2012; Pattachini and Zenou 2012; Uhlendorff and Zimmerman 2014). Because social networks play an important role in immigrants' job searches, it raises an important question of whether or not networks also lower their unemployment duration. This question is particularly important

[1] see https://www.cbo.gov/publication/44041.

around a period of economic crisis such as the Great Recession, which already has a large burden on the economy.

In this paper, we examine the role of immigrant's social networks on their unemployment duration, and in particular aim to explore if the role of networks changes for the periods before, during and after the Great Recession. While one may consider immigrants own networks to be able to facilitate information during periods of economic growth, during periods of economic crisis such as the Great Recession, social networks may have a negative impact on unemployment duration because of increasing competition among immigrants, or because the quality of the information of the networks declines as the share of unemployed immigrants increase.

Unemployment dynamics and unemployment duration analysis is best studied in a panel data framework. However, due to non-availability of panel data using cross sectional data to analyze unemployment duration at an individual level is very important. We use Guell and Hu (2006) - GH method that allows us to model the unemployment duration using repeated cross sectional data from the Current Population Survey. Most importantly this method estimates exit probability out of unemployment at an individual level and we are not limited to analyzing unemployment for various groups (see Sider, 1985 and Baker, 1992). Moreover, unlike other methods (e.g. Nickell, 1979), GH approach does not need stationarity assumption on the unemployment being constant over time.

In the absence of panel data there have been unemployment dynamics studies across group effects but not at an individual level and this paper proposes to use the cross sectional data at an individual level to model unemployment duration analysis at the individual level for immigrants around the Great Recession.

This paper makes three important contributions. First, we add to the literature on the effect of immigrant networks on labor market outcomes, shedding light on whether immigrant social networks are effective in lowering unemployment duration, and if that effect varies with the length of their current unemployment spell.

Second, we use monthly data on unemployed immigrants from the CPS for the years 2001 to 2013 and follow the econometric approach proposed by GH for the analysis of unemployment duration using repeated cross sectional data with uncompleted unemployment spells.

Third, we discuss the role of immigrant's social networks in regards to the consequences of the Great Recession. In particular, recent research highlights that immigrants have been less adversely affected by the Great Recession compared to natives due to the role of their social capital in aspects like homeownership (Painter and Yu 2014; Mundra and Uwaifo-Oyelere 2018) and labor market outcomes and mobility (Liu and Edwards 2015).

Using immigrant's country of origin, we identify potential immigrant's networks using the share of people born in the same country and living in the same state we find that networks significantly lower unemployment duration for short unemployment duration but not for longer periods of unemployment duration. Our findings are robust to our measure of networks, when immigrant's networks are identified using Census and American Community Survey (ACS) data, and when networks are measured at the local Metropolitan Statistical Area (MSA) level.

The rest of the paper is organized as follows. Section 2 discusses prior research on immigrant social networks and unemployment duration in detail and why immigrant networks may have a differential impact on unemployment duration around the Great Recession. In Section 3 we discuss our sample, construction of main variables and preliminary descriptive statistics. Section 4 presents our GH econometric approach and our empirical specification. Section 5 presents the discussion of our results and section 6 gives detail robustness of our findings. Finally, we conclude in Section 7.

2. Background and Conceptual Framework

2.1 Immigrants social networks and unemployment duration

The most influential definition of social networks is provided by Granovetter (1973, 1982) who distinguishes different types of networks based on the strength of the ties between their members. Granovetter defines that strong ties are typically maintained with family members, whereas weak ties are maintained with friends and acquaintances. Distinguishing between weak and strong ties Granovetter(1995) finds that more than fifty percent of jobs in neighborhoods are found through contacts and weak ties networks because those networks have larger access to information on job openings that strong ties networks do not.

Similar findings using different methods and measures of the strength of social networks are also seen in Holzer (1988), Montgomery (1991), Ionnides and Loury (2004) to name a few. For the U.S., Falcon and Melendez (2001) and Elliott (2001) show that Latinos are more likely to use individual social contacts and insider referrals to find jobs. For the U.K., Patacchini and Zenou (2012) show that the higher the residential proximity of individuals from the same ethnic group, the higher the probability of finding jobs through social contacts. Bentolila et al.(2010) using samples from the U.S. and Europe show that workers who found jobs using contacts show 1-2 percent lower unemployment duration but report a significant mismatch between their productive advantage and their occupational choice. Specifically, they find that workers who used contacts to find jobs earned 2.5 percent lower wages than those who found jobs without using contacts.[2]

In most of these empirical papers, a network's strength is quantified as the relative size of an individual's network compared to the population in a particular geographical area. The larger is the share of an individual's potential network group in the area where they live, the higher is the probability of the individual connecting with members of her network. The main caveat is that networks are, generally difficult to identify. Some of the ways in which the literature has measured potential networks includes the extent of an individual's linguistic concentration (Chiswick and Miller 1996), the proportion of individuals living in the vicinity of an individual who originate from the same migrant community (Munshi 2003), or a direct measure of the number of family members and acquaintances (Amuedo-Dorantes and Mundra 2007). Despite the different network measures used in the literature, the common finding is that networks unambiguously increase the chances of immigrants' employment, with mixed findings on the effect on earnings.[3]

There is, however, limited information regarding what the role of social networks is on the immigrant's unemployment duration. The literature has answered some of the questions of the heterogeneity of unemployment duration among immigrants in Europe. In a study for Germany, Uhlendorff and Zimmerman (2014) find that migrants are more likely to experience longer unemployment duration despite staying at their jobs for similar lengths of time when compared to natives with similar observable and unobservable characteristics. Diop-Christensen

[2] Social contacts with compatriots are crucial for future migration flows as well. International migration is perpetuated by social contacts between current migrants and non-migrants, generating what sociologists call "self-perpetuating" migration (Massey et al 1998).

[3] Chiswick and Miller (1996) show that an increased tendency of settling in enclaves lowers English language skills among immigrants and hence lowers their earnings whereas Mouw (2003) and Munshi (2003) find that with larger networks immigrants have a higher likelihood of finding higher paying jobs.

and Pavlopoulus (2016) find similar results for evidence from 12 European countries, but concludes that immigrants benefit more from increase in demand for low skilled workers. The heterogeneity of unemployment duration for immigrants has not been explored for the U.S. and particularly the role of social networks on unemployment duration for the U.S. is missing in the literature. If networks improve employment prospects for immigrants, then larger networks also help lower their unemployment duration.

2.2 Immigrant Networks and Duration Dependence

There is reason to believe that the effect of networks on unemployment duration depends on how long immigrants have been unemployed. Calvo-Armengol and Jackson (2004) present a theoretical model showing that social networks play an important role for individuals in the labor market because they help to reduce job search cost by providing access to information that facilitates the job search process. According to their theoretical model, the effect of networks on employment outcomes depends on the initial state of the networks and on the length the agent has been unemployed. The longer an individual is unemployed, the lower are her chances of finding a job due to duration dependence but also because the quality of networks worsens and her networks are less helpful in job searches. This might happen for two reasons.

First, in periods where unemployment is high, the longer an individual remains unemployed, the larger will be the share of unemployed migrants in her network and the larger will be the competition for the same job. Second, as the quality of a network deteriorates, the network consists of a larger number of unemployed individuals with less information and fewer contacts for finding information on hiring and vacancies and potential good job leads. In addition to these channels, it is also possible that individuals who have been unemployed for long periods of time have lost contact with their networks, reducing the potential supportive effect of networks on their labor outcomes.

Cingano and Rosalia (2012) also elaborate on the quality of networks and show that a one standard deviation increase in the network employment rate reduces the unemployment duration of a displaced worker by 8%. They also find that this effect is further strengthened when the contacts searched for a job recently and their employers are located closer to the displaced worker spatially and technologically.

Networks and Duration Dependence around the Great Recession

There is evidence suggesting that the recession had a heterogeneous effect on unemployment duration. Valletta and Kuang (2012) suggest that a weak labor market and job market skill mismatching, are the main factors explaining the rapidly increasing unemployment duration in the recent recession and recovery in the U.S. The weakness of the labor market, however, may have had a heterogeneous effect on unemployment duration due to the unemployment duration dependence. While the number and share of workers with less than 10 weeks of unemployment has remained relatively constant over time, the share of those with longer duration spells increased sharply during the recession, but has shown a slow recovery after the recession.

The literature also suggests that immigrants and natives have had different experiences regarding their unemployment outcomes through the Great Recession. Before the recession, immigrants' unemployment rate fell below that of native workers. However, as a result of the housing bust immigrants' labor outcomes deteriorated faster than for natives mainly because less-educated Hispanic immigrants are often employed as independent contractors and temporary workers making their jobs very sensitive to the business cycle (Orrenius and Zavodny 2009). On the other hand, because immigrants tend to be more geographically and occupationally mobile when searching for a job, these characteristics may offset some of the negative labor impacts of the recession.

Recent papers have shown that higher mobility among certain immigrant groups have helped them in their labor market outcomes around the Great Recession (Zhu et. al. 2014; Cadena and Kovak 2016). Sisk and Donato (2016) show that Mexican men immigrants were more likely to be continuously employed during the recession, though many experienced high levels of involuntary part-time employment. Zhu et al. (2014), using a sample for Latino immigrants from the American Community Survey 2008–2010 and measuring ethnic enclaves at the PUMA level, finds that in 2010 Latino immigrants who lived in the outer ring suburbs showed a higher likelihood of working but with a longer commute than compared to the year 2000. On the other hand, as described in Liu and Edwards (2015), in contrast to social networks arguments, immigrants may have suffered negative externalities due to the presence of a larger concentration of immigrants in the local labor market by facing tougher competition and having worse employment prospects.

Under financial stress, as experienced by many households in the recent financial meltdown and sub-prime crisis, immigrants may have relied on their social networks for income and financial support.[4] While a large proportion of minorities and immigrant households who obtained loans during the peak sub-prime period have lost their homes, the literature finds immigrants were less adversely affected by the recession (Allen 2011; Mundra 2013), possibly

[4] The recent literature on foreclosure and loss of homeownership has shown that the Great recession has had heterogeneous effect on natives and immigrants. A large proportion of minorities and immigrant households who obtained loans during the peak sub-prime period have lost their homes. However, the literature also finds that many immigrants were less adversely affected, particularly when comparing natives and immigrants of Hispanic origin (Allen 2011; Mundra 2013). Mundra and Uwaifo-Oyelere (2018) propose that part of the explanation is tied to immigrant's social capital in the U.S. and banking with ethnic banks.

due to immigrant's social capital in the U.S. and banking with ethnic banks (Mundra and Uwaifo-Oyelere, 2018).

In summary, the larger the size of the immigrant network the greater is the potential pool of job information and stronger are immigrant's chances of finding employment in the labor market, reducing their unemployment duration. However, networks might not be effective in job searches during the time of a national slowdown on the scale of the Great Recession. As indicated before, in periods of long economic stress with high unemployment and increasing unemployment duration, the quality of a network might decline rapidly and the likelihood of competition might increase, thereby reducing its effectiveness in job searches and in lowering unemployment duration.

3. Data and Descriptive Statistics

The data used in this paper is constructed from the monthly Current Population Survey (CPS) obtained from Integrated Public Use Microdata Series (IPUMS) for the years 2001–2013. Given that the focus of this paper is to analyze network effects on immigrant workers, we restrict the sample to people who indicate were born in a foreign country and excluding individuals born to American parents. We also restrict the sample to unemployed immigrants who are between 20 to 64 years of age in order to capture the core of the labor force among immigrants.

Unemployed immigrant workers are identified using self-reported unemployment status based on their activities during the week previous to the interview. For this individuals, the current length of unemployment spell is measured using the reported number of consecutive weeks that individual has been looking for work.

The years selected for the analysis were chosen to obtain a panorama of the changes in labor market dynamics, specifically changes in unemployment duration before, during and after the Great Recession. According to the National Bureau of Economic Research the Great Recession is defined as the period between December 2007 to June 2009, the pre-recession covers the period from January 2001 to November 2007, and the post-recession covers the period from July 2009 to December 2013.

3.1 Measuring Networks

Our network measure is based on a concentration index that captures the population share of immigrants at the state level who originated from the same birth country. Capturing potential networks as the share of the population is common in the literature.[5] Specifically, for each immigrant, networks are measured as the average share of population who migrated from the immigrant's birth country and lived in the same state as the immigrant during the previous calendar year. Thus for an immigrant surveyed in February of 2005 her birth-country networks is measured using information from January 2004 to January 2005. The network measures are estimated using survey weights and concentrates on the total employed and non-employed population 15 years or older, excluding individuals born abroad to American parents.[6]

There are several reasons why an immigrant's network is the strongest with other immigrant’s groups from their birth country. They are more likely to share the same language, same institutional background and are more likely to have similar cultural preferences. These factors all create different reasons for interaction and connection. Moreover, solidarity or allegiance with country of birth may also incentivize immigrants to connect with birth country compatriots and also create an obligation to see them succeed which could facilitate mutual

[5] McConnell and Akresh (2008) measure their immigrant context variable as the percent of the total state population in 2000 that was born in the same region of the world. Munshi (2003) measures network for each migrant by the proportion of the sampled individuals in the Mexican Migration Project from the origin community in Mexico who are located in the U.S. In empirical studies looking at the effect of immigrant networks on bilateral trade flows, networks are also measured as the share of the population (Gould 1994; Rauch and Trindade 2002 and Mundra 2005 to name a few).

[6] While our preferred measures use data for the previous calendar year, we used data for immigrant networks based on data from two years ago, finding no differences with the findings used in text. Results are available upon request.

insurance. In terms of affinity, cultural identification and trust among immigrant groups, the literature has shown that immigrants form networks and share labor market opportunities the strongest with compatriots rather than with migrants from other countries (Pattachini and Zenou 2012).

While intuitively one might prefer to measure networks based on small geographical areas, capturing impacts in local labor markets, there are many arguments that justify the use of a state level network variable. First, as noticed by Cadena and Kovak (2016), immigrants, who are disproportionately low-skilled workers, are more mobile across MSAs. This implies that immigrants are less restricted to gateway enclaves, and are likely to move to suburbs in their state with increasing decentralized residential patterns. In this sense, measuring networks in terms of the share of state population from your birth country is a more relevant measure of networks. In addition, while immigrants are more mobile, Kritz and Nogle (1994) and Gurak and Kritz (2000) find that immigrants are less likely to move across states, as immigrants hesitate to move away from the social capital their birth country networks provide. Furthermore, for many immigrant groups their birth place networks cover a wider area. There are many immigrant organizations in the U.S. that operate over a state level.[7]

Second, the record high unemployment rates and a weak labor market caused by the Great Recession might have created more competition for similar types of jobs and occupations among immigrants from certain countries in small geographical areas. In this scenario, measuring networks at the local labor market level may be more likely to capture a competition effect, rather than the information spreading effect of networks. Using a measure of networks at the state level will be less likely to be affected by the competition effect, under the assumption

[7] Nigerian Women Association of Georgia, Pakistan Association of Greater Houston and Bangladesh Association of California are a few examples of relevant immigrant social groups at the metro area/state level.

that the employment shock is heterogeneous across the state, while still capturing the effects of immigrant networks as a proxy for social networks.

Third, one of the main drawbacks of measuring networks based on country of birth using survey data is the reliability of the estimations. As pointed out in Aydemir and Borjas (2011), using small geographical areas may introduce a bias on the measured effects of immigration because of the larger noise to signal ratio that is introduced when estimating variables like the network measure used in this paper. Using a state level measure is a compromise between measuring immigrant networks with a smaller error and obtaining a precise estimate of immigrant networks at the local labor markets. While our main results are based on measuring networks at the state level, we provide robustness checks using more local level networks such as at the MSA level.[8]

Both unemployment duration and unemployment rates exhibit very similar trends over time and a significant rise during the Great Recession. Figure 1 shows weeks unemployed over time for three groups of networks: large networks (2.573% - 15.52%), medium networks (0.394% - 2.573%) and small networks (0% - 0.394%).[9] Interestingly, we do see that immigrants with large birth country networks show lower unemployment duration than immigrants with small to medium sized networks. This holds true for both during the boom and the bust.[10]

In Table 1, we present summary statistics for the full sample of immigrants and for immigrants across the recession period. There are significant differences among unemployed immigrants before and post the recession. We observe that the average duration spell increased

[8] For more discussion on how networks operate at the state level, see Mundra and Uwaifo-Oyelere (2018).
[9] For the purpose of this figure, small, medium and large networks were defined so that approximately one third of the unemployed immigrant population is in each group. Figure A in the appendix provides a simple histogram of the distribution of the network variable in the sample.
[10] Immigrants from one country can be in large networks in one state and in middle or low networks in the other. This also changes across time. Countries with the largest networks include Mexico, Philippines, Cuba, El Salvador, Dominican Republic, India, Japan, China and Portugal.

from almost 18 weeks before the recession to almost 35 weeks after the recession. Another important change observed across different time periods is the number of weeks of insurance available to eligible unemployed workers. Starting from 18.2 week of allowance in the pre-recession period, it increased to 19.9 weeks by the time of the recession and reached more than 35 weeks in the post-recession period. As described in Farber and Valletta (2015), while the increase in unemployment insurance benefits was a response to the increase in unemployment duration, these extensions could have caused part of the increases in the unemployment spell.

The CPS estimates of the potential immigrant networks seem to be robust when compared to the American Community Survey and the Census estimates (albeit smaller in 1990). There seem to be small changes in the size of networks across time periods. While there is a clear increase in immigrant network size between the pre-recession and the recession period, there seems to be a decline through the post-recession period.[11]

An interesting development in the shape of the characteristics is in terms of the share of "recent" unemployed immigrants.[12] While overall about 14.1% of the sample are recent immigrants, there was a sharp increase in the share of recent immigrants among the unemployed from 4.9% to 17% before and during the recession. By contrast the share increased by only three additional percentage points in the post-recession period. We also find that the share of citizens also increased during the post-recession period. As expected, during the Great Recession with slow and jobless recovery during the post-recession period, recent migrants tend to be more vulnerable to fluctuations in the labor market. Citizens, on the other hand, tend to be more settled and less mobile and show longer unemployment duration during and after the recession.

[11] See http://www.migrationpolicy.org/programs/data-hub/charts/immigrant-population-over-time.
[12] Recent immigrants are defined as those who indicate they have lived in the U.S. for less than 10 years.

Figure 2 shows the distribution of the weeks unemployed for immigrants after the digit preference correction. Almost 25% of the sample has been unemployed for less than 5 weeks, almost 24% has been unemployed for 5-12 weeks, 24% has been unemployed between 13 - 52 weeks and 14% has been unemployed greater than 52 weeks.

4. Econometric Model and Implementation

In order to analyze the impact of networks on unemployment duration, we implement the Maximum Likelihood (ML) alternative of the model proposed in Guell and Hu (2006), henceforth GH, which uses a synthetic cohort approach to identify the effect of observable characteristics on the individual's likelihood of continuing unemployment. This method is chosen over the standard survival analysis, as the later requires panel type data for the analysis of duration models.

While the CPS has a panel component that allows identifying individuals for up to 4 continuous months, inferences obtained from this data may be biased in the framework of immigrant labor market dynamics for various reasons. First, the restriction on immigration status, employment status and temporal availability would greatly reduce the immigrant sample to only 75%, 50% and 25% of the data, if two, three and four consecutive months match data were to be used respectively. Second, identification of the panel can introduce additional noise to the estimation because their panel identifier may result in erroneous links due to errors in the source data. Including information on immigration status, country of birth and current unemployment duration, in addition to sex, age and race, in the data match check shows a larger probability of misidentification for the population of interest. Third, the CPS are only able to follow individuals for up to 4 consecutive months, standard methodologies are only able to identify determinants for short term transition rates (month to month), providing little insight for analyzing medium and long term transition rates.

The GH approach does not require following individuals across time, which allows us to use all information available, without losing data by construction or attrition. This method avoids possible measurement errors generated by individuals mismatched across surveys. Finally, it allows incorporating short, middle and long term transitions rates in the analysis, which provides a better alternative for examining the dynamics of unemployment duration among immigrants. However, since we do not follow the same individuals across time, we are unable to differentiate between transitions into employment or out of the labor force, when analyzing unemployment duration.[13]

4.1 GH Formal description

Formally, the GH-MLE model involves estimating the probability of remaining unemployed between the base and continuation period, conditional on characteristics *X*. To do this, the estimator pools two samples of individuals with duration s at time t and duration $s+1$ at time $t+1$, and estimates the conditional probability $P(y=1|X=x)$ indirectly by modeling the probability that an observation belongs to the continuation sample conditional on X $P(\tilde{y}=1|X=x)$.

Let m_0 and m_1 be the number of observations of the base and the continuation sample. We do not observe y but we observe $\tilde{y}$ which is an indicator for whether an observation belongs to the continuation sample (1) or to the base sample (0). The joint distribution of $(X,\tilde{y})$ in the combined sample is:

[13] As will be observed in the results, individuals with the longest of unemployment duration have smaller probabilities to remain unemployed. Some of these immigrants might become discouraged and transition out of the labor force rather than into employment.

$$P(X=x,\tilde{y}=1)=\frac{m_1}{m_0+m_1}P(X=x|y=1)=\frac{m_1}{m_0+m_1}\frac{P(y=1|X=x)P(X=x)}{P(y=1)} \qquad (1a)$$

and

$$P(X=x,\tilde{y}=0)=\frac{m_0}{m_0+m_1}P(X=x) \qquad (1b)$$

Applying Bayes' Rule we have, and using (1a) and (1b) we have:

$$P(\tilde{y}=1|X=x)=\frac{P(X=x,\tilde{y}=1)}{P(X=x)}=\frac{P(X=x,\tilde{y}=1)}{P(X=x,\tilde{y}=0)+P(X=x,\tilde{y}=1)} \qquad (2)$$

$$P(\tilde{y}=1|X=x)=\frac{1}{1+\frac{m_0P(y=1)}{m_1P(y=1|X=x)}}=\frac{1}{1+\alpha\frac{1}{P(y=1|X=x)}} \qquad (3)$$

where $\alpha=\left(\frac{m_0}{m_1}\right)P(y=1)$

Assuming logit specification for $P(y=1|X=x)$ equation (3) can be rewritten as:

$$P(\tilde{y}=1|X=x)=\frac{1}{1+\alpha\frac{1+\exp(x\beta)}{\exp(x\beta)}}=\frac{\exp(x\beta)}{\alpha+(1+\alpha)\exp(x\beta)} \qquad (4)$$

Given that we are interested in the marginal effects of networks on unemployment duration, the effect on the probability of unemployment continuation can be estimated using the parameters estimated in equation (4):

$$\frac{\partial P(y=1|X=x)}{\partial x}=\hat{\beta}*\hat{P}(y=1|X=x)*\left(1-\hat{P}(y=1|X=x)\right) \qquad (5)$$

Equation (4) is a modified logit equation for observing whether a particular observation is in the base or continuation sample with the scaling factor α included, which can be estimated using Maximum Likelihood. Equation (5) gives the marginal effect on the probability of continuing an unemployment spell. We report this marginal effect for all our models.

4.2 Implementation

The GH methodology allows us to implement a duration analysis using cross-section data, taking into account time dependence components and uncompleted unemployment spells, using a type of synthetic cohort analysis. For the model to be properly identified it assumes absence of unobserved heterogeneity, absence of time varying characteristics, and that the sample of unemployed immigrants at time $t+1$ with unemployment duration $s+1$ was drawn from the same population as those unemployed immigrants with unemployment duration s at time t. The model estimation also requires data on unemployment duration to be equally spaced, so one can create unemployment duration cohorts that are followed across time. Unemployment duration in the CPS is measured in continuous weeks of unemployment, which provides enough flexibility to identify various unemployment duration cohorts for the analysis.

This estimator is implemented by arranging a base and a continuation samples across the full range of duration intervals or classes, which are pooled together for analysis. Individuals unemployed for 5-8 weeks in months' t are paired with those unemployed to less than 5 weeks in $t-1$; those unemployed for 9-12 weeks in months t to those unemployed for 5-8 weeks in $t-1$; third, 13-16 weeks in month t to 9-12 weeks in $t-1$; fourth, 27-39 weeks in t to 13-26 weeks in t-3; fifth, 53-78 weeks in month t to 27-52 weeks in t-6; and sixth, 105 + weeks in month t to 53-104 weeks in t-12. This approach uses the differences in the distribution of characteristics between the base sample (at time t-1) and the continuation sample (at time t) to infer the risk of an observation to remain unemployed, thus experiencing a longer unemployment spell.

One potential problem with the information on unemployment duration captured in the CPS is the tendency of respondents to report duration as multiples of one month, 3 months, or half a year.[14] In order to account for this "digit preference problem", we follow Sider (1985) and Valletta (2013) by randomly adding an additional week to the total numbers of continuous weeks of unemployment to 50% of the respondents that declared to be unemployed for 4, 8, 12, 16, 20, 26, 30, 39, 43, 52, 56, and 78 weeks.

4.3 Model Specification

In addition to the standard individual demographic controls (sex, race, age and education), we control for comprehensive set of individual and labor market characteristics that that could influence immigrants' unemployment duration status. Years since migration and current citizenship status are included to control for immigrant assimilation and determine their vulnerability in the labor market. In specific, we control for whether the immigrant has been in the U.S less than 10 years (*Recent Migrant*) and whether the immigrant is a naturalized citizen.

To account for the possibility that people may extend their unemployment spells because they are relying upon unemployment benefits, we control for the maximum number of weeks people can potentially benefit from unemployment insurance at the state level (Farber and Valletta 2015). As homeowners may be less mobile and more attached to the local labor market and hence face higher unemployment duration during an economic downturn (Blanchflower and Oswald 2013), we include a homeownership dummy to control for this potential effect.

In the last decade, some states have passed employment verification laws to protect native and legal immigrant employment against undocumented immigrants, particularly for the unskilled group.[15] To control for the differences and changes across time regarding employment

[14] Baker (1992) describes some of the consequences and popular solutions of this problem, providing a sensitivity analysis of correction strategies on the estimated average unemployment duration estimations.
[15] Studying the impact of 2007 Legal Arizona Workers Act (LAWA), the first E-Verify law to be passed, Bohn et al. (2014) show that in response to this Government policy there was a substantial decrease in the state's unauthorized population and that LAWA failed to improve the labor market outcome of legal low-skilled workers who compete

of immigrants and market regulations, we introduce as control an E-Verify variable that takes the value of one if there is partial implementation of the initiative and two if there is full implementation. We also control for whether the state implemented a policy like E-Verify

To measure the health of the labor market we use the share of employed migrants and non-migrants between the ages of 20 to 64 for each state, year and month. State fixed effects are included to account for unobserved time invariant factors that we are not able to control otherwise. Since immigrants with different origins and backgrounds might behave differently, or be treated differently, we include a set of dummies to capture the general region from which the immigrant originates. To account for the time dependence factor, we also include dummies to indicate how long the immigrant has been unemployed, based on the unemployment duration class described previously. For simplicity, on the lines of Valletta (2013), we assume that the effects of the covariates are uniform across duration classes, with the exception of the recession indicators.

In addition to these characteristics we include a recession dummy for months Dec 2007 - June 2009 and post-recession dummy for July 2009 - Dec 2013, to control for the recession effect in the model. Our key variable of interest *Network* is included in the model alone and interacted with the two recession dummies. The coefficient on the two interaction terms, *Network*Recession* and *Network*PostRecession*, will help to identify the difference in the conditional unemployment probability of immigrants during a recession and post-recession period compared to the pre-recession period. If networks are relied upon more during an economic crisis, particularly at the state level, these coefficients will be positive and statistically significant. We calculate the marginal effects (equation 5) and report the average of these for all

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with undocumented immigrants in the state. In contrast, focusing on the Mexican population, Orrenius and Zavodny (2015) show that employment increased for legal immigrants in states that adopted E-Verify policy.

immigrants to understand the magnitude of the effect of networks over the whole period and how this effect differed during the pre-recession, recession and post-recession periods.

4.4 Identification Strategy

In empirical studies there is an important problem of identifying the causal effect of networks on labor outcomes, as endogeneity problems caused by omitted or unobserved variables that are related to immigrant network sizes and unemployment duration and exit rates may create inconsistent estimates. Even though we control for a large set of characteristics that should capture most factors that may cause the endogeneity problem, the problem may remain due to uncontrolled reverse causality between network size and labor economic conditions (measured by unemployment duration).

Measuring networks as the share of the population at the state level instead of using a local geographic area helps mitigate this problem. If instead of measuring networks at the state level, networks were measured at the MSA or zip code level, the concern for endogeneity is stronger because local networks are likely to adjust faster to the local market shocks (i.e. local housing bust). At a more aggregated level, however, immigrant's network may not adjust to such shock since the adjustment would be observed within the state, rather than across states.

As described above, to control for some of unobserved factors that could be causing heterogeneity, we control for state fix effects as well as a large set of demographic characteristics and local economic conditions. In addition, we test the robustness of our results by using a Bartik type of instrument in order to obtain a measure of immigrant networks that is exogenous to changes in local market economic conditions.[16]

[16] We discuss this test in detail in Section 6.

5. Results

5.1 Basic specification

Table 2 displays the marginal effects of networks on the probability of unemployment continuation from different empirical specifications of equation (4). We report the overall average marginal effect of networks as well as the marginal effects of networks for the pre-recession, recession, and post-recession periods. Table 3 reports the coefficients for all explanatory variables of the corresponding modified logit models. A positive coefficient indicates that larger magnitudes of the variables are associated with higher probability of unemployment continuation rates, and hence longer unemployment duration, whereas a negative coefficient indicates the opposite. Because networks are measured using information from the previous 12 months, all results are clustered at the state and birth-country level.

Column 1 includes only the measure of social network, the recession/post-recession dummies, and the controls for unemployment duration. As expected, the results suggest that unemployment spells are longer during and after the recession, particularly during the recession period. According to this specification, if an immigrant's network were to increase in size by five percentage points (pps) the probability of her remaining unemployed would on average decrease by 0.76 pp (Table 2). In Column 2 we vary the effect of networks across the pre-recession, recession and post-recession periods and find that the interaction between the network coefficient and the recession period is insignificant. The marginal effects of networks across the recession are also similar to the ones observed from the specification in column 1.

Looking at the coefficients regarding the impact of unemployment duration on how networks influence the probability of coming out of unemployment, we observe some evidence of duration dependence. Compared to the base line (from less than four weeks unemployed to five weeks unemployed) we find that the probability of continuing to be unemployed increases for shorter spells of unemployment duration and then decreases for longer spells of 13 weeks or more. Estimates for duration dependence are comparable to those found in Farber and Valletta (2015) except for long term unemployment. This might be because immigrants who are unemployed for very long periods become discouraged, which implies immigrants may leave the labor force after being unemployed for more than two years. In Column 3 we add all individual level controls to the specification in column 2 and find that the effect of network on duration remains strong and significant, albeit smaller than in column 2. The estimate on the additional impact during the recession is now almost zero. According to the estimated marginal, a one pp increase in the size of networks reduces the probability of remaining unemployed by about 0.52pp (Table 2).

Regarding the additional estimates, we find evidence of a U shape relationship between unemployment duration and age. Women and immigrants with less than high school education are more likely to remain unemployed longer periods. We also find that household size, number of children, being a head of household (or spouse), and race are not related to the length of unemployment duration. Similar to findings in the earlier literature (Valletta 2013; Blanchflower and Oswald 2013), we find no evidence that being a home owner affects unemployment duration among immigrants. These results are in contrast with the theoretical foundation presented in Blanchflower and Oswald (2013), who suggest homeownership lowers labor mobility and translates into longer unemployment periods through the "house lock" effect. The controls for assimilation factors indicate that while being a recent immigrant (ten years or less since moving to the U.S.) is not related to longer unemployment spells, being a U.S. citizen increases the probability of an immigrant remaining unemployed. This may be because citizens can easily participate in U.S. welfare payments, allowing naturalized citizens to remain unemployed while searching for a job.

In column 4, we add state level controls for employment regulations, unemployment benefits, and labor market conditions. Regarding employment regulations, the variables identifying the level of implementation of E-Verify have the expected sign but are not statistically significant. Liu and Edwards (2015) describe similar results, namely, states in which E-Verify was in place or about to be adopted immigrants had an adverse effect on employment probabilities compared to other states. In contrast with Farber and Valletta (2015), we observe that the availability of longer unemployment benefits reduces the probability of an immigrant remaining unemployed. On the other hand, living in a healthier local labor market with high employment shares reduces the probability of staying unemployed and thus reduces unemployment duration.

Column 5 gives the results from estimating our preferred model. In addition to all the controls mentioned above this column includes the dummies for the immigrants' region of origin. We find that even after taking account of regional origin heterogeneity and with detailed labor market controls our baseline results hold; immigrants with larger networks have a higher probability of transitioning out of unemployment. From Table 2, for our preferred model, we find that a one pp increase in birth-country share lowers the unemployment continuation probability of immigrants by 0.35pp over the entire period of analysis. During the pre-recession period this reduction is 0.31pp, during the recession period this reduction drops to 0.26pp, but during the post-recession period this reduction rises to 0.40pp. All these effects are statistically significant.

In summary, after controlling for all individual and state level characteristics in various specifications, we find that immigrants benefit from larger networks as this variable remains negatively related to longer unemployment spells. After taking into account the impact of the recession timing factors, the marginal effect of networks in reducing the average likelihood of remaining unemployed after the recession is almost 50% larger than their effect during the recession period (Table 2- column 5).

5.2 Networks and Duration Dependence

This section explores how the effects of immigrant networks vary with the length of unemployment duration, following the theoretical model proposed by Calvo-Armengol and Jackson (2012). To test if there are any differential impacts of networks based on unemployment duration, we estimate an extension of our baseline model (Table 3–column 5) by including interactions of *Network* and *Recession* dummies with the unemployment duration categories. In Table 4, we present the marginal effect of networks estimated at different points of unemployment duration and for the pre-recession, recession and post-recession periods using different assumptions for the unemployment duration groupings.[17] Model 1 corresponds to the estimates from the unrestricted interaction between duration dummies with the network and recession dummies. Model 2 uses a restricted interaction where the duration category dummies correspond to: 1-8 weeks (baseline), 9-26 weeks, and 27-104 weeks of unemployment. Finally, model 3 uses an alternative restriction in unemployment duration which corresponds to: 1-4 weeks (baseline), 5-12 weeks and, 13-52 weeks and 52-104 weeks of unemployment.

We find that after including interactions between network size and duration, there is a differential effect before and after the recession. Across all specifications, larger networks

[17] The coefficient estimates for all models are given in Table A1 While the marginal effects at each duration level are different in all models, the coefficients in the underlying model are restricted to be the same, as it can be seen in table A1.

significantly lower the unemployment continuation probability for immigrants with short unemployment spells (1-4 weeks), with the strongest effect in the post-recession period. We also find that larger networks reduce the unemployment continuation probability for immigrants with long unemployment spells before the recession (27-104 weeks). This effect decreased during and after the recession.

The results are less clear towards the middle of the distribution of unemployment duration (5-12 weeks of unemployment). On average, larger networks reduce the probability of unemployment continuation, however, the evidence suggests that this effect declined in the post-recession period for immigrants with 5-8 weeks of unemployment (models 1 and 3) and may have increased for immigrants with 9-12 weeks of unemployment (models 1 and 2). As it is reasonable to assume the experience of individuals with 5-8 weeks of unemployment would be similar to individuals with 9-12 weeks of unemployment, we suggest model 3 provides the best approximations for the effect of network size for this group of immigrants. This model suggests that networks are relatively less effective in reducing unemployment continuation probability compared to recently unemployed immigrants, and that this effect declines during the recession and post-recession period.

For immigrants who have been unemployed between 13 to 52 weeks our findings are somewhat mixed. Based on the average results from model 3 we conclude that the network effect on unemployment probability in the pre-recession period and recession period is smaller compared to immigrants with smaller duration spells but increases considerably during the post-recession period. This suggests an increasing role of networks in the employment dynamics of immigrants in the middle range of unemployment duration. Using models 1 and 2, we can also conclude that networks became mostly ineffective in reducing the probability of unemployment continuation during the post-recession period for immigrants with more than 27 weeks of unemployment.

To put our findings into context we use the results of model 1 and estimate the average probability of continuation of unemployment at different network sizes for immigrants who have been unemployed between 1 - 4 weeks and for those who have been unemployed between 27 and 52 weeks for each of the three periods. In this case we use the estimates of the preferred model and make predictions about the probability of unemployment continuation for various simulated changes in network size. Figures 4 and 5 display these effects for immigrant groups who have been unemployed for 1-4 weeks and 27-52 weeks respectively, using the coefficients for pre-recession, recession and post-recession. We see that larger networks help to lower unemployment duration for all periods for immigrants who have been unemployed for 1-4 weeks and that post-recession immigrants with larger birthplace networks have a lower risk of continuing to be unemployed versus immigrants with smaller networks (Figure 3). However, this is not the case for immigrants with 27-52 weeks of unemployment, as the predicted post-recession continuation probability is almost the same regardless of network size (Figure 4).[18]

Overall, examining whether immigrant social networks have a significant differential effect over various duration categories we find that networks are significantly more effective in lowering unemployment duration over the first two months of unemployment duration, and this effect further increased after the recession. However, networks are ineffective when immigrants have been unemployed for a longer period. This supports the hypothesis that for immigrants who are unemployed for a longer duration, particularly 53 weeks and more, have lower quality

[18] Figures 4 and 5 provide the predicted probability that an average person in the sample would remain unemployed for any given network size. Marginal effects and confidence intervals are shown in table 4. Standard errors and confidence intervals for Figures 4 and 5 are available upon request.

networks with poorer new job information and their networks are not as effective in finding jobs as that of immigrants with shorter unemployment duration. It is also possible that after the Great Recession, a period where unemployment continued to increase, networks are measuring increasing competition in the labor market among compatriots with longer durations of unemployment. This would explain why networks appear to increase unemployment for immigrants with long unemployment spells.

6. Robustness

As described in the data section, the analysis until now uses monthly CPS data to measure the size of immigrant networks, based on the average share of people living in any given state during the previous 12 months. We expect that using this lagged information would reduce potential endogeneity problems caused by using contemporaneous data, while allowing us to pool a larger body of data to obtain a more accurate measure of networks compared to data from a single month. Nevertheless, there is a possibility that this measure is not exogenous and the estimates may be inconsistent, or that using state level data is not appropriate to capture network effects on unemployment duration. In this section we explore various alternative measures of birth country networks as well as implement an instrumental variable strategy to assess the robustness of our results.

6.1 Measuring Networks using Census and ACS

As a first robustness test we measure immigrant networks using Census and American Community Survey (ACS) data to test the robustness of the CPS network measures. Using these data may reduce possible endogeneity problems by constructing the network variables with an exogenous data source that may also present smaller measurement errors. We present three estimates where the network variable is measured using annual data from ACS and using data drawn from the 5% Census data for the years 1990 and 2000, all obtained from the IPUMS.[19] The marginal effects of the models are given in Table 5.

First, in column 2, we present the estimates using the last year immigrant network measure based on ACS data over the period 2000 – 2012. While there is less variation in this year to year measure, compared to month-to-month from the CPS measure, the estimated impact of networks on unemployment duration are consistent with our main findings. The coefficients are somewhat smaller for the network coefficient when interacted with the recession and post-recession dummies, but they show the same sign as in the preferred model and remain insignificant.[20]

While using an external dataset such as ACS to estimate network size might alleviate possible endogeneity problems, using last year network information might not be enough to deal with a second potential type of endogeneity. Migrants will tend to move into areas with already large migrant enclaves because of labor market opportunities as well as social network pulls. In Columns 3 and 4, we address this concern by using a network measure based on data drawn from the 1990 and 2000 Census. The advantage of using Census data is that we have a more precise measure of network size compared to ACS or CPS estimates, and potentially more exogenous. To account for the fact that migration was less prevalent in 1990 than in the year 2000, the network size estimate is adjusted by inflating the share of immigrants in the year 1990 to that observed in the year 2000. Our estimations indicate that using both of these network measures provides results consistent with the preferred model, with somewhat smaller marginal effects when data from the 1990 Census is used.

[19] https://cps.ipums.org/cps/
[20] Coefficients of all the explanatory variables are given in Table A2.

6.2 MSA level Networks

As mentioned earlier, birth country networks are measured at the state level because we want a measure that: is not sensitive to local market conditions; reduces the bias that can be caused by migrants moving for job search reasons within the same state; reduces the attenuation biases caused by measurement errors; and, that takes into account the existence of networks that operate beyond small local labor markets. Nevertheless, it could be argued that a more effective measure of birthplace network can be estimated using a smaller geographical area such as county, city or MSA.

Despite these potential drawbacks of using MSA level networks, we created a network variable using the share of immigrants at the MSA level and the results are presented in column 5 (Table 5a). While the marginal effect of networks remains negative, the magnitude of the effect is almost three times smaller than the benchmark model and is insignificant, except for the pre-recession period.

It is also possible that the estimates are smaller because we are using a sample that excludes individuals whose MSA cannot be identified. To account for the sample change, we re-estimate the benchmark model using the state level network measure and the same sample as in Column 5. Results are given in Column 6. We find that the network effect for those living in Metro areas is smaller compared to the benchmark, but statistically significant and larger than the estimate in column 5. This suggests that the smaller effect of networks measured at the MSA level are not driven only by differences in the composition of immigrants living in metropolitan areas. There are two possible explanations regarding the smaller observed effect of networks on unemployment duration. On the one hand, as discussed before, it is possible that the smaller effect of networks is driven by attenuation bias and/or endogeneity bias. On the other hand, it is also possible that MSA level networks are a better measure of networks with *stronger* ties, in the spirit of Granovetter (1995), who suggests that redundant information from *stronger* ties has a weaker effect on labor market outcomes. Nevertheless, the results still support the hypothesis that networks help reduce unemployment duration by reducing the probability of unemployment continuation.

6.3 Adjustment for Small Networks

While using survey data for our analysis allows for variation within state and across time, which may help to better identify the effect of networks on unemployment duration, we also introduce some level of attenuation bias (Aydemir and Borjas 2011). This happens because the survey data, such as CPS, may not be large enough to accurately identify networks for immigrants from underrepresented countries and states with limited immigrant population.

We examine the severity of this problem analyzing the sensitivity of the estimates by constraining the sample to immigrants for whom our estimated network size is at least 0.1%, 0.25% and 0.5%, which imply a reduction in the sample by 6.6%, 18.1% and 29.6% respectively, compared to the benchmark sample. The marginal effects of these models are presented in Table 5b. In general, while some results are less statistically significant, but the core results of our model remain consistent. Networks have a negative impact on unemployment duration, reducing the probability of an immigrant remaining unemployed. One interesting take of these estimates, however, is that the impact of networks in the post-recession period is relatively stronger than in the recession and pre-recession periods when compared to the benchmark results.

6.4 Bartik Type IV Approach

One potential problem with the identification strategy used by this methodology is that the size of immigrant networks, as measured by the concentration of migrants from the same country in a given state, might be endogenous due to a simultaneity problem. The reason for this is that unmeasured local market conditions can both affect the unemployment duration of workers and attract or discourage migrant workers into the state. In this case, changes in the size of migrant networks and changes in unemployment duration might be spuriously related.

On the other hand, the drawback of using networks measures using 1990 and 2000 Census data is that we lose time variation and the effect is only identified through variation across countries of birth. An alternative solution is to use the tendency of migrants to move to areas with already high concentrations of migrants as an instrument for our networks measure, in what is commonly known as the Bartik instrument (Bartel 1989, Bartik 1991). This instrumental variable is used to decompose the total migration change (i.e. change in network size) into an exogenous supply-push component (inflow of immigrants) and an endogenous component (caused by changes in labor market conditions).

To implement this methodology, we use the 5% public use Census data for 1980 to construct the estimates of the distribution of immigrants, 15 years of age or older, by country of origin, across all the states in the U.S. Based on this concentration of immigrants by state, we use the CPS estimated total immigrant population between 2000 and 2013 to obtain a prediction of what the immigrant population by country of origin and state would look like today if the concentration of immigrants observed in 1980 remained constant. Finally, the Bartik instrument for network size is estimated as the ratio between the estimated number of immigrants for a specific country and state, and the total state population, based on the weighted CPS data from the 1980 Census. [21]

[21] In a recent paper Jaeger et al (2018) examine the effect of immigration on wages and argue that using past immigration flow as an instrument to identify the impact of current immigration on the labor market maybe biased. This is likely to happen if the labor market adjustment from past immigration flow is very slow, which will confound the effect of current immigration on wages thus conflating short run and long run effect of immigration on wages. We suspect that the bias of past immigration flows as an IV in the context of unemployment duration due to slow labor market adjustment is less severe than in the case for wages and hence we use Bartik type IV as an additional robustness test for the research question in hand.

We apply a two-step procedure to implement the IV estimator in the framework of the GH-MLE model. In the first stage, we regress the constructed Bartik instrument and all variables used in the GH model on the immigrant network measure using the CPS data in a linear model. Once the model is estimated, we take the predicted errors and include them into the GH-MLE specification to account for the endogeneity problem. This two-step residual inclusion strategy, also known as a control function approach, has been shown to be a reasonable strategy to deal with endogeneity in non-linear models (Terza et al, 2008). The process is bootstrapped to obtain the corrected standard errors in the model (Table 5b column 6). Because the data used from the summary files has a different classification compared to CPS data, and a few countries are not identified, the results are no longer comparable to the benchmark results presented in Table 5b (column 1). We therefore present estimates using a sample consistent with the IV-Bartik estimates, which are presented in column 5 for comparison. Based upon these estimates, the Bartik consistent sample and the Bartik IV estimates are consistent with the benchmark results, although the marginal effects are smaller, particularly for the IV estimations. Nevertheless, the overall effects are robust even after accounting for possible endogeneity factors.

7. Conclusion

This paper explores whether the size of immigrant networks affect immigrant unemployment duration, particularly around the Great Recession using CPS monthly data on unemployed immigrants over the years 2001 – 2013 and estimating a novel GH model where the risk of continuing to be unemployed is estimated from repeated cross-sectional data at an individual level. Using the share of immigrants from the same country of origin as a measure of network size and based on our preferred results, we find that birth country networks have a significant effect on lowering the duration of unemployment. When we do not allow this network effect to vary with the duration of unemployment we find that networks have mostly the same effect in the post-recession period and in the pre-recession period. However, that is not the case when we allow the role of networks to vary with unemployment duration. This finding supports the hypothesis taken from social network theory that the longer an agent is unemployed, the poorer is the quality of labor market information available within her network and, consequently, the less effective is the network in aiding her job search.

Interestingly, using different classifications of unemployment duration categories we find some evidence that networks are more effective in lowering unemployment duration for immigrants who have been unemployed for a shorter period. After accounting for the heterogeneity of the effectiveness of networks across duration intervals we find that the risk of continuing to be unemployed is significantly lower for immigrants with 1-4 weeks of unemployment duration and with larger network size during the post-recession period than the pre-recession period. This finding persists if we use network measures calculated from other data sources, Bartik Type IV estimation, or measure networks at the MSA level.

Using a well-represented sample of immigrants in the U.S. over more than a decade and robust econometric methods and network measures this paper makes an important contribution in establishing a persistent role of networks in reducing the immigrant's risk of continuing to be unemployed at the state level. This research provides an important insight into the role of immigrant social networks of compatriots in labor market adjustment, particularly at the time of an economic crisis. Our results also highlight the importance of accounting for the quality of social networks when examining the role of immigrant networks on labor market outcomes.

Conflict of Interest: The authors declare that they have no conflict of interest.

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Figure 1: Unemployment Duration Monthly Trend for Immigrants across Large, Medium and Small Birth-country networks over 2000 - 2013

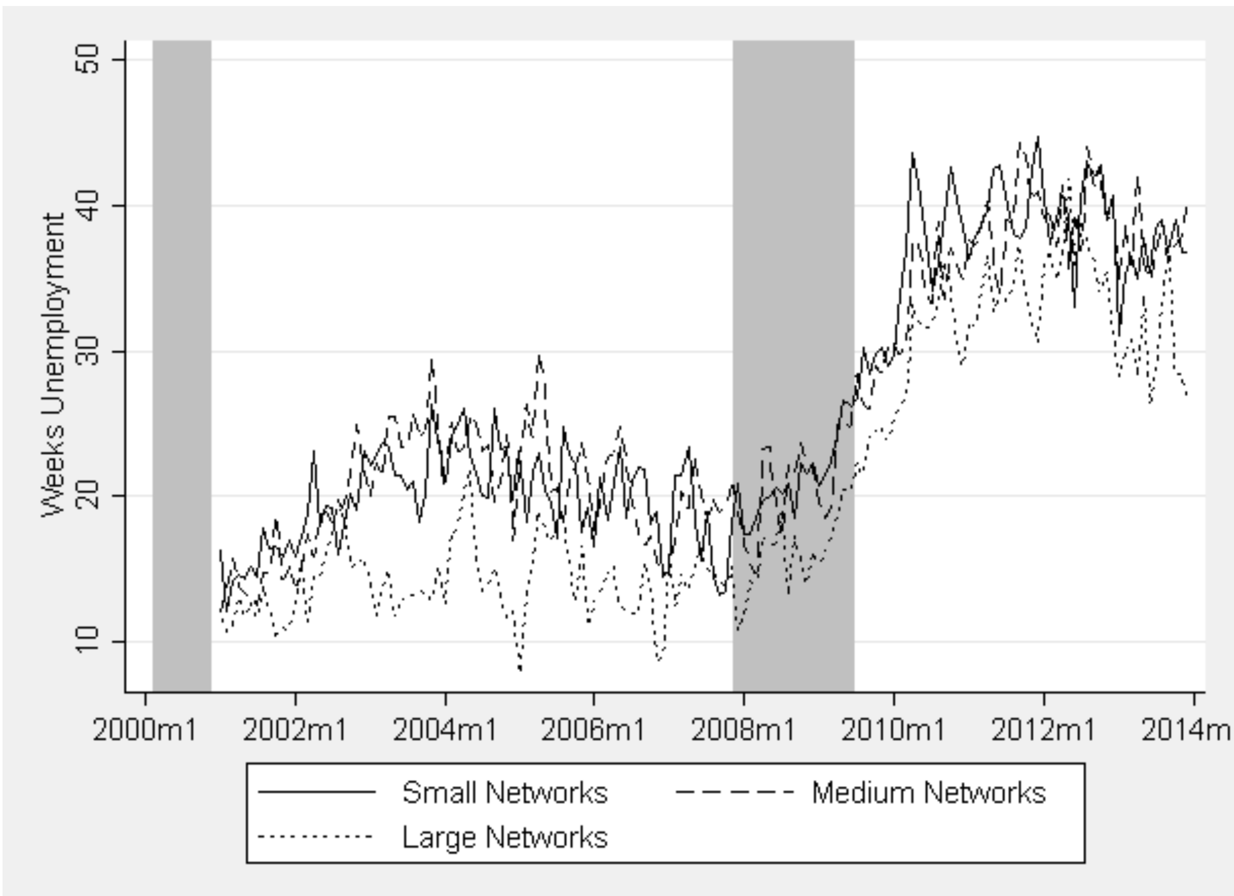

Figure 2. Continuous weeks of Unemployment

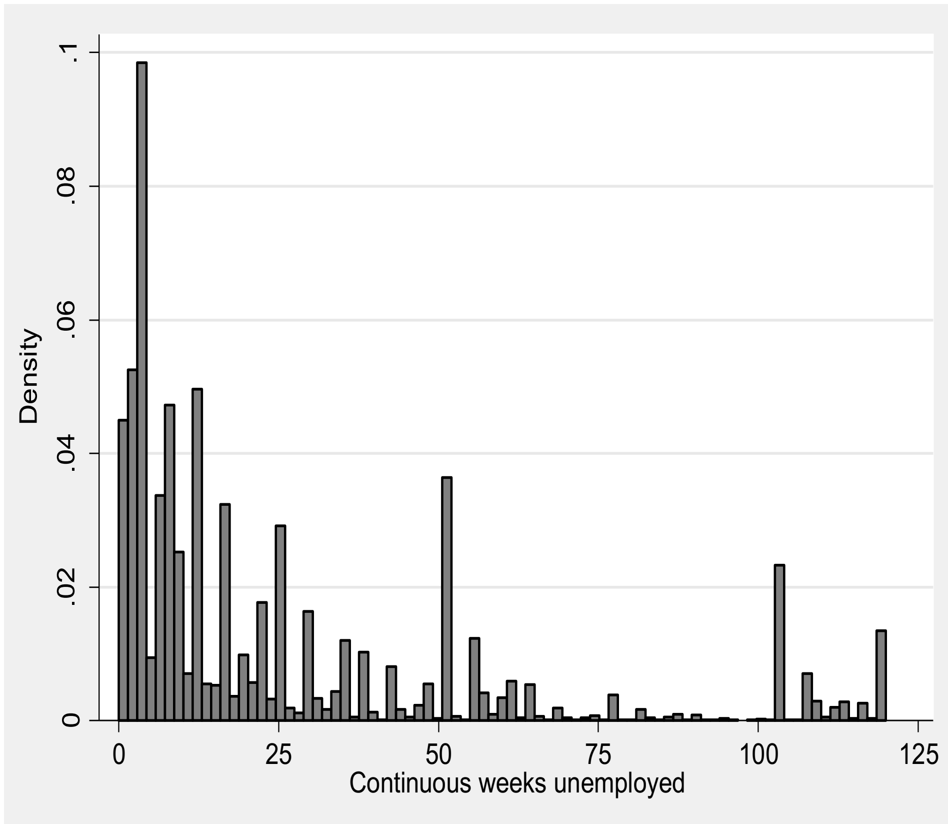

Figure 3: Predicted Probability of Staying Unemployed: Effect of Network Size for Immigrants who are unemployed less than 4 weeks

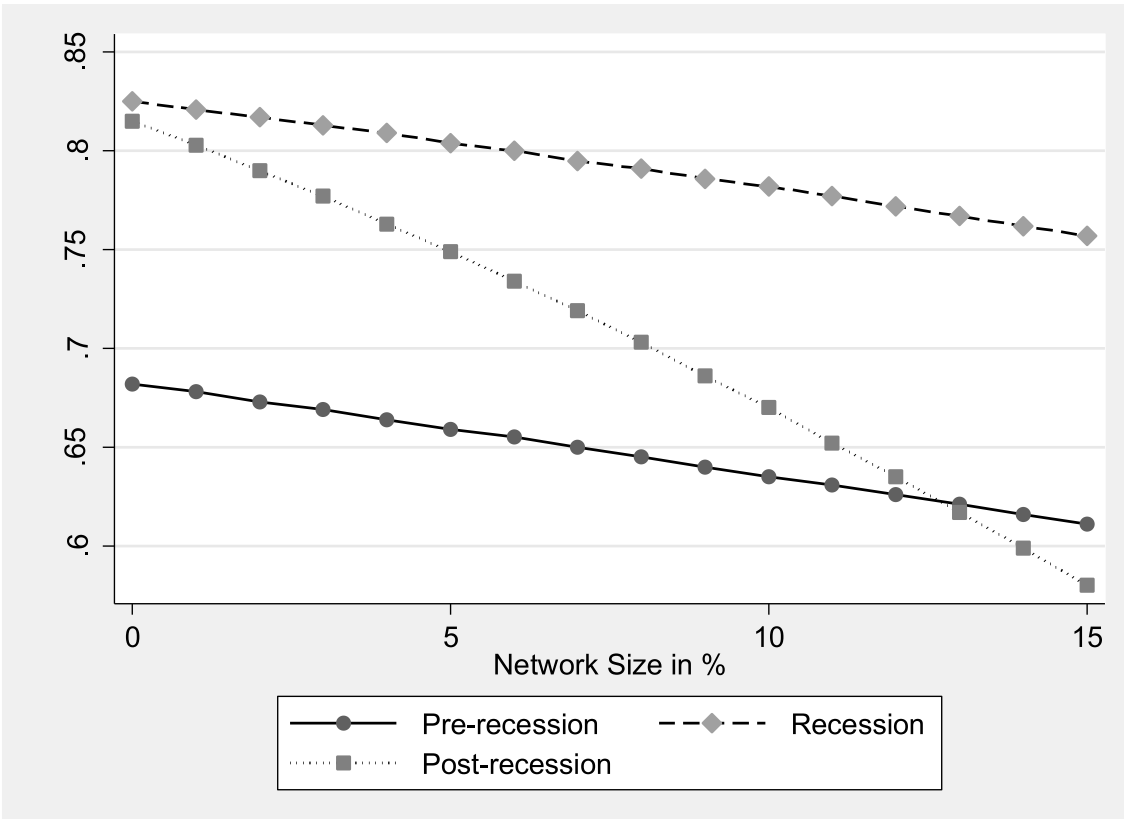

Figure 4: Predicted Probabilities of Staying Unemployed: Effect of Network Size for Immigrants who are unemployed between 27 to 54 weeks

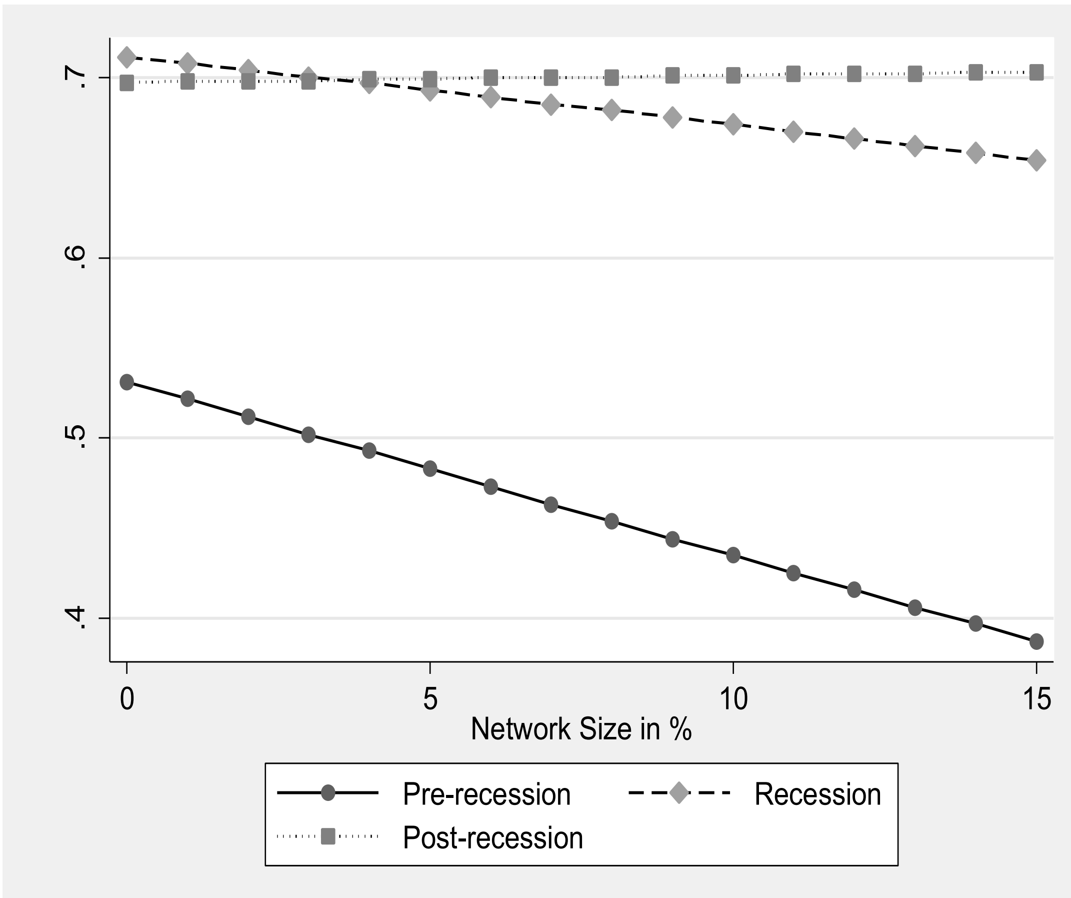

Table 1: Descriptive Statistics: Mean Values of Selected Variables for All Migrants (2001 – 2013)

	All Migrants	Pre-Recession	Recession	Post-Recession
U. Duration Weeks	26.62	18.22	19.36	35.05
Network Country of Birth: CPS	4.18%	4.05%	4.72%	4.13%
Network Country of Birth: ACS	4.18%	4.25%	4.49%	4.04%
Network Country of Birth: Census	2.53%	2.52%	2.73%	2.48%
U. Insurance Weeks	58.77	30.67	46.15	83.84
Emp. Share by Skill	64.7%	66.6%	64.7%	63.3%
Share of Recent Migrants	14.1%	4.9%	17.0%	20.4%
US Citizen	35.5%	31.4%	32.2%	39.6%
%Head of Household	48.5%	47.7%	48.9%	49.0%
%Spouse	27.3%	27.6%	27.2%	27.1%
Married	59.7%	59.2%	61.3%	59.7%
Age	39.59	38.23	39.01	40.79
Women	45.8%	47.5%	42.6%	45.3%
HS Graduate + some college	44.0%	41.1%	43.2%	46.4%
College + Grad	20.7%	20.2%	18.9%	21.5%
HH Size	3.86	3.83	3.86	3.87
# Children	1.17	1.18	1.17	1.15
%White	15.8%	16.4%	15.6%	15.4%
%Own a house	42.8%	41.1%	42.6%	44.1%
Full Everify	11.9%	1.3%	17.6%	18.5%
Partial Everify	2.4%	0.0%	2.1%	4.3%
Like Everify	8.9%	0.7%	12.6%	14.3%
Lives Metro Area	92.3%	95.9%	92.9%	89.4%

Source: Authors calculation based on monthly CPS: January 2001-December 2013

Table 2: GH-ML Estimate: Average Marginal effects

	(1)	(2)	(3)	(4)	(5)
Average Marginal Effect *					
Overall Network	-0.764	-0.766	-0.522	-0.526	-0.349
	(0.097)	*(0.097)*	*(0.094)*	*(0.090)*	*(0.089)*
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**	**[0.000]**
Network Pre-recession	-0.847	-0.837	-0.531	-0.500	-0.307
	(0.115)	*(0.145)*	*(0.141)*	*(0.131)*	*(0.134)*
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**	**[0.022]**
Network recession	-0.750	-0.664	-0.461	-0.388	-0.264
	(0.094)	*(0.204)*	*(0.187)*	*(0.130)*	*(0.125)*
	[0.000]	**[0.001]**	**[0.014]**	**[0.003]**	**[0.035]**
Network Post recession	-0.675	-0.705	-0.512	-0.573	-0.397
	(0.087)	*(0.107)*	*(0.105)*	*(0.099)*	*(0.098)*
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**	**[0.000]**
Time Dependence Dummies	x	x	x	x	x
Recession X Network interaction		x	x	x	x
Demographic Characteristics			x	x	x
State level characteristics				x	x
Region of Origin FE					x
State Fixed effects	x	x	x	x	x

Note: Standard errors in parentheses, p-values in brackets. Standard errors were clustered at the state-birth country level.

Table 3: GH-ML Estimates: Estimated coefficients

	(1)	(2)	(3)	(4)	(5)
Coefficients					
Networks	-4.143***	-4.094***	-2.633***	-2.499***	-1.536**
	(0.692)	(0.849)	(0.763)	(0.670)	(0.673)
Networks x Recession		0.442	0.0714	0.125	-0.0870
		(1.319)	(1.326)	(1.056)	(1.087)
Networks x Post-Recession		-0.233	-0.475	-0.822	-0.772
		(0.630)	(0.636)	(0.645)	(0.646)
Recession	0.571***	0.545***	0.537***	0.781***	0.801***
	(0.097)	(0.105)	(0.102)	(0.166)	(0.167)
Post-Recession	0.877***	0.887***	0.820***	0.661***	0.666***
	(0.140)	(0.132)	(0.113)	(0.194)	(0.192)
Household head or spouse			0.0528	0.0450	0.0464
			(0.054)	(0.054)	(0.053)
Married			0.0358	0.0421	0.0330
			(0.045)	(0.044)	(0.042)
Age			-0.00620	-0.00768	-0.00928
			(0.013)	(0.013)	(0.013)
Age^2/100			0.0349**	0.0356**	0.0378**
			(0.017)	(0.016)	(0.016)
Women			0.197***	0.223***	0.226***
			(0.040)	(0.040)	(0.040)
HS education + Some college			0.104**	0.0997*	0.0721
			(0.052)	(0.053)	(0.047)
College or Grad School			0.147**	0.140**	0.0942*
			(0.058)	(0.056)	(0.055)
Household Size			0.0226	0.0173	0.0160
			(0.017)	(0.016)	(0.016)
Number of Children			-0.0226	-0.0187	-0.0174
			(0.021)	(0.019)	(0.019)
White			0.00189	-0.00476	-0.0634
			(0.055)	(0.054)	(0.086)
House Owner			-0.0215	-0.0192	-0.0180
			(0.044)	(0.042)	(0.042)
Recent Migrant (10 yrs or less)			0.0779	0.0615	0.0269
			(0.071)	(0.072)	(0.068)
US Citizen			0.274***	0.262***	0.242***
			(0.052)	(0.050)	(0.052)
Partial EVerify				-0.0823	-0.0744
				(0.130)	(0.130)
Full EVerify				0.144	0.160
				(0.383)	(0.386)
Similar to EVerify Policy				0.130	0.134*
				(0.080)	(0.081)
ln(Unemployment weeks benefits)				-0.501**	-0.504**
				(0.212)	(0.210)
State level Employment share				-0.3298***	-0.3302***
All workers 20-64				(0.0651)	(0.0644)
Time Dependence					
5-8 wks unemp	1.235***	1.234***	1.148***	1.090***	1.075***

	(0.286)	(0.284)	(0.206)	(0.182)	(0.175)
9-12 wks unemp	1.070***	1.067***	1.007***	0.915***	0.920***
	(0.190)	(0.189)	(0.163)	(0.146)	(0.147)
13-26 wks unemp	-0.775***	-0.773***	-0.835***	-0.853***	-0.857***
	(0.099)	(0.101)	(0.102)	(0.105)	(0.103)
27-52 wks unemp	-0.337***	-0.334***	-0.423***	-0.521***	-0.526***
	(0.126)	(0.127)	(0.127)	(0.137)	(0.135)
53-104 wks unemp	-1.603***	-1.601***	-1.773***	-1.823***	-1.840***
	(0.226)	(0.226)	(0.228)	(0.221)	(0.221)
Share of OCC predominantly immigrant					
Share of IND predominantly immigrant					
_cons	0.818***	0.813***	0.148	0.139	25.58***
	(0.223)	(0.229)	(0.292)	(0.276)	(5.477)
Region of Origin FE					X
State FE	X	X	X	X	X
alpha					
_cons	1.162***	1.161***	1.144***	1.158***	1.137***
	(0.063)	(0.063)	(0.058)	(0.053)	(0.054)
N	125778	125778	125778	125778	125778

Note: Standard errors in parentheses and clustered at the state-birth country level. * p<0.1, **p<o.05, ***p<0.01

Table 4: Networks and Duration Dependence: Average Marginal Effects of Networks across Various Unemployment Duration Categories

	Model 1			Model 2			Model 3		
	Pre-Recession	Recession	Post-Recession	Pre-Recession	Recession	Post-Recession	Pre-Recession	Recession	Post-Recession
1-4 Weeks	-0.464	-0.428	-1.382	-0.517	-0.471	-1.246	-0.474	-0.423	-1.381
	(0.234)	*(0.149)*	*(0.262)*	*(0.198)*	*(0.130)*	*(0.240)*	*(0.238)*	*(0.147)*	*(0.263)*
	[0.047]	**[0.004]**	**[0.000]**	**[0.009]**	**[0.000]**	**[0.000]**	**[0.047]**	**[0.004]**	**[0.000]**
5-8 Weeks	-0.588	-0.379	0.035	-0.314	-0.225	-0.670	-0.308	-0.271	-0.188
	(0.177)	*(0.130)*	*(0.190)*	*(0.132)*	*(0.067)*	*(0.181)*	*(0.138)*	*(0.107)*	*(0.094)*
	[0.001]	**[0.004]**	**[0.855]**	**[0.017]**	**[0.001]**	**[0.000]**	**[0.026]**	**[0.012]**	**[0.045]**
9-12 weeks	0.120	-0.156	-0.429	0.046	-0.086	-0.467	-0.336	-0.303	-0.211
	(0.226)	*(0.127)*	*(0.175)*	*(0.115)*	*(0.061)*	*(0.099)*	*(0.130)*	*(0.101)*	*(0.110)*
	[0.595]	**[0.218]**	**[0.014]**	**[0.689]**	**[0.160]**	**[0.000]**	**[0.010]**	**[0.003]**	**[0.056]**
13-26 weeks	0.063	-0.200	-1.013	0.073	-0.213	-0.988	-0.248	-0.265	-0.637
	(0.190)	*(0.171)*	*(0.209)*	*(0.184)*	*(0.166)*	*(0.219)*	*(0.155)*	*(0.177)*	*(0.216)*
	[0.742]	**[0.241]**	**[0.000]**	**[0.689]**	**[0.198]**	**[0.000]**	**[0.111]**	**[0.136]**	**[0.003]**
27-52 weeks	-0.954	-0.373	0.040	-0.820	-0.254	0.130	-0.249	-0.239	-0.586
	(0.217)	*(0.374)*	*(0.319)*	*(0.251)*	*(0.337)*	*(0.263)*	*(0.156)*	*(0.162)*	*(0.192)*
	[0.000]	**[0.319]**	**[0.901]**	**[0.001]**	**[0.451]**	**[0.620]**	**[0.111]**	**[0.140]**	**[0.002]**
53-104 weeks	-0.344	-0.058	0.181	-0.563	-0.280	0.143	-0.327	-0.028	0.176
	(0.570)	*(0.422)*	*(0.314)*	*(0.163)*	*(0.359)*	*(0.287)*	*(0.571)*	*(0.428)*	*(0.320)*
	[0.546]	**[0.891]**	**[0.564]**	**[0.001]**	**[0.435]**	**[0.618]**	**[0.567]**	**[0.948]**	**[0.582]**

Note: Standard Error in the parenthesis and p-value in the bracket.

Table 5a: Robustness of Networks Measure and Baseline Results: Average Marginal Effect

	Benchmark	ACS	Census 1990	Census 2000	Using MSA level Network	CPS data MSA Consistent sample+
	(1)	(2)	(3)	(4)	(5)	(6)
Marginal Effects Variables of Interest*						
Overall Network	-0.349	-0.351	-0.227	-0.302	-0.109	-0.325
	(0.089)	*(0.081)*	*(0.072)*	*(0.079)*	*(0.095)*	*(0.100)*
	[0.000]	**[0.000]**	**[0.002]**	**[0.000]**	**[0.251]**	**[0.001]**
Network Pre-recession	-0.307	-0.315	-0.25	-0.3	-0.128	-0.256
	(0.134)	*(0.116)*	*(0.090)*	*(0.111)*	*(0.060)*	*(0.145)*
	[0.022]	**[0.006]**	**[0.005]**	**[0.007]**	**[0.034]**	**[0.078]**
Network recession	-0.264	-0.313	-0.16	-0.256	-0.081	-0.266
	(0.125)	*(0.141)*	*(0.114)*	*(0.147)*	*(0.105)*	*(0.100)*
	[0.035]	**[0.026]**	**[0.162]**	**[0.080]**	**[0.442]**	**[0.008]**
Network Post recession	-0.397	-0.38	-0.223	-0.31	-0.101	-0.384
	(0.098)	*(0.094)*	*(0.081)*	*(0.089)*	*(0.144)*	*(0.127)*
	[0.000]	**[0.000]**	**[0.006]**	**[0.001]**	**[0.486]**	**[0.002]**

Note: Standard errors in parentheses, p-values in brackets. Standard errors were clustered at the state-birth country level. *Coefficients are given in Appendix Table A2. +Networks measured at the state level

Table 5b: Robustness of Networks Measure and Baseline Results: Average Marginal Effect

	Benchmark	Adjustment for small Networks			Using Sample consistent with Bartik	Using Bartik IV Bootstrap Std-Error
		Network >0.1%	Network >0.25%	Network >0.5%		
	(1)	(2)	(3)	(4)	(5)	(6)
Marginal Effects Variables of Interest						
Overall Network	-0.349	-0.315	-0.285	-0.233	-0.339	-0.226
	(0.089)	*(0.096)*	*(0.109)*	*(0.122)*	*(0.091)*	*(0.088)*
	[0.000]	**[0.001]**	**[0.009]**	**[0.056]**	**[0.000]**	**[0.010]**
Network Pre-recession	-0.307	-0.248	-0.237	-0.136	-0.255	-0.185
	(0.134)	*(0.14)*	*(0.134)*	*(0.153)*	*(0. 127)*	*(0.089)*
	[0.022]	**[0.076]**	**[0.077]**	**[0.373]**	**[0.045]**	**[0.038]**
Network recession	-0.264	-0.206	-0.184	-0.17	-0. 330	-0.202
	(0.125)	*(0.119)*	*(0.122)*	*(0.127)*	*(0. 146)*	*(0.135)*
	[0.035]	**[0.084]**	**[0.132]**	**[0.180]**	**[0.024]**	**[0.131]**
Network Post recession	-0.397	-0.389	-0.346	-0.324	-0. 415	-0.268
	(0.098)	*(0.105)*	*(0.128)*	*(0.147)*	*(0. 111)*	*(0.143)*
	[0.000]	**[0.000]**	**[0.007]**	**[0.028]**	**[0.000]**	**[0.062]**

Note: Bartik IV is constructed using 1980 Census data. Standard errors in parentheses, p-values in brackets. Standard errors were clustered at the state-birth country level.

APPENDIX

Figure A. Distribution of network size

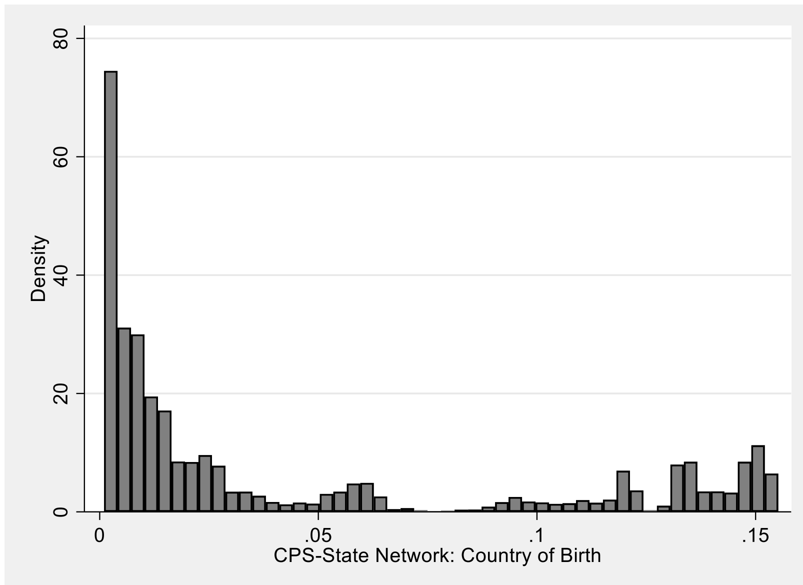

Table A1. Recession and Duration Interaction: Estimated coefficients for the all Models.

	Model 1		Model 2		Model 3
Ntwrk	-2.222**	Ntwrk	-2.454**	Ntwrk	-2.295*
	(1.133)		(0.962)		(1.179)
Ntwrk X	-0.659	Ntwrk	-0.625	Ntwrk	-0.633
Recession	(1.475)	x Recession	(1.207)	x Recession	(1.475)
Ntwrk X	-5.960***	Ntwrk	-4.811***	Ntwrk	-6.046***
x Post	(1.974)	x Post	(1.687)	x Post	(1.941)
Ntwrk x 1-4 x Pre		Ntwrk x 1-8 x Pre		Ntwrk x 1-4 x Pre	
Ntwrk x 5-8 x Pre	-2.222	Ntwrk x 9-26 x Pre	2.770***	Ntwrk x 5-12 x Pre	-0.119
	(2.011)		(0.764)		(1.290)
Ntwrk x 9-12 x Pre	3.074**	Ntwrk x 27-104 x Pre	-1.116	Ntwrk x 13-52 x Pre	1.215
	(1.347)		(1.369)		(1.025)
Ntwrk x 13-26 x Pre	2.492***			Ntwrk x 53-104 x Pre	0.263
	(0.935)				(3.653)
Ntwrk x 27-52 x Pre	-1.952				
	(1.463)				
Ntwrk x 53-104 x Pre	0.0816				
	(3.635)				
Ntwrk x 1-4		Ntwrk x 1-8		Ntwrk x 1-4	
x Recession		x Recession		x Recession	
Ntwrk x 5-8	-2.104	Ntwrk x 9-26	2.099**	Ntwrk x 5-12	-0.783
x Recession	(2.107)	x Recession	(0.837)	x Recession	(1.721)
Ntwrk x 9-12	1.086	Ntwrk x 27-104	1.813	Ntwrk x 13-52	1.690*
x Recession	(1.714)	x Recession	(1.560)	x Recession	(0.992)
Ntwrk x 13-26	1.952**			Ntwrk x 53-104	2.803
	(0.984)			x Recession	(1.929)
Ntwrk x 27-52	1.003				
x Recession	(1.864)				
Ntwrk x 53-104	2.623				
x Recession	(1.841)				
Ntwrk x 1-4 x Post		Ntwrk x 1-8 x Post		Ntwrk x 1-4 x Post	
Ntwrk x 5-8 x Post	8.716**	Ntwrk x 9-26 x Post	2.839*	Ntwrk x 5-12 x Post	5.793***
	(3.606)		(1.717)		(2.160)
Ntwrk x 9-12 x Post	3.905	Ntwrk x 27-104 x Post	7.910***	Ntwrk x 13-52 x Post	5.440***
	(2.599)		(2.276)		(1.945)
Ntwrk x 13-26 x Post	3.607**			Ntwrk x 53-104 x Post	9.134***
	(1.822)				(2.456)
Ntwrk x 27-52 x Post	8.382***				
	(2.591)				
Ntwrk x 53-104 x Post	8.997***				
	(2.476)				

Note: **Ntwrk =** Country of Birth Network. Pre=Pre-Recession period. Post=Post-Recession period. This model uses the specification in Table 3 col 5. Marginal effects are presented in table 4. * p<0.1, **p<o.05, ***p<0.01

Table A2a. Robustness of Networks Measure and Baseline Results: Coefficient estimates

	ACS	Census 1990	Census 2000	Using MSA level Network	CPS measure MSA Consistent sample
	(1)	(2)	(3)	(4)	(5)
Networks	-1.572***	-1.262***	-1.494***	-0.666*	-1.325*
	(0.579)	(0.452)	(0.559)	(0.344)	(0.765)
Networks x Recession	-0.329	0.271	-0.0626	0.107	-0.501
	(1.040)	(0.705)	(1.013)	(0.646)	(1.115)
Networks x Post-Recession	-0.611	-0.0507	-0.287	0.0284	-1.087
	(0.653)	(0.512)	(0.654)	(0.813)	(0.907)
Recession	0.801***	0.790***	0.788***	0.886***	0.922***
	(0.166)	(0.165)	(0.160)	(0.267)	(0.270)
Post-Recession	0.647***	0.659***	0.632***	0.685**	0.724***
	(0.186)	(0.188)	(0.181)	(0.301)	(0.270)
Household head or spouse	0.0529	0.0631	0.0557	-0.00217	-0.00755
	(0.052)	(0.053)	(0.052)	(0.060)	(0.057)
Married	0.0352	0.0155	0.0335	0.0502	0.051
	(0.043)	(0.042)	(0.043)	(0.051)	(0.050)
Age	-0.00915	-0.0106	-0.00804	-0.0133	-0.0136
	(0.013)	(0.013)	(0.012)	(0.016)	(0.016)
Age^2/100	0.0369**	0.0399**	0.0360**	0.0470**	0.0471**
	(0.016)	(0.017)	(0.016)	(0.021)	(0.021)
Women	0.223***	0.235***	0.223***	0.248***	0.253***
	(0.040)	(0.039)	(0.039)	(0.056)	(0.058)
HS education + Some college	0.0639	0.0814*	0.075	0.0625	0.0514
	(0.045)	(0.048)	(0.046)	(0.054)	(0.050)
College or Grad School	0.104*	0.127**	0.105*	0.102	0.0882
	(0.055)	(0.058)	(0.054)	(0.065)	(0.068)
Household Size	0.0203	0.0179	0.0194	0.0109	0.0104
	(0.015)	(0.016)	(0.016)	(0.018)	(0.019)
Number of Children	-0.0264	-0.0239	-0.0262	-0.0136	-0.0107
	(0.019)	(0.019)	(0.019)	(0.023)	(0.025)
White	-0.0378	-0.0476	-0.0418	-0.0571	-0.0798
	(0.085)	(0.089)	(0.086)	(0.098)	(0.089)
House Owner	-0.0215	-0.017	-0.0213	-0.034	-0.0277
	(0.042)	(0.043)	(0.042)	(0.051)	(0.059)
Recent Migrant (10 yrs or less)	0.00635	0.0252	0.016	0.016	0.013
	(0.064)	(0.069)	(0.064)	(0.083)	(0.077)
US Citizen	0.246***	0.245***	0.245***	0.260***	0.257***
	(0.050)	(0.053)	(0.051)	(0.063)	(0.051)
Partial EVerify	-0.0532	-0.0821	-0.0565	-0.126	-0.147
	(0.123)	(0.126)	(0.120)	(0.154)	(0.173)
Full EVerify	0.19	0.181	0.176	0.000595	-0.0116
	(0.388)	(0.418)	(0.382)	(0.451)	(0.486)
Similar to EVerify Policy	0.127	0.121	0.144*	0.192	0.192*
	(0.077)	(0.085)	(0.079)	(0.124)	(0.099)
ln(Unemployment weeks benefits)	-0.502**	-0.537**	-0.506**	-0.609*	-0.594
	(0.206)	(0.210)	(0.205)	(0.345)	(0.372)
State level Employment share	-32.55***	-33.75***	-32.53***	-40.41***	-40.31***
All workers 20-64	(6.294)	(6.315)	(6.209)	(11.377)	(11.450)

Time Dependence					
5-8 weeks unemp	1.079***	1.124***	1.084***	1.139***	1.131***
	(0.177)	(0.189)	(0.180)	(0.262)	(0.243)
9-12 weeks unemp	0.920***	0.917***	0.918***	0.987***	0.989***
	(0.147)	(0.145)	(0.146)	(0.218)	(0.216)
13-26 weeks unemp	-0.851***	-0.869***	-0.849***	-0.848***	-0.829***
	(0.103)	(0.109)	(0.103)	(0.135)	(0.126)
27-52 weeks unemp	-0.504***	-0.536***	-0.507***	-0.582***	-0.559***
	(0.135)	(0.141)	(0.135)	(0.183)	(0.158)
53-104 weeks unemp	-1.815***	-1.864***	-1.816***	-1.778***	-1.752***
	(0.219)	(0.234)	(0.223)	(0.290)	(0.236)
_cons	25.09***	26.07***	25.00***	31.24***	31.18***
	(5.280)	(5.292)	(5.207)	(9.474)	(9.577)
alpha					
_cons	1.131***	1.147***	1.132***	1.190***	1.184***
	(0.054)	(0.053)	(0.054)	(0.072)	(0.065)
N	122742	120975	123415	102437	101749

Note: All models include the Region of Origin and State Fixed effect, Following the preferred model as shown in table 3 column 5. * p<0.1, **p<o.05, ***p<0.01

Table A2b. Robustness of Networks Measure and Baseline Results: Coefficient estimates

	Adjustment for small Networks			Using Sample consistent with Bartik	Using Bartik IV (Bootstrap Std. Errors)
	Network >0.1%	Network >0.25%	Network >0.5%		
	(1)	(2)	(3)	(4)	(5)
Networks	-1.239*	-1.157*	-0.657	-1.232*	-1.035**
	(0.690)	(0.658)	(0.733)	(0.706)	(0.492)
Networks x Recession	-0.0160	0.0804	-0.309	-0.479	-0.0903
	(1.062)	(0.939)	(1.014)	(1.122)	(0.713)
Networks x Post-Recession	-1.013	-0.728	-1.042	-0.933	-0.454
	(0.667)	(0.634)	(0.745)	(0.658)	(0.824)
Recession	0.796***	0.750***	0.771***	0.837***	0.855***
	(0.177)	(0.201)	(0.212)	(0.170)	(0.187)
Post-Recession	0.686***	0.566**	0.534**	0.651***	0.679***
	(0.207)	(0.224)	(0.230)	(0.195)	(0.213)
Household head or spouse	0.0630	0.0852	0.0681	0.0677	0.0684
	(0.054)	(0.053)	(0.054)	(0.052)	(0.055)
Married	0.0311	0.0140	0.0304	0.0277	0.0268
	(0.045)	(0.043)	(0.048)	(0.042)	(0.044)
Age	-0.0121	-0.0192	-0.0224	-0.00636	-0.00579
	(0.013)	(0.013)	(0.015)	(0.013)	(0.013)
Age^2/100	0.0414**	0.0482***	0.0512**	0.0339**	0.0342**
	(0.017)	(0.018)	(0.020)	(0.016)	(0.017)
Women	0.242***	0.241***	0.260***	0.224***	0.238***
	(0.040)	(0.045)	(0.045)	(0.041)	(0.045)
HS education + Some college	0.0717	0.0627	0.0583	0.0721	0.0802*
	(0.048)	(0.046)	(0.046)	(0.047)	(0.046)
College or Grad School	0.0742	0.0454	0.0870	0.0985*	0.112**
	(0.057)	(0.058)	(0.060)	(0.056)	(0.057)
Household Size	0.0179	0.0180	0.0150	0.0268*	0.0268*
	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
Number of Children	-0.0188	-0.0215	-0.0177	-0.0348*	-0.0354*
	(0.020)	(0.018)	(0.016)	(0.020)	(0.021)
White	-0.0359	-0.0988	-0.0705	-0.0470	-0.0442
	(0.093)	(0.093)	(0.108)	(0.091)	(0.096)
House Owner	-0.0166	-0.0232	-0.0222	-0.0124	-0.0200
	(0.044)	(0.045)	(0.046)	(0.041)	(0.044)
Recent Migrant (10 yrs or less)	0.0503	0.0299	0.0221	0.0266	0.0478
	(0.075)	(0.072)	(0.074)	(0.069)	(0.069)
US Citizen	0.243***	0.248***	0.262***	0.246***	0.257***
	(0.054)	(0.059)	(0.066)	(0.053)	(0.056)
Partial EVerify	-0.103	-0.107	-0.101	-0.0841	-0.0602
	(0.134)	(0.144)	(0.156)	(0.130)	(0.132)
Full EVerify	0.129	-0.0390	0.0178	0.126	0.311
	(0.391)	(0.333)	(0.369)	(0.374)	(0.235)
Similar to EVerify Policy	0.131	0.107	0.0863	0.167**	0.219*
	(0.083)	(0.085)	(0.090)	(0.079)	(0.112)
ln(Unemployment weeks benefits)	-0.520**	-0.434*	-0.394	-0.495**	-0.558**
	(0.222)	(0.249)	(0.242)	(0.214)	(0.247)
State level Employment share	-33.49***	-31.99***	-31.58***	-32.76***	-34.75***
All workers 20-64	(6.769)	(7.732)	(7.596)	(6.576)	(7.903)
Time Dependence					
5-8 weeks unemp	1.106***	1.024***	1.071***	1.054***	1.126***
	(0.192)	(0.189)	(0.220)	(0.171)	(0.193)

9-12 weeks unemp	0.931***	0.899***	0.870***	0.911***	0.969***
	(0.155)	(0.162)	(0.168)	(0.151)	(0.169)
13-26 weeks unemp	-0.863***	-0.794***	-0.760***	-0.853***	-0.870***
	(0.111)	(0.106)	(0.100)	(0.104)	(0.103)
27-52 weeks unemp	-0.466***	-0.392***	-0.333***	-0.490***	-0.512***
	(0.133)	(0.131)	(0.125)	(0.134)	(0.137)
53-104 weeks unemp	-1.824***	-1.725***	-1.647***	-1.797***	-1.863***
	(0.233)	(0.240)	(0.249)	(0.221)	(0.226)
_cons	25.76***	24.60***	24.12***	25.05***	26.69***
	(5.679)	(6.512)	(6.374)	(5.520)	(6.585)
alpha					
_cons	0.126**	0.106*	0.0836	0.120**	0.140***
	(0.050)	(0.063)	(0.070)	(0.049)	(0.048)
N	115152	101095	86884	119073	119073

Note: All models include the Region of Origin and State Fixed effect, Following the preferred model as shown in table 3 column 5. Model in Column 5 includes the predicted errors from the first stage. * p<0.1, **p<o.05, ***p<0.01