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Making Connections: How Do Immigrants' Social Networks Influence Their Employment Outcomes?

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Economics Senior Honors Thesis

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Abstract

This paper examines the relationship between the size of local ethnic networks and immigrants' likelihood of being self-employed in 11 metropolitan areas in the U.S. I use American Community Survey data from 2005 to 2011. A two-stage discrete choice logistic specification models agents' decisions to have a job or not, and if so, to work for wages or be self-employed. Generally, the likelihood of being self-employed decreases with network size, but the opposite holds true for salaried employment. I also interview self-employed Hmong in Saint Paul to explore the effect immigrants' attitudes toward different employment options have on their work outcomes.

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I. Introduction

In the United States, business ownership is an important aspect of the foreign-born population's role in economic growth. In 1990, immigrants made up 9 percent of the labor force and 12 percent of small business owners. In 2010, 16 percent of the labor force and 18 percent of small business owners were foreign-born (Fiscal Policy Institute Report, 2012). Foreign-born business ownership rates grow with immigrant share of the labor force, and business formation rates among immigrants follow the same general cycle as the national rate: rising in recessions and falling during periods of strong economic growth. Interestingly, there seemed to be an even greater movement of enterprise among immigrants than among natives during the Great Recession (Fairlie, 2012). In 2010, the business formation rate per month among immigrants was 0.62 percent (or 620 out of 100,000), compared to the U.S.-born 0.28 percent (or 280 out of 100,000).

Unsurprisingly, factors influencing business ownership among the foreign-born in the United States are a subject of interest among policymakers, academics, and business people alike. Various theories explain the "enterprising immigrant" narrative, emphasizing human capital characteristics (Borjas, 1986; Fairlie and Meyer, 1996); personal traits (McClelland, 1961); blocked mobility and labor market discrimination (Light, 1972; Light and Bonacich, 1998); family composition and social capital (Sanders and Nee, 1995), and access to financial capital (Bates, 1992) as primary determinants of immigrants' employment outcomes. While more recent empirical literature demonstrates that informal search channels play an important role in employment outcomes (Ioannides and Loury, 2004), few papers study the effect of social networks on immigrants' specific decision to become self-employed and start a business.

This paper examines the effect local social networks have on immigrants' employment outcomes – specifically unemployment, salaried employment, and self-employment. The umbrella term "self-employment" encompasses both small business owners and entrepreneurs. The former are freelancers, operating their own small business as opposed to working for an employer. On the other hand, entrepreneurs organize and operate businesses that often involve large financial risks. Although these individuals are engaged in significantly different kinds of self-employment, the American Community Survey – and consequently, my paper – does not make a distinction between the two. The terms "immigrant" and "foreign-born", meaning anyone who was not a U.S. citizen when they were born, are interchangeable. These include refugees, asylees, and both documented and undocumented immigrants. Although it would be ideal to take the foreign-born community's heterogeneity into account, existing individual-level datasets do not include details such as visa type.

My empirical analysis shows that, in general, an increase in an immigrant's network size slightly decreases her likelihood of being self-employed and increases her likelihood of working for wages. The network effect on the probability of a salaried or self-employed outcome is remarkably robust across different metropolitan statistical areas and specifications. I structure the rest of this paper as follows: section II outlines a theory of network effects on employment outcomes and my conceptual model. Section III reviews relevant empirical research, discussing estimation techniques and results. Section IV provides summary statistics. Sections V and VI follow with regression results and robustness checks. Section VII contains samples of qualitative data I gathered for a case study that support my econometric estimates. I conducted semi-structured interviews with self-employed Hmong in Saint Paul, Minnesota and provide some interpretation. Section VIII comments on this study's limitations and outlines areas for improvement in future research.

II. Theory

Workers and employers both engage in a labor market characterized by information asymmetry (Stigler, 1962). Workers search for wage offers, and employers for job demands, until the marginal cost of search is equal to the expected marginal benefit. The larger the cost of search, the "less search will be undertaken" (101) by the job seeker at any given distribution of wage offers. The standard job search model, as outlined by Fitzgerald (1998), only provides individuals with two options – market employment and unemployment – without considering social networks or the alternative of self-employment. I outline a simple model wherein self-employment is considered alongside unemployment and market employment. This section is structured as follows: first, I describe the process by which workers transmit information via networks; and how network size affects the costs of job search, as well as the returns to both self-employment and salaried employment. Then, I outline a worker's two-stage optimization problem that determines her employment outcome.

The individual's optimization problem is to maximize the expected present value of her lifetime income, which can be expressed by

$$E \sum_{t=0}^{\infty} \beta^t y_t \quad (1)$$

where β is a discount factor from 0 to 1. y represents the individual's income at time t, and is a function of several variables, such as human capital characteristics (e.g. experience and education) and demographic characteristics (e.g. age and sex). Assuming there are three sectors (market employment, self-employment, and unemployment), y can be market wage w_m, self-employed earnings w_s, or unemployment benefits w_u, depending on the individual's employment outcome. Therefore, in this framework, individuals choose whether or not to work, and what kind of work to do i.e. market-employment or self-employment, to maximize the expected value of their lifetime incomes.

Foreign-born agents can be "pushed" or "pulled" into self-employment for pecuniary and non-pecuniary reasons. For example, the middleman-minority theory (Bonacich, 1973) suggests that ethnic groups face labor market discrimination, and are forced into self-employment to make a living. On the other hand, the ethnic enclave hypothesis (Bach and Portes, 1985) argues that immigrants enter self-employment because they have a comparative advantage in providing goods and services to other immigrants, especially those of the same ethnicity. Enterprising immigrants who exploit this comparative advantage might therefore receive large monetary rewards. Others still choose to be self-employed as a path to upward mobility (Light, 1972) or as a means to unobservable rewards, such as personal autonomy (Allen, 2000). Human capital also affects individuals' employment choices: those who are not fluent in English are more likely to experience difficulties entering market employment and are therefore more likely to take the entrepreneurial path (Bates and Dunham, 1991).

This paper estimates the specific effect social networks have on an immigrant's choice to become self-employed. Contacts can act as sources of emotional and material support, especially in the form of financial capital or unpaid labor, for the enterprising immigrant. This reduces the monetary and psychological costs of being self-employed (Sanders and Nee, 1996). Social networks can also help a self-employed agent both form a customer base and promote her services, resulting in lower advertising costs. Therefore, the expected value of being self-employed is equal to the net wage w_s, which is an increasing function of network size j. A larger social network increases an agent's expected value of self-employment by factor b where $b > 0$.

$$Ev_{self} = w_s(H, j) = w_s(bH, \mu j) \tag{2}$$

Equation (2), gives the expected value of being self-employed. w_s is self-employed wage and is a function of H and j. H represents a set of human capital characteristics that influence productivity, such as managerial skills and experience; and b quantifies the effect those characteristics have on an agent's probability of entering self-employment. In the same vein, j is the contact network size and μ measures the influence network size has on an individual's decision to become self-employed.

On the other hand, social networks also reduce the cost of finding wage work (Montgomery, 1991; Rees, 1996; Calvo-Armengol and Jackson, 2004; Calvo-Armengol and Jackson, 2006). Agents can receive offers both directly from a firm and indirectly through a contact in their social network. That is, contacts can act as additional sources of information about job vacancies for market employment. The expected value of being salaried is thus a function of both the probability of directly receiving an offer and the agent's network size (Equation 3). This function is increasing in both variables – that is, as an agent's network increases in size, the expected value of her market wage increases, and consequently, the probability of being market-employed increases as well.

$$Ev_{mkt} = w_m(a, H, j) = w_m(a, cH, \gamma j) \tag{3}$$

Equation (3) represents the expected value of an individual being market-employed, where w_m is her market wage and is a function of a, H, and j. a is the probability of being directly offered a job; H represents a set of human capital characteristics that influence productivity, such as educational attainment and experience; j is network size; and c is the extent to which human capital affects her employment outcome. Similarly, γ is the extent to which network size influences the magnitude of a, and thus the individual's likelihood of being market-employed.

At the beginning of the period, individual *i* is without work and considered unemployed. Individual *i* has a social network of size *j* and is offered a salaried job with probability a. *i* decides whether or not to hold a job for that period. If *i* chooses to not take a job for that period, she remains unemployed. If *i* chooses to take a job for that period, then she must decide what kind of work to engage in: self-employment or salaried employment (equation 4).

$$\mathrm{E}v_{emp} = \max\left[Ev_{mkt}, Ev_{self}\right] \tag{4}$$

Equations 5 and 6 below show that at each stage of the decision-making process, *i* chooses the option that maximizes the expected value of her earnings:

$$\max\left[Ev_{emp}, Ev_{unemp}\right] \tag{5}$$

Substituting equation (4) in equation (5) gives:

$$\max\left[Ev_{emp}\left(\max\left(Ev_{mkt}, Ev_{self}\right)\right), Ev_{unemp}\right] \tag{6}$$

III. Literature Review

A. Social networks and labor market outcomes

Social networks have significant effects on individual employment prospects. Networks reduce job search friction, improve information transmission (Rees, 1996), and have a strong spatial component. That is, networks are likely to form within bound geographic areas such as neighborhoods or cities. Topa (2000) estimates Census tract spillover effects on spatial unemployment patterns in Chicago, and finds that in adjacent tracts, individuals with different ethnic ancestries are less likely to interact with each other than individuals of the same ethnicity. Moreover, the network effect is stronger in tracts with lower levels of education and higher fractions of non-whites. He hypothesizes that agents looking for low-skilled jobs are more likely to use informal search channels, i.e. their social network. Conversely, poorer and less educated individuals could be more geographically concentrated, and are thus more likely to share information about job opportunities. These results motivate further study of local social ties and their effects on different demographic communities' employment outcomes. How can researchers isolate the network effect on employment outcomes, given other confounding variables?

Conley and Topa (2002) extend this study and examine unemployment clustering in Chicago. They proxy agents' social networks using 1) physical distance to each other's tracts, 2) travel time between tracts, 3) differences in ethnic ancestries and 4) occupational distribution between tracts. They discover that the higher the employment rate in one's network, the higher one's probability of getting a job. Additionally, information sharing is more likely to happen between tracts with similar ethnic compositions. Although they make a case for analyzing these spatial patterns with a geographic unit smaller than the Census tract, data by block groups and blocks are difficult to find. In addition, their smaller sample sizes result in larger standard errors, making them more unreliable. Furthermore, while metropolitan statistical areas (MSAs) are much larger areas than Census tracts or block groups, they are commonly treated as the geographical measure for social networks (Borjas, 1942; Borjas, 1994). Consequently, this paper also uses MSAs as the network proxy's geographic unit of analysis.

Calvo-Armengol and Jackson (2001, 2003) use a longitudinal dataset and find that in the short-run, agents embedded in larger networks experience competition effects. That is, network-connected individuals compete for jobs and information in the short run, resulting in a negative relationship between number of job contacts and probability of employment. In the long run, this result reverses; employment outcomes for connected agents are positively correlated. Therefore, I expect to see a positive relationship between network size and probability of having a job in the short-run, and the reverse in the long run.

Calvo-Armengol and Zenou (2001) examine the impact "a partial reliance on social networks as a method of job search has on labor market outcomes" (4). In this model, agents have other means of seeking employment, such as employment agencies, advertisements, etc. In smaller networks, the equilibrium unemployment rate falls with network size. Conversely, in larger networks, the equilibrium unemployment rate increases with network size. There exists a critical network size[1], above which the rise in job-search coordination failures exceeds the rise in individual job-acquisition rate. As a network increases in size, an unemployed agent is likely to hear about more job opportunities; conversely, after a certain point, information about multiple vacancies might reach the same individual, which is inefficient. These predictions match Calvo-Armengol and Jackson's (2003) because they too support the short-run competition hypothesis.

B. Immigrants and labor market outcomes

Two well-known hypotheses connecting immigration and self-employment are 1) the middleman-minority theory (Bonacich, 1973) and 2) the ethnic enclave hypothesis (Bach and Portes, 1985). The first suggests that ethnic groups facing discrimination in the labor market are forced into self-employment. In particular, those who are not fluent in English are more likely to take the entrepreneurial path (Bates and Dunham, 1991). This implies that migrants' English-speaking skills are a significant factor in determining their labor market outcome. The second hypothesis argues that immigrants enter self-employment because they have a comparative advantage in providing goods and services to other immigrants. Borjas' (1986) research on immigrants' self-employment experience documents the differences between self-employment propensities for immigrant and native-born men, and finds support for the enclave hypothesis.

[1] The critical network size is uniquely determined as the value at which the change in the probability of being employed – given the current unemployment and vacancy rates – as the network size changes is equal to zero.

Yuengert (1993) uses a switching regression model of earnings to test three different hypotheses comparing immigrant and native self-employment rates, but finds little support for the enclave hypothesis. His results contradict Borjas's (1986), who argues that enclave effects are a large contributing factor to immigrants' self-employment decisions. Their results differ potentially because Borjas's control sample is narrower. Yuengert also finds that self-employed immigrants compete with each other in the product market, and thus face depressed earnings. However, they might tolerate lower earnings in order to continue participating in the ethnic enclave community. These results further motivate my research on ethnic-based social ties and their effect on labor market outcomes.

Beaman's (2006) research offers insight into the specific intersection of resettled refugee networks and their employment decisions. Using a national refugee resettlement voluntary agency's data from 2001 and 2005, she defines social networks as non-family reunification refugees resettled by the International Rescue Committee living in the same city[2]. An increase in the number of refugee arrivals of a given ethnicity for a given city results in a lower probability of employment for the cohort immediately following. On the other hand, an increase in the number of tenured refugees in an agent's network results in better labor market outcomes for that agent. These results support the hypothesis of competition effects within migrant networks. Although Beaman's paper examines how different facets of refugees' networks impact the probability of their

[2] Her data includes men only. Her controls are: command of English, educational attainment, religious affiliation (i.e. dummy variable for being Muslim), and IRC exception from employment. She finds that education variables are not jointly significant, but higher levels of English are positively correlated with employment status.

employment, it does not study how social networks' affect their propensity to be self-employed.

The literature makes clear that social networks play a role in migrants' labor market outcomes, but social networks have been defined and measured in a variety of ways. While the foreign-born population at large has been the subject of many studies, less research has been done on refugees – a subset of the migrant community – and their employment decisions. My paper attempts to paint a more holistic picture of the relationship between ethnic networks labor market outcomes by integrating both quantitative and qualitative data. I draw migrant data from the American Community Survey and create a social network proxy similar to Beaman's (2006). I use a two-stage discrete-choice model instead of a linear probability model to distinguish 3 employment outcomes (self-employment, salaried employment, and unemployment or not in labor force) from each other. The next section provides my empirical specification, data sources, and summary statistics.

IV. Data and Summary Statistics

How do migrants' social networks influence their employment outcomes? How do they affect their likelihood of being self-employed? Ideally, I would answer these questions using individual –level panel data with network sizes and employment outcomes of migrants from all over the United States over a long period of time. Since these data are not available to me, I estimate the network effect using American Community Survey data for 11 MSAs from 2005 to 2011. I restrict each MSA sample to include only prime age adults – that is, adults between 25 and 54 years of age only. Each

MSA sample contains between 7,000 and 135,000 observations. I adopt Beaman's (2006) network proxy of all prime age adults with the same ethnic ancestry living in the same metropolitan area. For example, if there are 86 Hmong living in Minneapolis-Saint Paul in 2005, then for each of them, their network size is equal to 86. My control variables are ethnic ancestry, age, age-squared (to proxy experience), educational attainment, marital status, household size[3], how long the individual has been in the United States, whether or not the individual speaks English, and industry. I construct the length of stay control by differencing two American Community Survey variables: Census year (i.e. when the interview was conducted) and year of arrival. Thus, my econometric specification is:

$$y_{ijkt} = \alpha + \beta_0 \ln\left(N_{ijkt}\right) + \beta_1 X_{ijkt} + \varphi_j + \delta_k + \varepsilon_{ijkt}$$

where y_{ijkt} is the employment outcome for individual *i* of ethnic ancestry *j* living in metropolitan statistical area *k* at time *t*. If *i* is in the labor force, y_{ijkt} can represent 3 employment outcomes: self-employment, salaried employment, and unemployment. This paper categorizes individuals as self-employed if they work in their own incorporated or unincorporated business, professional practice, or farm[4]. N_{ijkt} represents an individual's social network size, and X_{ijkt} represents individual-specific control variables. Finally, φ_j and δ_k are city and ethnic-group controls, respectively.

I gather data for the following MSAs: Atlanta, Boston, Chicago, Dallas-Fort Worth, Houston-Brazoria, Los Angeles-Long Beach, Miami-Hialeah, Minneapolis-Saint Paul, New York-Northeastern New Jersey, Philadelphia, and Washington D.C.[5]. Table 1 compiles summary statistics on each MSA. New York-Northeastern New Jersey has the

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[3] Household size is not synonymous with family size. A family member not living in the surveyed individual's household is not counted in this measure.
[4] Taken from the American Community Survey questionnaire.
[5] In the tables found in the appendix, I refer to MSAs by these respective codes: ATL, BOS, CHI, DAL, HOU, LAX, MIA, MSP, NYC, PHL, and WDC.

largest number of observations, followed by Los Angeles, Chicago, and then Washington D.C. (Figure 1). All individuals in my samples arrived between 1950 and 2011, and are between 25 and 54 years old. Ethnic networks range from 1 to over 9,000 individuals. The average household size in all 11 MSAs is between 3 and 4, even though the range extends to 20 household members.

Figure 2 shows when migrants in these samples arrived in the United States. Common peak arrival years are 1980, 1990, and 2000. Los Angeles' foreign-born arrivals peaked higher in 1980 and 1990 than in 2000. Conversely, Houston's foreign-born arrivals peaked higher in 2000 than in either 1980 or 1990. Figure 3, 4, and 5 compare the migrant samples across MSAs by marital status, educational attainment, and command of English. The majority of migrants across MSAs are married with a spouse present. Boston has the highest proportion of foreign-born with more than 5 years of education (25 percent), compared to Los Angeles at 8.69 percent. Dallas has the largest percent of migrants who do not speak English (12.17 percent) followed by Houston (11.82 percent). The individuals in my samples identify with almost 200 different ethnic ancestries. Figure 6 displays the 10 most populous ethnic groups for each MSA.

I hypothesize that having a larger local ethnic network in the United States leads to a higher probability of working for wages than being self-employed or unemployed. Table 2 summarizes employment outcomes; the average unemployment rate across all MSAs and all years is 4.85 percent. Figure 7 presents the general distribution of these employment outcomes. Most individuals work for wages or are salaried employees. In Boston, 70 percent of the surveyed individuals work for wages or a salary, compared to only 7 percent who identify as self-employed. Similarly, in Los Angeles, 62 percent of the individuals work for wages, whereas only 10 percent are self-employed. The MSA with the lowest fraction of migrants who identify as self-employed is Minneapolis-Saint Paul at 6.75 percent, and the MSA with the highest is Miami-Hileah at 12.2 percent.

V. Analysis

I analyze the effect of migrants' social networks on their employment outcomes beginning with a two-stage logit. In the first stage, I test the network effect on a migrant having job or not, conditional on being in the labor force[6]; having a job includes both salaried employment and self-employment. The second stage evaluates the network effect on the probability of either working for wages or being self-employed, conditional on having a job. Table 3[7] shows the magnitude, sign, and significance of the estimated network effect for all 11 MSAs. Boston's network coefficients for the first-stage logit and second-stage salaried logit have the highest magnitudes out of all of the MSAs. A single-individual increase in a migrant's ethnic network in Boston increases the predicted log-odds of her having a job by 0.000632. More specifically, that network increase is associated with a 0.000889 predicted log-odds increase in her finding salaried work. On the other hand, Philadelphia's network coefficient for the second stage self-employed outcome has the highest magnitude of all the MSAs.

The network coefficient on the probability of self-employment is small and negative for all MSAs but Los Angeles-Long Beach. Holding all other predictors constant, an increase in network size slightly decreases a migrant's likelihood of being

[6] This measure does not consider immigrants who are working but are not in the labor force (i.e. undocumented employment).
[7] Coefficients on controls are not shown for brevity. The signs and statistical significance on all control coefficients align with previous literature. For example, being female is associated with a lower likelihood of salaried employment, but a less negative likelihood of self-employment across all MSAs.

self-employed. For example, in Philadelphia, a single-individual increase in a migrant's ethnic network corresponds to a decrease of 0.00164 predicted log-odds of being self-employed. The network estimates on self-employment for Atlanta, Minneapolis-Saint Paul, and Washington D.C. are statistically equal to zero; all of the other MSAs have coefficients that are statistically significant at the 95 percent level. On the other hand, the network coefficient on the probability of salaried employment is positive for all MSAs except for Los Angeles-Long Beach, and statistically significant at the 95 percent level for all MSAs except for Minneapolis-Saint Paul. It is plausible that all three estimates (i.e. the network effect on the three employment outcomes) for Minneapolis-Saint Paul are insignificant because it has a small sample size of less than 7,000 individuals.

Los Angeles-Long Beach stands out as an exception, where the network effect is negative for salaried employment and positive for self-employment. As an MSA, it hosts the largest foreign-born population in the country. It could be that there exists a certain threshold immigrant population above which immigrants experience a within-network competition effect[8]. That is, below the threshold, a larger network generally increases an unemployed immigrant's likelihood of finding salaried employment, because her contacts pass on information about job vacancies to her. As the network increases, she becomes one of many more recipients of that information, and the probability of her filling a particular vacancy decreases.

Since log-odds are difficult to interpret, I provide coefficients on the marginal effect networks have on the probability of different employment outcomes in Table 4.

[8] In order to account for this in my model, I try including a network-squared variable. There is no statistically significant difference when I add this variable to the initial specification, where network has a linear relationship with the log-odds of an employment outcome. Consequently, I do not include it in any of the tables.

These estimates tell us how the predictive margins of an outcome change if an individual's network doubles (i.e. increases by 100 percent) and all other variables are fixed at the mean. A 100 percent increase in a migrant's network in Chicago is associated with a 1.5 percent increase in the probability of being market-employed, and a 0.75 percent decrease in the probability of being self-employed. On the other hand, a similar increase in a migrant's network in Los Angeles-Long Beach is associated with a 0.51 percent decrease in the probability of being market-employed and 0.39 percent in the probability of being self-employed. Again, all three estimates for Minneapolis-Saint Paul are statistically insignificant, ostensibly due to the small sample size. In general, an increase in network size is associated with an increased probability of having a salaried job and a decreased probability of being self-employed.

Table 5 shows how well the two-stage logit predicted migrants' employment outcomes. For the first-stage, it predicted above the naïve rule[9] for all 11 MSAs. In the second-stage, the two-stage logit performed well predicting salaried employment for all 11 MSAs. On the other hand, it was a poor predictor of self-employment for almost all MSAs except New York, Los Angeles-Long Beach, and Minneapolis-Saint Paul.

VI. Robustness Checks

The first robustness check is a two-stage probit, and Table 6 presents its results. The signs and significance of all MSAs except New York are remarkably robust compared to the two-stage logit estimates. Ethnic networks seem to have a consistently positive effect

[9] The naïve rule is simply the percent of that sample that have a particular employment outcome. For example, in Boston, where 6.96 percent of prime-age foreign-born individuals are self-employed, the naïve rule for self-employment equals 6.96 percent.

on the probability of working for wages. Conversely, they seem to have a consistently negative effect on the probability of being self-employed. The negative effect on a salaried outcome and positive effect on a self-employed outcome in Los Angeles-Long Beach is significant at the 95 percent level in both the logit and probit models.

Table 7 and Figure 8 show the marginal estimates of network's effect on labor market outcomes. The coefficients describe how the predictive margins of an employment outcome change with a 100 percent increase in network size, with all other variables fixed at the mean. In general, if a migrant's network size doubles, they are more likely to have a job, and a salaried job at that. Once again, Los Angeles is the only exception to the trend at the 95 percent significance level. For the foreign-born in Los Angeles, a 100 percent increase in network is associated with a 0.5 percent decrease in the probability of salaried employment and a 0.39 percent increase in the probability of self-employment, on average.

Table 5 also shows how well the probit model predicted probabilities for different employment outcomes. It predicts over 95 percent of the first stage probit correctly for all 11 MSAs, and over 85 percent of the second stage probit correctly for all MSAs except Houston (it only predicted 4 percent of the salaried outcomes accurately). For example, it predicts that 98 percent of New York's self-employed immigrants are in fact self-employed. On the other hand, it performs poorly for the self-employed outcome, with noticeably similar results as the logit predictions. The MSA with the highest predictions for the self-employed category is New York-Northeastern New Jersey at 45 percent. This means that the probit model predicts that only 45 percent of the self-employed immigrants in New York are self-employed. In summary, the two-stage probit and logit models are very comparable. The logit model predicts salaried outcomes slightly better, but the probit model predicts self-employed outcomes slightly better.

The second and third robustness checks are a multinomial logit[10] and a multinomial probit. These coefficients in Table 8 and 9 show the probability of an individual choosing one out of many options based on individual-specific characteristics. For example, migrants living in Los Angeles experiencing an increased network also experience an increase in the log-odds of being self-employed relative to working for wages. This effect is statistically significant at the 95 percent level. Conversely, a migrant in Atlanta experiencing an increased network size also experiences a decrease in the log-odds of being self-employed relative to working for wages. In general, an increase in network size decreases the log-odds of being self-employed as opposed to being a salaried worker.

Table 10 and 11 give the marginal effects of network size on employment outcome using multinomial logit and probit specifications respectively. With all other variables fixed at the mean, it is clear that an increase in network size generally increases the log-odds of being market-employed, and decreases the log-odds of being self-employed. Network has an ambiguous effect on the log-odds of being unemployed. Figures 9 to 12 represent network's marginal effects, using a multinomial logit, for migrants living in 4 out of the 11 MSAs: Los-Angeles-Long Beach, New York-Northeastern New Jersey, Houston-Brazoria, and Minneapolis-Saint Paul. Figures 12 to 15 represent the same effects, but using the two-stage logit.

[10] The multinomial logit produces coefficients that are interpreted as the change in the log-odds of one outcome relative to some base outcome. Here, all regression results have their base outcome set as "Works for wages". I can run these specifications as robustness checks because they do not fail the Irrelevance of Independent Alternatives assumption after using a Hausman test.

Finally, I run an ordinary least-squares (OLS) regression to test how well OLS predicts employment outcomes in Los Angeles. Table 20 shows that OLS predicts market employment and unemployment relatively well compared to the naïve rule, but performed poorly in predicting the other outcomes. These results suggest that discrete choice estimation techniques, such as nested or multinomial logit and probit, are more appropriate than OLS.

VII. Case Study: Self-Employed Hmong in Saint Paul, Minnesota

While the econometric estimates strongly suggest that local ethnic networks play a statistically significant role in migrants' employment outcomes, I include a qualitative case study on resettled refugees for a more nuanced understanding of the relationship between social networks and labor market decisions. Resettled refugees form a subset of the larger migrant community in the United States. Compared to self-selected migrants, refugees are behind in terms of "learning English, modifying their original skills, and finding out where and how those skills could be used to increase income" (Cafferty et al., 1983, 356). I study the Hmong refugee population in Saint Paul to explore if and how the size of their local ethnic network influences their employment outcomes.

The first wave of Hmong migrants arrived in the country as refugees from Vietnam and Laos in the mid 70s. The second wave was more spread out over the 2000s. Many of them initially settled in California, but several families later moved to Minnesota to reunite with their extended family and clan. According to the 2010 Census, Minnesota has the second-largest Hmong population in the country. The Twin Cities alone have 64,000 Hmong, compared to the 31,000 and 27,000 in the Fresno and

Sacramento metropolitan areas in California. This case study takes advantage of the fact that Minneapolis-Saint Paul hosts the largest metropolitan Hmong community in the United States. In addition, Hmong-owned and operated businesses are well represented in key commercial areas of Saint Paul, such as Rice Street and University Avenue (Kaplan, 1997).

The information that I present in this section comes from semi-structured interviews with 10 self-employed Hmong adults who were willing to share information about their personal and employment histories. I obtained IRB approval for the study. I first approached various stalls at the Hmongtown Marketplace in Saint Paul, and asked vendors if I could interview them for my research. After they gave consent, I asked open-ended questions about factors that influenced their decision to enter and stay in self-employment[11]. I had no existing relationship with any of the interviewees, and identified potential interviewees by how busy they seemed at the time. I conducted 10 interviews in English and took notes, but did not record the entirety of all conversations; all of these interviews took place at the window of or in the store. Since we were in an indoor marketplace, a few customers and other vendors were often present or in close proximity during the interviews.

Several questions related to the vendor's personal and family employment histories. One vendor responded,

> "We came to the United States in 1988 […] We lived in a really small town in California – it was hard to find work […] My dad used to be a chef at a restaurant […] but it was hard work […] Then, he and my mom

[11] The schedule of interview questions can be found in the appendix. I did not ask every question at every interview.

> had another job, but […] they got paid cash, so it was kind of under the table. My dad, he wanted to make money and not be tired all the time."

He made clear his parents' desire for autonomy and a flexible working schedule. His family experienced difficulty entering the salaried labor market because of their low English-speaking skills. On the other hand, the language tie they held to the Hmong community impacted their decision to run their own business. He said that many of their Hmong customers feel "more comfortable if they can speak their own language" when negotiating prices – it made sense to do business with those who share your ethnic identity.

His narrative reflects the broader literature on Hmong enterprise. When the Hmong first arrived, U.S. firms were unfamiliar with hiring individuals who had neither work histories nor English-speaking skills, and were thus unprepared to deal with the influx of Hmong seeking employment. Many Hmong experienced structural unemployment because American employers perceived hiring them as too risky (Taggart, 1981). Consequently, small business ownership became a way for refugees to move out of dependence on public assistance to self-reliance (Fass, 1986). Some of the earliest Hmong ventures were sewing projects and small farming schemes. In the 1990s, Hmong businesses were grocery stores, as well as car repair shops or dealerships (Yang, 2001). By 2000, Hmong enterprise was relatively more concentrated in insurance sales, financial services, and real estate compared to other minority businesses in Minneapolis-Saint Paul (Toussaint-Comeau and Rhine, 2003).

Dunnigan (1982) finds that Hmong businesses recruit primarily from a pool of "clan connections to the owner family" (128), as well as Hmong non-relatives.

Consequently, I was not surprised to hear many vendors mention the local Hmong network as a factor in their employment decisions. Hmong culture honors ethnic social ties, particularly those within a clan. Therefore, the large local Hmong community can be a labor pool, a strong customer base, or both for the self-employed Hmong. One vendor, who inherited the stall from his mother, said,

> "I would definitely say the Hmong community here in Saint Paul had a big impact on our business […] We cater to Hmong people because we know their preferences and […] we can offer better customer service. Friends and family are important too […] we give them discounts."

On the other hand, many stall-owners and operators emphasized economic independence over an ethnic network-based customer base as the primary motivation for being self-employed. A female stall-owner, who helped Hmong families file their taxes, described self-employment as a way to deal with the discrimination she experienced when doing wage work:

> "At my other job, some people got a raise easily […] no matter how hard I worked, I was unhappy with my wages. […] I like being my own boss – I decide how much I get paid, and it's good."

Another vendor enjoyed owning his own store for more personal reasons. "Time flies," he remarked, "You meet a lot of people." He expressed distaste for working in a cubicle with little to no social interaction.

Many interviewees seemed to find their work satisfying. One male shop-owner moved to the United States in 1990, and came to Minnesota in 2004. When I spoke with him, he had been selling CDs and DVDs for "almost 10 years". "Working a business is much better than working for a company, but sometimes [doing business] is hard," he admitted. He felt concerned about the economy and how it would affect his business, but was quick to clarify that running his store was "still good [because] it's flexible and relaxed." The autonomy he experienced managing his own business seemed to compensate for its accompanying challenges.

Based on my interviews, having a large local ethnic network is not necessarily a primary determinant for self-employment within the Hmong community. The individuals that I interviewed focused more on personal preferences for the level of autonomy and flexibility associated with that particular type of work. In addition, local refugee resettlement voluntary agencies, Hmong community organizations, and job training programs helped the Hmong in Saint Paul prepare for both salaried work and self-employment. In the empirical section, the two-stage logit and probit regressions also saw statistically insignificant results for the network effect on employment outcomes for the foreign-born in Minneapolis-Saint Paul. Although these results cannot be extrapolated to all foreign-born individuals in the United States, they confirm other factors' (e.g. fluency in English or length of stay in the United States) effect on employment decisions. My findings also reiterate the importance of including individual characteristics associated with enterprise, such as level of risk aversion or desire for independence.

VIII. Conclusion

This paper presents empirical evidence that migrants' networks have different effects, both in sign and magnitude, on employment outcomes depending on the MSA. As network size increases, migrants in the labor force are more likely to work for wages and less likely to be self-employed. These network effects, though small, are statistically significant in most of the 11 MSAs. Ethnic networks do not necessarily play a large role in migrants' decisions to become self-employed; if they do, their relationship is negative. Based on my interviews with Hmong business owners, preferences for autonomy and flexible hours seem to be more significant positive determinants of self-employment. The marginal network effect on the probability of a migrant working for wages is positive and statistically significant at the 95 percent level for 10 of the 11 tested MSAs. These results align with previous empirical literature, supporting the hypothesis that networks are associated with a higher likelihood of market employment for immigrants.

The limited scope of this research paper bears several caveats worth mentioning. First, the structure of the ACS questionnaire does not allow me to easily separate documented foreign-born workers from the undocumented, so I consider documented immigrants in the labor force only. Since the estimates do not account for undocumented employment, they might be downward-biased – that is, the coefficients on network size might be smaller than they ought to be. Second, outcome-specific variables, such as the level of autonomy associated with that particular employment outcome, would have also been useful. In addition, since online platforms are growing increasingly relevant to networking and job searches, this research would benefit from controlling for individuals' Internet access.

While it would be ideal to include individual-level data on attitudes towards self-employment in my specification, the American Community Survey does not record such information. Consequently, I acknowledge that my estimates might exhibit upward omitted variable bias. The semi-structured interviews with local self-employed Hmong shed light on some of these variables, and holds significant potential. However, my analysis is raw and unsophisticated. Future improvements would include interviewing a larger, more representative sample of the self-employed Hmong population; recording and transcribing the conversations; and running those data through qualitative analysis software packages such as NVivo.

Finally, American Community Survey data does not distinguish between different migrant groups, such as asylees, refugees, and economic immigrants. While including ethnic ancestry and year of arrival variables does partially control for group-specific characteristics, it is possible that my estimates do not reflect the true relationship between networks and employment outcomes. For examples, refugees might be less inclined to rely on their ethnic ties for employment opportunities because their resettlement agency is partially responsible for helping them find a job. The literature would benefit from a study that had data distinguishing different migrant groups to better isolate the network effect. Future research should also consider the effect local ethnic networks have on wages and wealth in foreign-born communities, and how to interpret discuss empirical results in terms of their economic significance.

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Table 1: Summary statistics for all metropolitan areas, all years

	Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
	Female	25852	0.49	0.50	0	1
	Age	25852	38.54	8.13	25	54
Atlanta	HH Size	25852	3.38	1.78	1	14
	Year of arrival	25852	1992.36	11.12	1950	2011
	Network size	25852	189.02	222.47	0	700
	Female	25026	0.52	0.50	0	1
	Age	25026	39.30	8.28	25	54
Boston	HH Size	25026	3.11	1.64	1	13
	Year of arrival	25026	1991.63	11.64	1951	2011
	Network size	25026	121.79	109.33	0	417
	Female	50555	0.50	0.50	0	1
	Age	50555	39.49	8.24	25	54
Chicago	HH Size	50555	3.67	1.85	1	14
	Year of arrival	50555	1990.21	11.14	1951	2011
	Network size	50555	1056.83	1144.77	0	2646
	Female	41131	0.49	0.50	0	1
	Age	41131	38.64	8.00	25	54
Dallas	HH Size	41131	3.75	1.87	1	17
	Year of arrival	41131	1991.27	10.90	1950	2011
	Network size	41131	1252.37	1265.80	0	2906
	Female	41450	0.50	0.50	0	1
	Age	41450	39.19	8.10	25	54
Houston	HH Size	41450	3.72	1.82	1	15
	Year of arrival	41450	1991.22	10.65	1950	2011
	Network size	41450	4087.13	4176.25	0	9666

Table 1: Summary statistics for all metropolitan areas, all years

	Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Los Angeles	Female	129426	0.52	0.50	0	1
	Age	129426	40.11	8.19	25	54
	HH Size	129426	3.82	2.07	1	20
	Year of arrival	129426	1988.63	10.36	1951	2011
	Network size	129426	78.49	432.80	0	5874
Miami	Female	39124	0.52	0.50	0	1
	Age	39124	40.99	8.13	25	54
	HH Size	39124	3.23	1.64	1	14
	Year of arrival	39124	1990.03	12.28	1952	2011
	Network size	39124	686.70	770.18	0	1970
Minneapolis-Saint Paul	Female	6551	0.50	0.50	0	1
	Age	6551	37.96	8.05	25	54
	HH Size	6551	3.57	2.08	1	15
	Year of arrival	6551	1992.24	11.23	1952	2011
	Network size	6551	365.92	955.17	1	5874
New York City	Female	162754	0.53	0.50	0	1
	Age	162754	40.16	8.34	25	54
	HH Size	162754	3.41	1.81	1	19
	Year of arrival	162754	1990.57	11.00	1950	2011
	Network size	162754	935.11	763.55	1	2281
Philadelphia	Female	16537	0.51	0.50	0	1
	Age	16537	39.84	8.33	25	54
	HH Size	16537	3.32	1.71	1	12
	Year of arrival	16537	1990.51	12.22	1951	2011
	Network size	16537	85.12	84.12	0	291

Table 1: Summary statistics for all metropolitan areas, all years

	Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
	Female	44887	0.52	0.50	0	1
	Age	44887	39.40	8.22	25	54
Washington D.C.	HH Size	44887	3.35	1.78	1	15
	Year of arrival	44887	1991.46	11.44	1951	2011
	Network size	44887	185.87	173.13	0	606

Table 2: Summary of Migrant Employment Outcomes for All MSAs

	ATL	BOS	CHI	DAL	HOU	LAX	MIA	MSP	NYC	PHL	WDC
Self-employed	9.98	6.96	7.71	6.96	7.41	10.3	12.17	6.75	8.03	7.95	8.16
Works for wages	66.04	69.59	66.92	69.59	68.3	62.3	63.09	82.8	65.5	66.33	72.78
Unemployed	5.67	5.13	5.67	5.13	4.74	5.63	6.4	0.55	5.01	5.25	4.21
Not in labor force	18.31	18.32	19.7	18.32	20.64	21.8	18.34	9.93	20.64	20.48	14.85

Table 3: Two-Stage Logit Estimates of Network Effect on Employment Outcomes, Conditional on Being in Labor Force

	First-Stage (Job or No Job)			**Second-Stage (Salaried or Not)**			**First-Stage (Self-Employed or Not)**		
MSA	*Magnitude*	*Sign*	*Significance*	*Magnitude*	*Sign*	*Significance*	*Magnitude*	*Sign*	*Significance*
Atlanta	0.0002998	(+)	Significant	0.0003348	(+)	Significant	0.0001845	(-)	Insignificant
Boston	0.0006315	(+)	Significant	0.0008892	(+)	Significant	0.0012059	(-)	Significant
Chicago	0.0000944	(+)	Significant	0.0002136	(+)	Significant	0.000391	(-)	Significant
Dallas	0.0000214	(+)	Insignificant	0.0000418	(+)	Significant	0.000054	(-)	Significant
Houston	0.00000126	(+)	Insignificant	0.00000837	(+)	Significant	0.000013	(-)	Significant
Los Angeles	0.0000449	(-)	Significant	0.0000781	(-)	Significant	0.000069	(+)	Significant
Miami	0.0000519	(+)	Significant	0.0000798	(+)	Significant	0.0000747	(-)	Significant
Minneapolis-Saint Paul	0.00000473	(+)	Insignificant	0.0000168	(+)	Insignificant	0.0016591	(-)	Insignificant
New York	0.00000128	(+)	Significant	0.00000542	(+)	Significant	0.0001321	(-)	Significant
Philadelphia	0.0000688	(-)	Insignificant	0.0005572	(+)	Significant	0.001641	(-)	Significant
Washington D.C.	0.0006071	(+)	Significant	0.0005635	(+)	Significant	0.0001681	(-)	Insignificant

**Significance calculated at 95 percent level*

Table 4: Two-Stage Logit Estimates of Marginal Network Effect on Employment Outcomes (100 Percent Increase in Network Size)

	Job or not			**Salaried or not**			**Self or not**		
MSA	*Magnitude*	*Sign*	*P>|z|*	*Magnitude*	*Sign*	*P>|z|*	*Magnitude*	*Sign*	*P>|z|*
Atlanta	0.337	(+)	0.019	0.324	(+)	0.056	0.063	(+)	0.582
Boston	0.792	(+)	0.000	0.792	(+)	0.000	0.549	(-)	0.000
Chicago	0.654	(+)	0.000	1.536	(+)	0.000	0.755	(-)	0.000
Dallas	0.313	(+)	0.002	0.508	(+)	0.000	0.145	(-)	0.037
Houston	0.438	(+)	0.000	0.614	(+)	0.000	0.124	(-)	0.071
Los Angeles	0.077	(-)	0.129	0.508	(-)	0.000	0.388	(+)	0.000
Miami	0.440	(+)	0.000	1.369	(+)	0.000	0.823	(-)	0.000
Minneapolis-Saint Paul	0.102	(+)	0.701	0.260	(+)	0.375	0.166	(-)	0.267
New York	0.307	(+)	0.000	1.258	(+)	0.000	0.815	(-)	0.000
Philadelphia	0.320	(+)	0.098	0.706	(+)	0.001	0.366	(-)	0.005
Washington D.C.	0.578	(+)	0.000	0.740	(+)	0.000	0.094	(-)	0.24

Table 5: Predicted Hits and Misses for Two-Stage Logit and Probit

		Probit Hits (%)	Logit Hits (%)	Naïve rule (%)
	Employed or not	95.11	96.89	73.72
ATL	Salaried or not	92.11	93.56	89.49
	Self-employed or not	0	0	10.51
	Employed or not	96.55	98.06	76.55
BOS	Salaried or not	94.07	95.72	90.91
	Self-employed or not	13.24	0	9.09
	Employed or not	95.44	95.26	76.64
CHI	Salaried or not	92.44	92.44	89.66
	Self-employed or not	0	0	10.34
	Employed or not	95.06	95.06	73.72
DAL	Salaried or not	92.18	92.18	89.49
	Self-employed or not	0	0	10.51
	Employed or not	95.48	95.43	72.63
HOU	Salaried or not	92.36	4.38	87.79
	Self-employed or not	3.9	3.04	12.21
	Employed or not	96.08	96.05	72.83
LAX	Salaried or not	91.88	92.13	86.16
	Self-employed or not	22.85	22.84	13.84
	Employed or not	97.41	97.37	76.02
MIA	Salaried or not	88.03	88.28	83.82
	Self-employed or not	0	0	16.18
	Employed or not	97.1	97.98	76.59
MSP	Salaried or not	95.71	96.6	92.46
	Self-employed or not	5.71	11.16	7.54
	Employed or not	97.61	98.06	74.9
NYC	Salaried or not	94.09	95.72	89.26
	Self-employed or not	45.01	12.82	10.74
	Employed or not	95.14	95.14	74.28
PHL	Salaried or not	90.36	90.36	89.3
	Self-employed or not	0	0	10.7
	Employed or not	98.5	95.77	80.94
WDC	Salaried or not	96.53	96.63	89.91
	Self-employed or not	0	0	10.09

Table 6: Two-Stage Probit Estimates of Network Effect on Employment Outcomes

	First-Stage (Job or No Job)			**Second-Stage (Salaried or Not)**			**Second-Stage (Self-Employed or Not)**		
MSA	*Magnitude*	*Sign*	*Significance*	*Magnitude*	*Sign*	*Significance*	*Magnitude*	*Sign*	*Significance*
Atlanta	0.0001825	(+)	Significant	0.0002062	(+)	Significant	0.0000985	(-)	Insignificant
Boston	0.0004701	(+)	Significant	0.0006005	(+)	Significant	0.0005159	(-)	Significant
Chicago	0.0000518	(+)	Significant	0.0001269	(+)	Significant	0.0001952	(-)	Significant
Dallas	0.0000168	(+)	Significant	0.0000259	(+)	Significant	0.0000251	(-)	Significant
Houston	0.00000132	(+)	Insignificant	0.0000525	(+)	Significant	0.0000061	(-)	Significant
Los Angeles	0.0000273	(-)	Significant	0.000047	(-)	Significant	0.0000396	(+)	Significant
Miami	0.0000286	(+)	Significant	0.0000468	(+)	Significant	0.0000413	(-)	Significant
Minneapolis-Saint Paul	0.0000166	(+)	Insignificant	0.0000162	(+)	Insignificant	0.0000172	(-)	Insignificant
New York	0.00000633	(-)	Significant	0.0000269	(+)	Significant	0.00000675	(-)	Significant
Philadelphia	0.00000354	(-)	Insignificant	0.0003479	(+)	Significant	0.0008322	(-)	Significant
Washington D.C.	0.0003544	(+)	Significant	0.0003323	(+)	Significant	0.0000866	(-)	Insignificant

**Significance calculated at 95 percent level*

Table 7: Two-Stage Probit Estimates of Marginal Network Effect on Employment Outcomes (100 Percent Increase in Network Size)

	Job or not			**Salaried or not**			**Self or not**		
MSA	*Magnitude*	*Sign*	*P>|z|*	*Magnitude*	*Sign*	*P>|z|*	*Magnitude*	*Sign*	*P>|z|*
Atlanta	0.351	(+)	0.017	0.338	(+)	0.047	0.044	(+)	0.695
Boston	0.270	(+)	0.066	0.819	(+)	0.000	0.546	(-)	0.000
Chicago	0.658	(+)	0.000	1.549	(+)	0.000	0.778	(-)	0.000
Dallas	0.346	(+)	0.001	0.513	(+)	0.000	0.141	(-)	0.043
Houston	0.452	(+)	0.000	0.624	(+)	0.000	0.115	(-)	0.096
Los Angeles	0.085	(-)	0.098	0.504	(-)	0.000	0.394	(+)	0.000
Miami	0.446	(+)	0.000	1.358	(+)	0.000	0.836	(-)	0.000
Minneapolis-Saint Paul	0.106	(+)	0.692	0.271	(+)	0.357	0.165	(-)	0.275
New York	0.322	(+)	0.000	1.281	(+)	0.000	0.839	(-)	0.000
Philadelphia	0.365	(+)	0.061	0.733	(+)	0.001	0.384	(-)	0.003
Washington D.C.	0.608	(+)	0.000	0.744	(+)	0.000	0.100	(-)	0.211

Table 8: Multinomial Logit - Network Effect on Employment Outcomes (Individuals in the Labor Force Only)

	Self-employed			Unemployed		
MSA	*Magnitude*	*Sign*	*Significance*	*Magnitude*	*Sign*	*Significance*
Atlanta	0.000312	(-)	Significant	0.000368	(-)	Significant
Boston	0.0012044	(-)	Significant	0.0005118	(-)	Insignificant
Chicago	0.0004221	(-)	Significant	0.0000568	(-)	Significant
Dallas	0.0000648	(-)	Significant	0.0000446	(-)	Insignificant
Houston	0.000015	(-)	Significant	0.00000429	(-)	Insignificant
Los Angeles	0.000081	(+)	Significant	0.000018	(+)	Insignificant
Miami	0.0000856	(-)	Significant	0.0000519	(+)	Insignificant
Minneapolis-Saint Paul	0.0000438	(-)	Insignificant	0.0001612	(-)	Insignificant
New York	0.0001372	(-)	Significant	0.0000332	(+)	Significant
Philadelphia	0.0017491	(-)	Significant	0.0006941	(-)	Insignificant
Washington D.C.	0.0003396	(-)	Significant	0.0001562	(-)	Insignificant

** Base outcome is working for wages. Significance is measured at 95 percent level.*

Table 9: Multinomial Probit - Network Effect on Employment Outcomes (Individuals in the Labor Force Only)

	Self-employed			Unemployed		
MSA	*Magnitude*	*Sign*	*Significance*	*Magnitude*	*Sign*	*Significance*
Atlanta	0.0002469	(-)	Significant	0.000269	(-)	Significant
Boston	0.0008587	(-)	Significant	0.0004162	(-)	Significant
Chicago	0.0002972	(-)	Significant	0.0000643	(-)	Significant
Dallas	0.0000444	(-)	Significant	0.0000369	(-)	Significant
Houston	0.0000105	(-)	Significant	0.0000039	(-)	Insignificant
Los Angeles	0.0000649	(+)	Significant	0.0000193	(+)	Insignificant
Miami	0.0000653	(-)	Significant	0.0000233	(+)	Insignificant
Minneapolis-Saint Paul	0.0000313	(-)	Insignificant	0.0000962	(-)	Insignificant
New York	0.0000938	(-)	Significant	0.0000128	(+)	Significant
Philadelphia	0.0012603	(-)	Significant	0.0005724	(-)	Insignificant
Washington D.C.	0.0002488	(-)	Significant	0.0001255	(-)	Insignificant

** Base outcome is working for wages. Significance is measured at 95 percent level.*

Table 10: Multinomial logit - network's marginal effect on probability of employment outcome (ILF Only)

	ATL	BOS	CHI	DAL	HOU	LAX	MIA	MSP	NYC	PHL	WDC
Self-employment	(+)	(-)	(-)	(-)	(-)	(+)	(-)	(-)	(-)	(-)	(-)
Market employment	(+)	(+)	(+)	(+)	(+)	(-)	(+)	(+)	(+)	(+)	(+)
Unemployment	(-)	(+)	(-)	(-)	(-)	(+)	(+)	(-)	(+)	(-)	(-)

Table 11: Multinomial probit - network's marginal effect on probability of employment outcome (ILF Only)

	ATL	BOS	CHI	DAL	HOU	LAX	MIA	MSP	NYC	PHL	WDC
Self-employment	(-)	(-)	(-)	(-)	(-)	(+)	(-)	(-)	(-)	(-)	(-)
Market employment	(+)	(+)	(+)	(+)	(+)	(-)	(+)	(+)	(+)	(+)	(+)
Unemployment	(-)	(-)	(-)	(-)	(-)	(+)	(+)	(+)	(+)	(-)	(-)

Table 12: Marginal effects of two-stage logit regressors on probability of employment outcomes (LAX)

	Employed or not		Salaried or not		Self-employed or not	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
Network size	-3.98E-07	0.001	1.50E-06	0	-1.84E-06	0
Female	-0.24	0	-0.19	0	-0.058	0
Age	0.019	0	0.0087	0	0.015	0
Age-squared	-0.00023	0	-0.00014	0	-0.00015	0
Marital status						
Married, spouse absent	0.022	0	0.039	0	-0.014	0
Separated	0.070	0	0.068	0	0.0050	0.3
Divorced	0.074	0	0.068	0	0.0049	0.17
Widowed	0.038	0	0.047	0	-0.0040	0.62
Never married/single	0.029	0	0.044	0	-0.014	0
HH size	-0.0033	0	0.00025	0.72	-0.0042	0
Year of arrival	-0.0019	0	-0.0019	0	0.000036	0.71
Educational attainment						
Nursery school to grade 4	0.051	0	0.042	0	0.011	0.086
Grade 5, 6, 7, or 8	0.071	0	0.061	0	0.011	0.024
Grade 9	0.080	0	0.061	0	0.019	0.001
Grade 10	0.048	0	0.035	0.002	0.013	0.071
Grade 11	0.031	0.004	0.029	0.011	0.00046	0.95
Grade 12	0.087	0	0.078	0	0.0068	0.14
1 year of college	0.11	0	0.10	0	0.0065	0.20
2 years of college	0.13	0	0.14	0	-0.0051	0.36
4 years of college	0.16	0	0.15	0	0.0066	0.19
5+ years of college	0.18	0	0.16	0	0.016	0.004
Speaks English						
Yes, speaks only English	0.076	0	0.071	0	0.012	0.004
Yes, speaks very well	0.12	0	0.12	0	0.0054	0.12
Yes, speaks well	0.088	0	0.082	0	0.017	0
Yes, but not well	0.040	0	0.033	0	0.016	0
Ethnic ancestry	-0.000049	0	0.000013	0.058	-0.000051	0

Note: dy/dx for factor levels is the discrete change from the base level.

Table 13: Marginal effects of two-stage logit regressors on probability of employment outcomes (NYC)

	Employed or not		Salaried or not		Self-employed or not	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
Network size	2.29E-06	0.01	1.16E-05	0.00	-9.59E-06	0.00
Female	-1.62E-01	0.00	-1.12E-01	0.00	-4.95E-02	0.00
Age	2.32E-02	0.00	1.15E-02	0.00	1.63E-02	0.00
Age-squared	-2.61E-04	0.00	-1.37E-04	0.00	-1.77E-04	0.00
Marital status						
Married, spouse absent	2.83E-02	0.00	2.95E-02	0.00	-5.54E-04	0.88
Separated	4.41E-02	0.00	4.27E-02	0.00	2.93E-03	0.53
Divorced	5.30E-02	0.00	4.33E-02	0.00	9.93E-03	0.01
Widowed	1.34E-02	0.27	1.22E-02	0.38	3.77E-03	0.67
Never married/single	5.88E-04	0.88	1.42E-02	0.00	-1.38E-02	0.00
HH size	-2.79E-03	0.00	-1.44E-03	0.12	-1.88E-03	0.00
Year of arrival	-2.79E-04	0.07	-3.92E-05	0.82	-2.37E-04	0.01
Educational attainment						
Nursery school to grade 4	1.11E-02	0.55	4.03E-02	0.04	-2.65E-02	0.01
Grade 5, 6, 7, or 8	7.91E-02	0.00	8.37E-02	0.00	-2.95E-03	0.68
Grade 9	3.80E-02	0.01	4.35E-02	0.01	-5.41E-03	0.54
Grade 10	2.39E-02	0.11	3.21E-02	0.04	-9.05E-03	0.29
Grade 11	3.96E-02	0.01	4.78E-02	0.00	-8.22E-03	0.35
Grade 12	1.06E-01	0.00	1.07E-01	0.00	2.27E-05	1.00
1 year of college	1.38E-01	0.00	1.37E-01	0.00	2.84E-04	0.97
2 years of college	1.82E-01	0.00	2.04E-01	0.00	-2.13E-02	0.00
4 years of college	1.91E-01	0.00	1.99E-01	0.00	-7.22E-03	0.29
5+ years of college	2.29E-01	0.00	2.32E-01	0.00	-5.08E-03	0.47
Speaks English						
Yes, speaks only English	1.06E-01	0.00	1.07E-01	0.00	3.99E-03	0.38
Yes, speaks very well	9.90E-02	0.00	9.74E-02	0.00	7.64E-03	0.10
Yes, speaks well	6.78E-02	0.00	5.91E-02	0.00	1.47E-02	0.00
Yes, but not well	3.33E-02	0.00	2.42E-02	0.00	1.41E-02	0.00
Ethnic ancestry	-1.66E-05	0.01	-1.05E-05	0.12	-5.66E-06	0.15

Note: dy/dx for factor levels is the discrete change from the base level.

Table 14: Marginal effects of two-stage logit regressors on probability of employment outcomes (HOU)

	Employed or not		Salaried or not		Self-employed or not	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
Network size	-2.91E-06	0.00	-1.26E-06	0.06	-1.71E-06	0.00
Female	-3.20E-01	0.00	-2.73E-01	0.00	-4.68E-02	0.00
Age	1.90E-02	0.00	8.63E-03	0.00	1.42E-02	0.00
Age-squared	-2.27E-04	0.00	-1.18E-04	0.00	-1.54E-04	0.00
Marital status						
Married, spouse absent	1.54E-02	0.11	2.21E-02	0.04	4.56E-04	0.94
Separated	1.19E-01	0.00	9.87E-02	0.00	3.06E-02	0.00
Divorced	1.18E-01	0.00	9.80E-02	0.00	2.29E-02	0.00
Widowed	9.41E-02	0.00	7.24E-02	0.00	4.02E-02	0.02
Never married/single	4.62E-02	0.00	5.37E-02	0.00	-2.16E-03	0.63
HH size	-8.06E-03	0.00	-7.36E-03	0.00	-5.16E-04	0.56
Year of arrival	-3.04E-03	0.00	-1.98E-03	0.00	-9.37E-04	0.00
Educational attainment						
Nursery school to grade 4	4.07E-02	0.01	3.92E-02	0.02	6.03E-04	0.96
Grade 5, 6, 7, or 8	3.54E-02	0.01	3.89E-02	0.01	-5.67E-03	0.52
Grade 9	2.58E-02	0.07	2.85E-02	0.07	-6.53E-03	0.50
Grade 10	3.84E-02	0.03	2.15E-02	0.27	1.63E-02	0.20
Grade 11	-3.97E-03	0.83	-1.14E-02	0.58	4.34E-03	0.73
Grade 12	4.39E-02	0.00	3.73E-02	0.01	3.92E-03	0.65
1 year of college	6.18E-02	0.00	6.61E-02	0.00	-7.23E-03	0.45
2 years of college	7.01E-02	0.00	8.36E-02	0.00	-1.54E-02	0.14
4 years of college	9.28E-02	0.00	1.17E-01	0.00	-2.62E-02	0.00
5+ years of college	1.36E-01	0.00	1.40E-01	0.00	-1.20E-02	0.20
Speaks English						
Yes, speaks only English	7.78E-02	0.00	1.05E-01	0.00	-1.24E-02	0.05
Yes, speaks very well	1.10E-01	0.00	1.15E-01	0.00	7.09E-03	0.22
Yes, speaks well	8.12E-02	0.00	7.08E-02	0.00	2.38E-02	0.00
Yes, but not well	5.94E-02	0.00	5.36E-02	0.00	1.79E-02	0.00
Ethnic ancestry	1.17E-05	0.27	4.26E-06	0.72	5.90E-06	0.41

Note: dy/dx for factor levels is the discrete change from the base

Table 15: Marginal effects of two-stage logit regressors on probability of employment outcomes (MSP)

	Employed or not		Salaried or not		Self-employed or not	
	dy/dx	P>z	dy/dx	P>z	dy/dx	P>z
Network size	7.68E-07	0.91	3.28E-06	0.63	-3.29E-06	0.30
Female	-1.37E-01	0.00	-1.05E-01	0.00	-3.16E-02	0.00
Age	1.02E-02	0.13	7.12E-03	0.34	1.04E-02	0.02
Age-squared	-1.36E-04	0.11	-1.29E-04	0.17	-9.55E-05	0.09
Marital status						
Married, spouse absent	9.71E-03	0.72	2.77E-02	0.36	-1.51E-02	0.36
Separated	3.70E-02	0.24	6.47E-02	0.07	-2.34E-02	0.25
Divorced	3.08E-02	0.13	5.04E-02	0.03	-1.83E-02	0.12
Widowed	-9.01E-02	0.18	-1.28E-01	0.10	3.14E-02	0.51
Never married/single	-4.25E-02	0.01	-1.64E-02	0.38	-2.60E-02	0.01
HH size	-2.58E-03	0.40	-5.95E-03	0.08	3.31E-03	0.08
Year of arrival	-2.11E-03	0.00	-1.67E-03	0.01	-2.67E-04	0.40
Educational attainment						
Nursery school to grade 4	2.75E-02	0.70	6.53E-02	0.39	.	
Grade 5, 6, 7, or 8	1.11E-01	0.01	1.32E-01	0.00	-1.82E-02	0.38
Grade 9	1.02E-01	0.08	1.10E-01	0.08	2.26E-04	0.99
Grade 10	3.72E-02	0.55	5.00E-02	0.45	-6.36E-03	0.83
Grade 11	-2.82E-02	0.68	-5.96E-02	0.41	4.25E-02	0.31
Grade 12	1.11E-01	0.00	9.38E-02	0.01	2.91E-02	0.10
1 year of college	1.31E-01	0.00	1.06E-01	0.01	3.52E-02	0.07
2 years of college	1.79E-01	0.00	1.69E-01	0.00	2.01E-02	0.32
4 years of college	1.31E-01	0.00	1.39E-01	0.00	1.44E-03	0.94
5+ years of college	1.71E-01	0.00	1.75E-01	0.00	4.83E-03	0.79
Speaks English						
Yes, speaks only English	2.12E-01	0.00	1.84E-01	0.00	4.82E-02	0.00
Yes, speaks very well	1.98E-01	0.00	1.79E-01	0.00	4.45E-02	0.00
Yes, speaks well	1.57E-01	0.00	1.27E-01	0.01	5.30E-02	0.00
Yes, but not well	7.30E-02	0.10	5.33E-02	0.26	3.75E-02	0.02
Ethnic ancestry	-3.81E-05	0.10	1.83E-05	0.46	-5.11E-05	0.00

Note: dy/dx for factor levels is the discrete change from the base level.

Table 16: Marginal effects of network in two-stage logit on probability of employed outcomes (LAX)

	Job or not		Salaried or not		Self-employed or not	
	Margin	P>z	Margin	P>z	Margin	P>z
Every 1500 people						
1	0.73	0	0.61	0	0.13	0
2	0.73	0	0.61	0	0.12	0
3	0.73	0	0.61	0	0.12	0
4	0.73	0	0.61	0	0.12	0
5	0.73	0	0.61	0	0.11	0
6	0.73	0	0.62	0	0.11	0
7	0.73	0	0.62	0	0.11	0
8	0.73	0	0.62	0	0.10	0
9	0.73	0	0.62	0	0.10	0
10	0.73	0	0.63	0	0.10	0
11	0.73	0	0.63	0	0.10	0
12	0.73	0	0.63	0	0.09	0
13	0.72	0	0.63	0	0.09	0
14	0.72	0	0.63	0	0.09	0
15	0.72	0	0.64	0	0.09	0
16	0.72	0	0.64	0	0.08	0
17	0.72	0	0.64	0	0.08	0
18	0.72	0	0.64	0	0.08	0
19	0.72	0	0.65	0	0.08	0
20	0.72	0	0.65	0	0.08	0
21	0.72	0	0.65	0	0.07	0

Table 17: Marginal effects of network in two-stage logit on probability of employed outcomes (NYC)

		Job or not		**Salaried or not**		**Self-employed or not**	
		Margin	P>z	Margin	P>z	Margin	P>z
Every 500 people							
	1	0.73	0	0.63	0	0.10	0
	2	0.74	0	0.64	0	0.095	0
	3	0.74	0	0.65	0	0.090	0
	4	0.74	0	0.65	0	0.085	0
	5	0.74	0	0.66	0	0.080	0
	6	0.74	0	0.66	0	0.075	0
	7	0.74	0	0.67	0	0.071	0
	8	0.74	0	0.67	0	0.067	0
	9	0.74	0	0.68	0	0.063	0
	10	0.74	0	0.69	0	0.059	0
	11	0.75	0	0.69	0	0.055	0
	12	0.75	0	0.70	0	0.052	0
	13	0.75	0	0.70	0	0.049	0

Table 18: Marginal effects of network in two-stage logit on probability of employed outcomes (HOU)

		Job or not		Salaried or not		Self-employed or not	
		Margin	P>z	Margin	P>z	Margin	P>z
Every 500 people							
	1	0.74	0	0.64	0	0.097	0
	2	0.74	0	0.64	0	0.096	0
	3	0.74	0	0.64	0	0.095	0
	4	0.73	0	0.64	0	0.095	0
	5	0.73	0	0.64	0	0.094	0
	6	0.73	0	0.64	0	0.093	0
	7	0.73	0	0.64	0	0.092	0
	8	0.73	0	0.64	0	0.091	0
	9	0.73	0	0.64	0	0.090	0
	10	0.73	0	0.64	0	0.089	0
	11	0.72	0	0.64	0	0.088	0
	12	0.72	0	0.64	0	0.088	0
	13	0.72	0	0.63	0	0.087	0
	14	0.72	0	0.63	0	0.086	0
	15	0.72	0	0.63	0	0.085	0
	16	0.72	0	0.63	0	0.084	0
	17	0.72	0	0.63	0	0.083	0
	18	0.71	0	0.63	0	0.083	0
	19	0.71	0	0.63	0	0.082	0
	20	0.71	0	0.63	0	0.081	0

Table 19: Marginal effects of network in two-stage logit on probability of employed outcomes (MSP)

		Job or not		Salaried or not		Self-employed or not	
		Margin	P>z	Margin	P>z	Margin	P>z
Every 500 people							
	1	0.77	0	0.70	0	0.065	0.065
	2	0.77	0	0.71	0	0.063	0.063
	3	0.77	0	0.71	0	0.062	0.062
	4	0.77	0	0.71	0	0.060	0.060
	5	0.77	0	0.71	0	0.059	0.059
	6	0.77	0	0.71	0	0.057	0.057
	7	0.77	0	0.71	0	0.056	0.056
	8	0.77	0	0.72	0	0.054	0.054
	9	0.77	0	0.72	0	0.053	0.053
	10	0.77	0	0.72	0	0.051	0.051
	11	0.77	0	0.72	0	0.050	0.050
	12	0.77	0	0.72	0	0.049	0.049

Table 20: Predicted Hits for OLS (LAX)

	Hit (%)	Naïve rule (%)
Self-employed	0	10.3
Works for wages/salary	64.8	62.3
Unemployed	43.4	5.62
Not in labor force	0	21.8

Schedule of Interview Questions

- When did you arrive in the U.S.? What country did you leave?
- Where did you live when you first arrived? When did you move here?
- What was the highest grade you completed?
- What language do you speak at home? How would you rate your command of English (written/reading/spoken)?
- How would you describe the demographic composition of your neighborhood?
- Can you tell me more about what it was like trying to find a job here when you first arrived? How did you go about looking for employment?
- What kinds of organizations reached out to you?
- What kinds of resources did they provide? Which ones did you use or find most helpful?
- How does owning/operating your own business compare to working a salaried/wage-rate job?
- What do you enjoy about owning/operating your own business?
- What are some of the challenges of running your own business?
- Can you tell me more about the kind of hours that you work?
- What kind of work did you do before starting [insert business/organization name]? What companies did you work for?
- What factors did you consider when deciding to start [insert business/organization name]?
- When did you officially start operating [insert business/organization name]?
- How much did it cost to start [insert business/organization name]?
- Tell me about how you gathered the capital and resources to get [insert business/organization name] off the ground.
- Before you decided to become self-employed, whom did you discuss your ideas/plans with?
- How did you meet these people (referring to response to previous question)?
- How would you describe your relationship with them (e.g. friends, acquaintances, colleagues, neighbors)?
- How would you describe the demographic composition of your social networks (i.e. friends, colleagues, fellow churchgoers, neighbors, etc.)? What role did they play in your decision to become self-employed?
- How would you describe your ties with the local Hmong community?

Figure 1: Comparing MSA sample sizes, all years

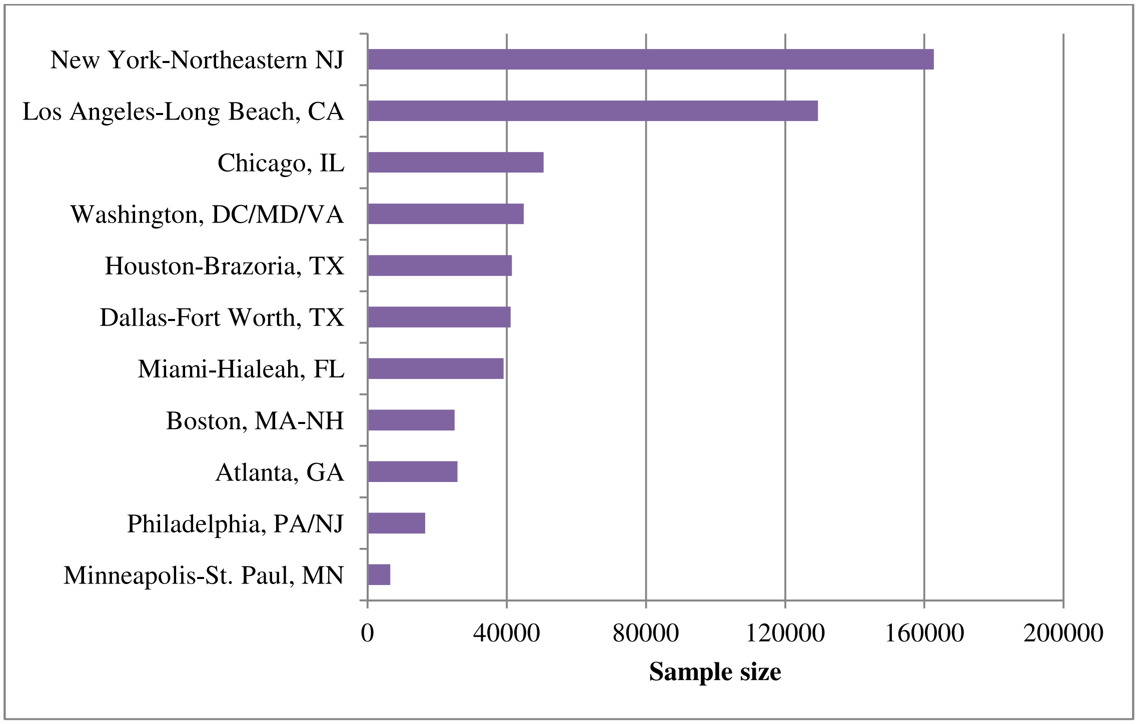

Figure 2: Histogram and kernel density plot of year of arrival for all MSAs

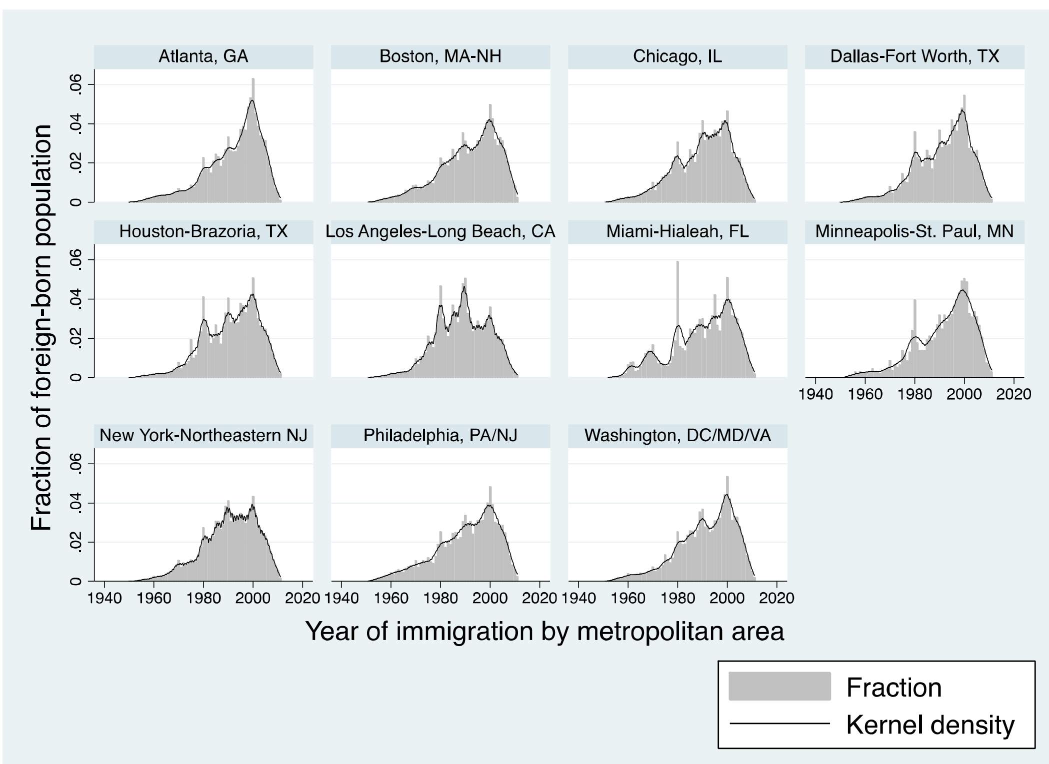

Figure 3: Marital status as percent of MSA sample by MSA

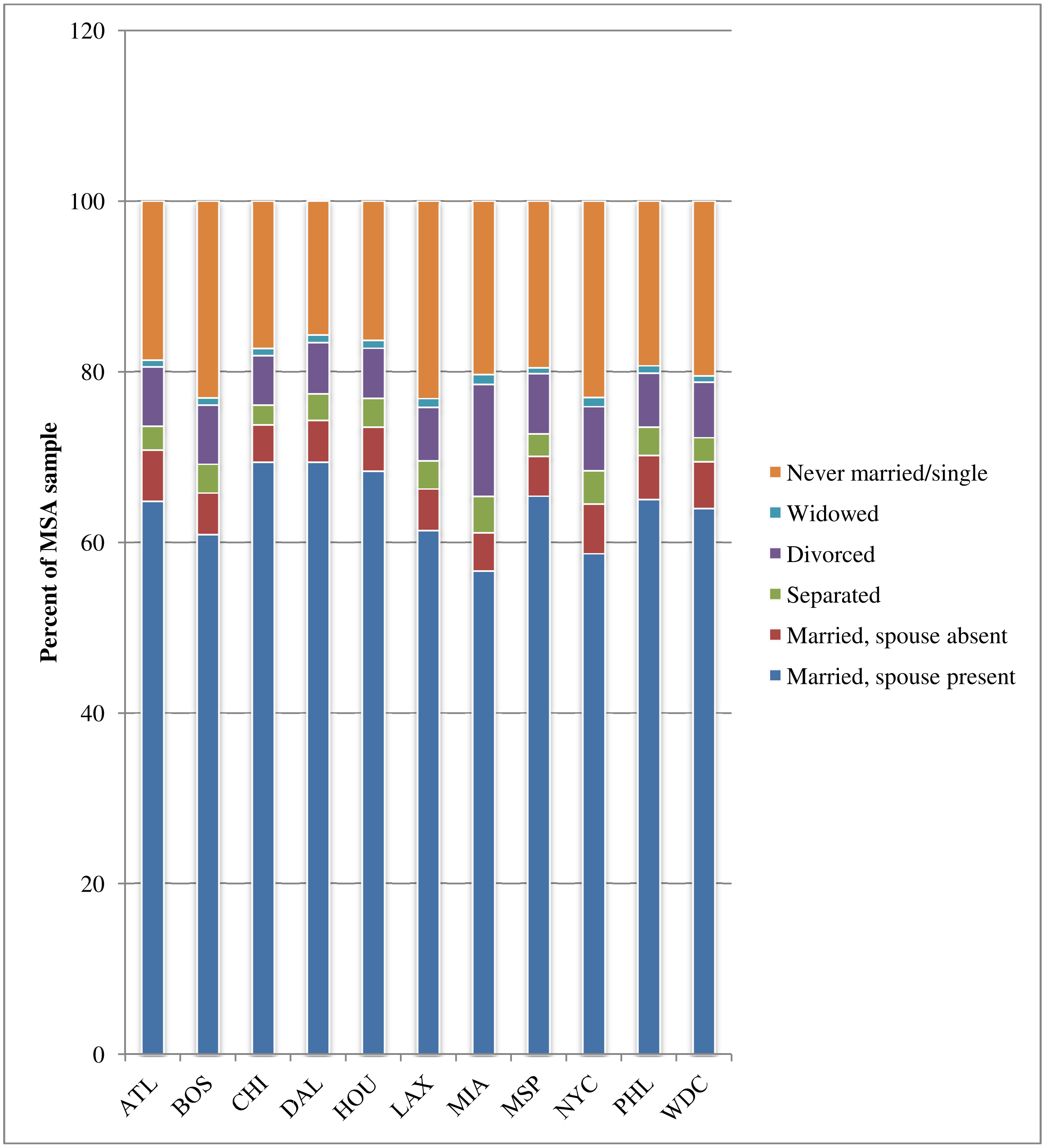

Figure 4: Educational attainment as percent of MSA sample by MSA

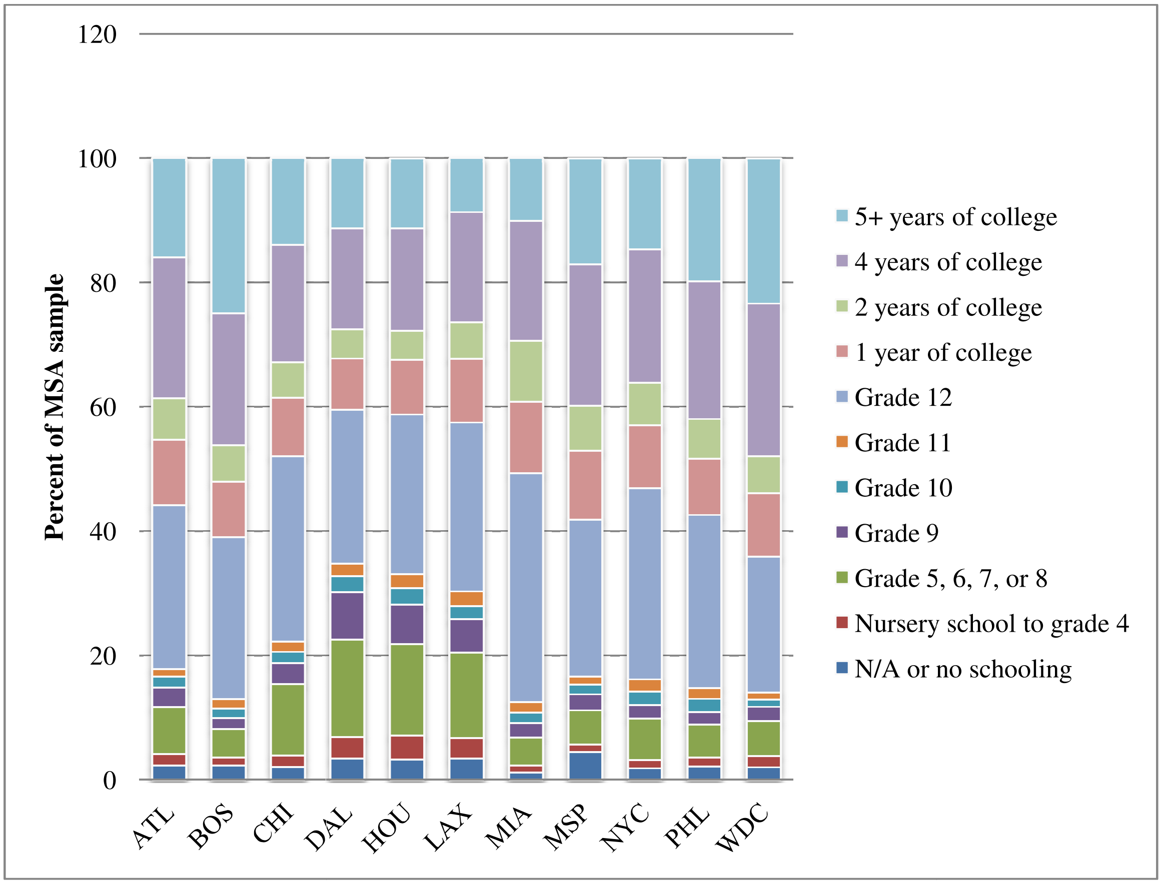

Figure 5: English-speaking ability as percent of MSA sample by MSA

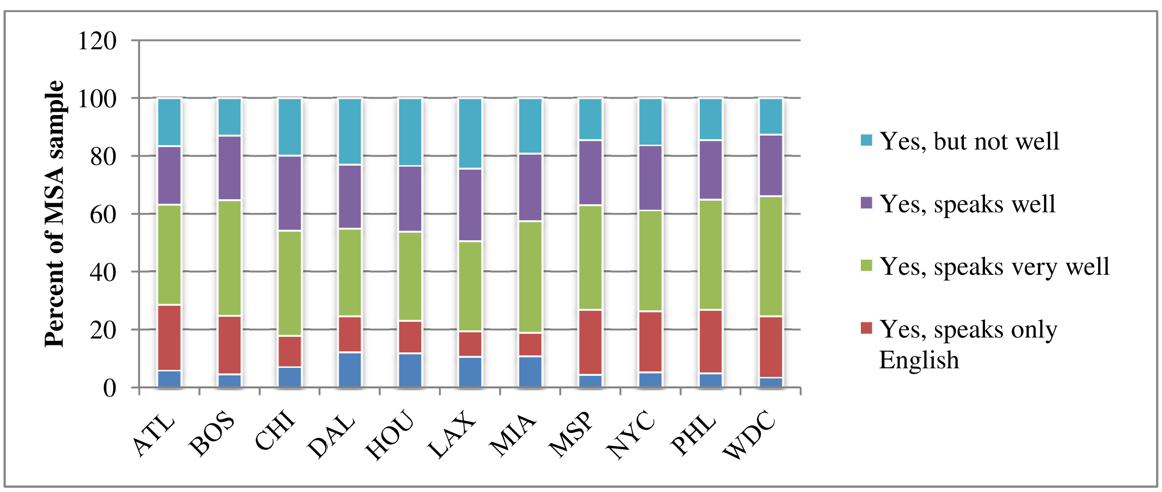

Figure 6: Top 10 ethnic ancestries for all years by MSA

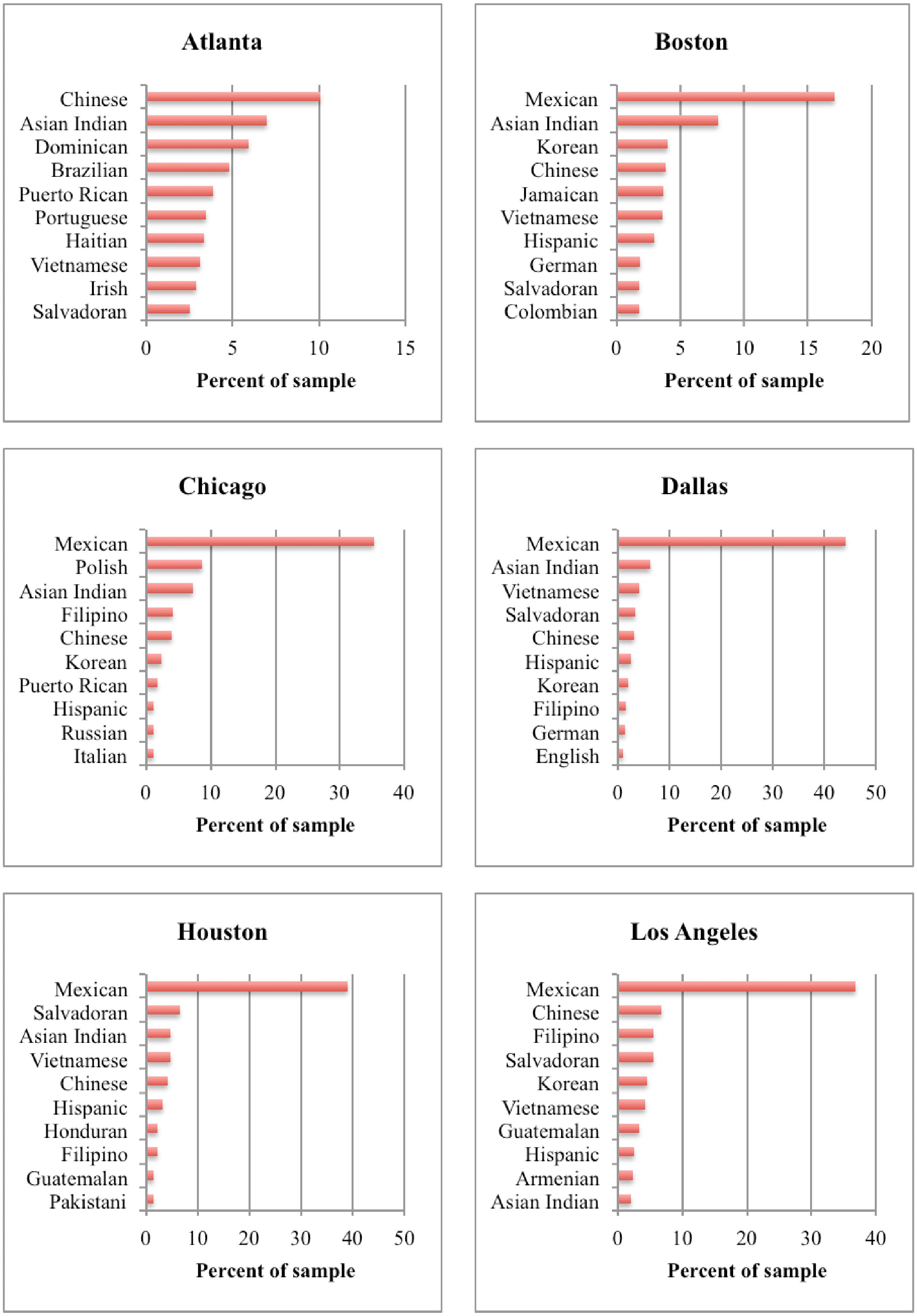

Figure 6 [continued]: Top 10 ethnic ancestries for all years by MSA

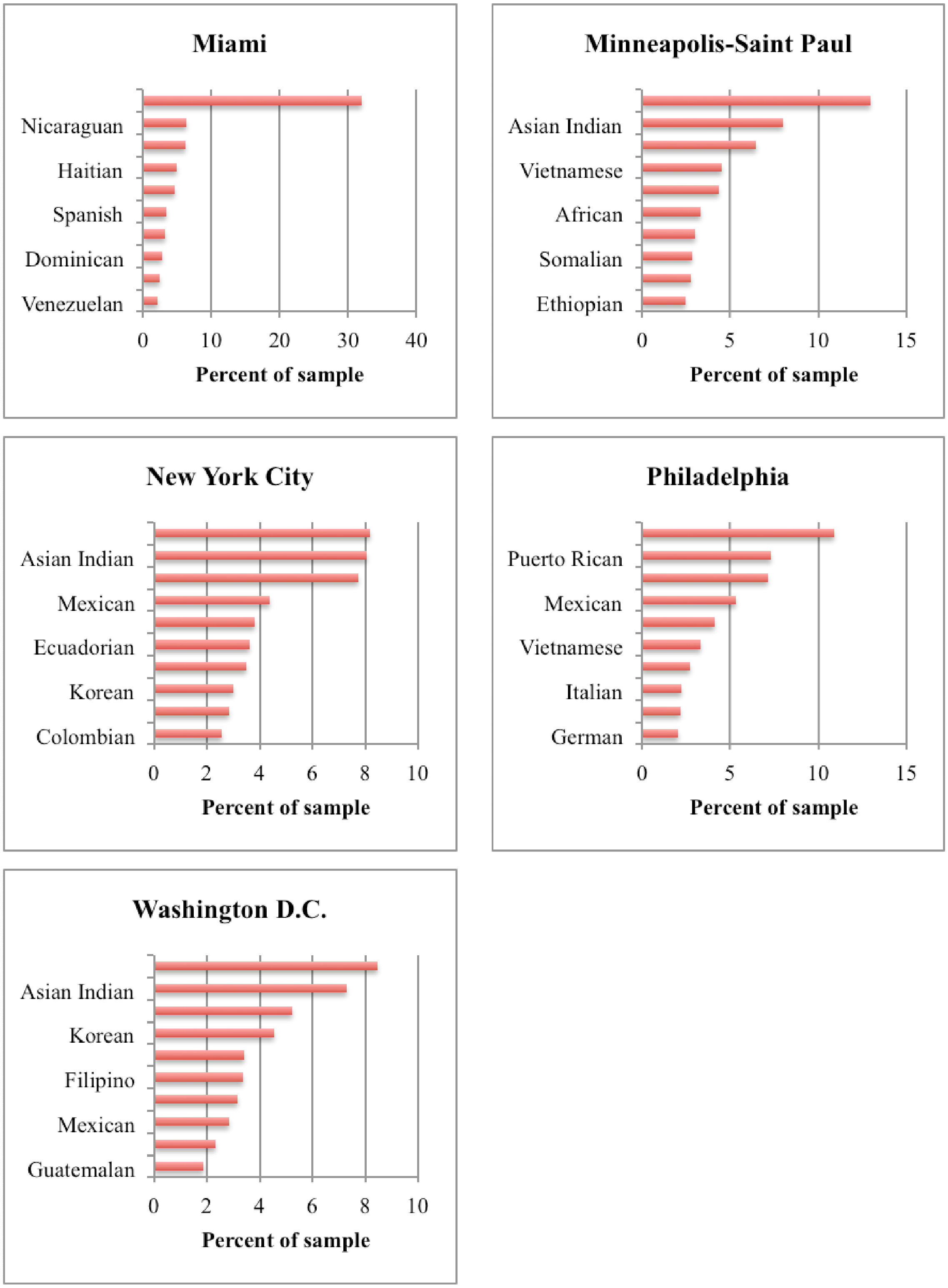

Figure 7: Distribution of employment outcomes for all 11 MSAs, all years

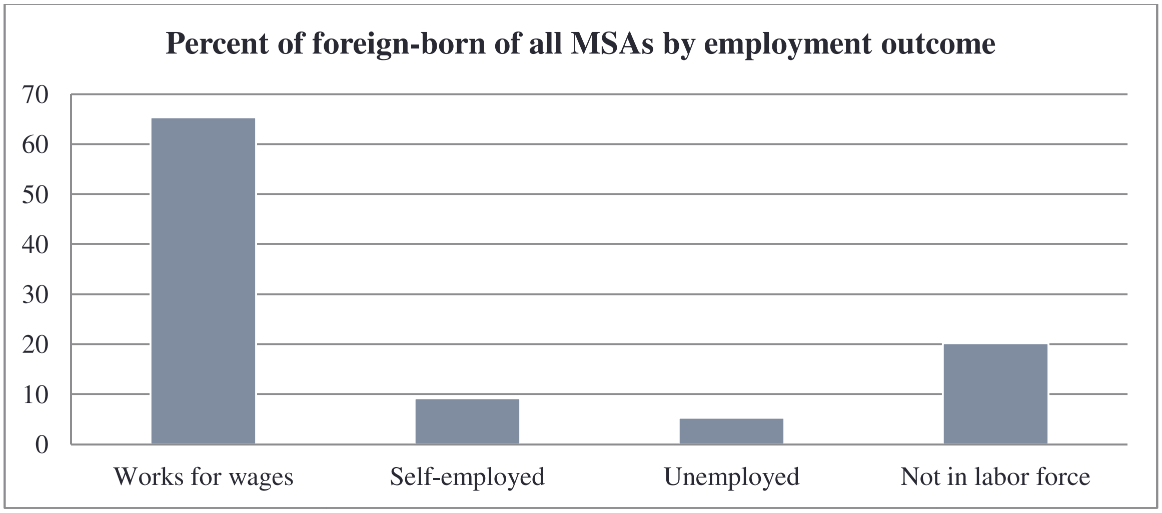

Figure 8: Two-Stage Probit Estimates of Marginal Network Effect on Employment Outcomes

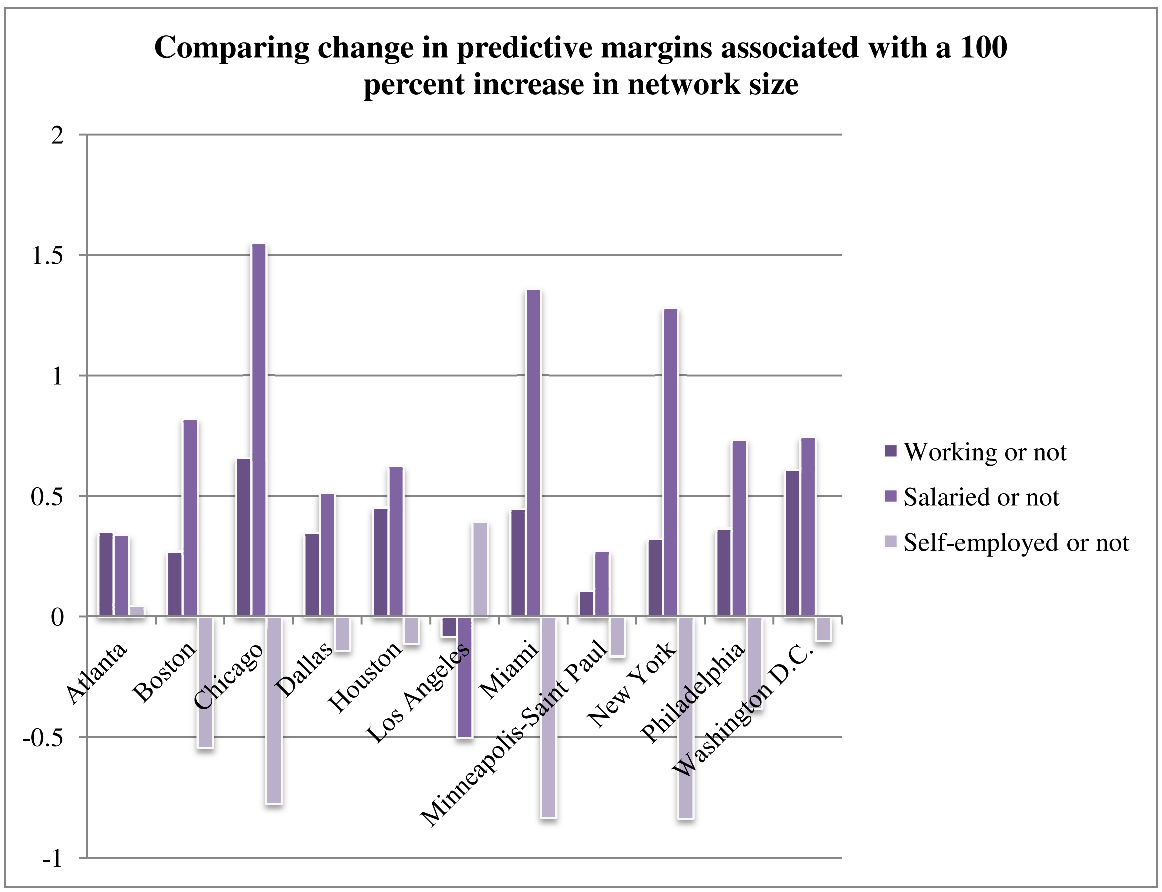

Figure 9: Network's marginal effect on probability of employment outcomes in LAX
(From top-left to bottom-right: self-employment, salaried employment, unemployment, and not in labor force – respectively)

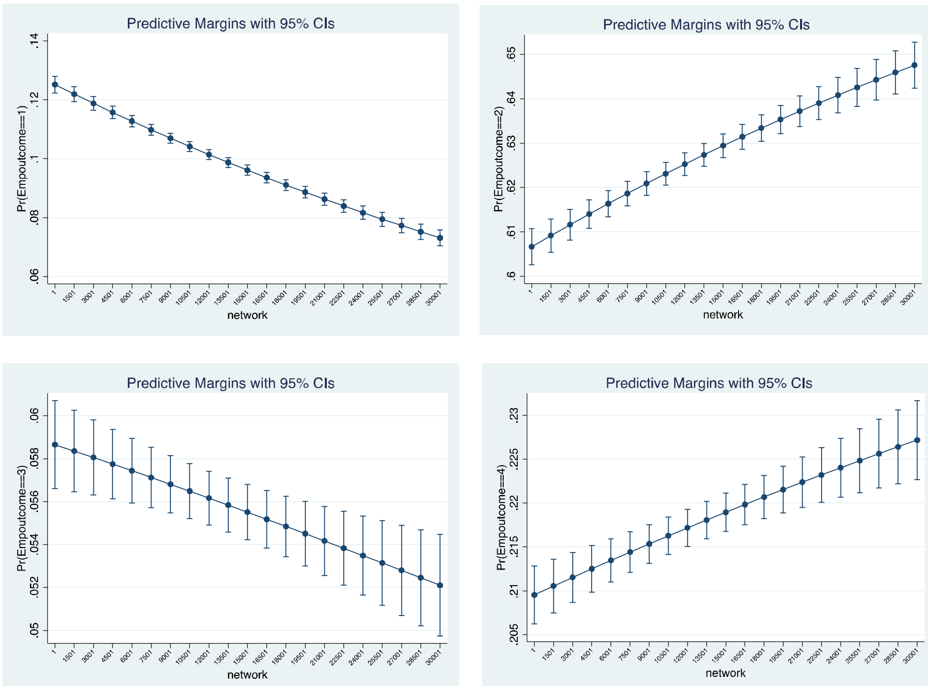

Figure 10: Network's marginal effects on employment outcomes in New York-NJ
(From top-left to bottom-right: self-employment, salaried employment, unemployment, and not in labor force – respectively)

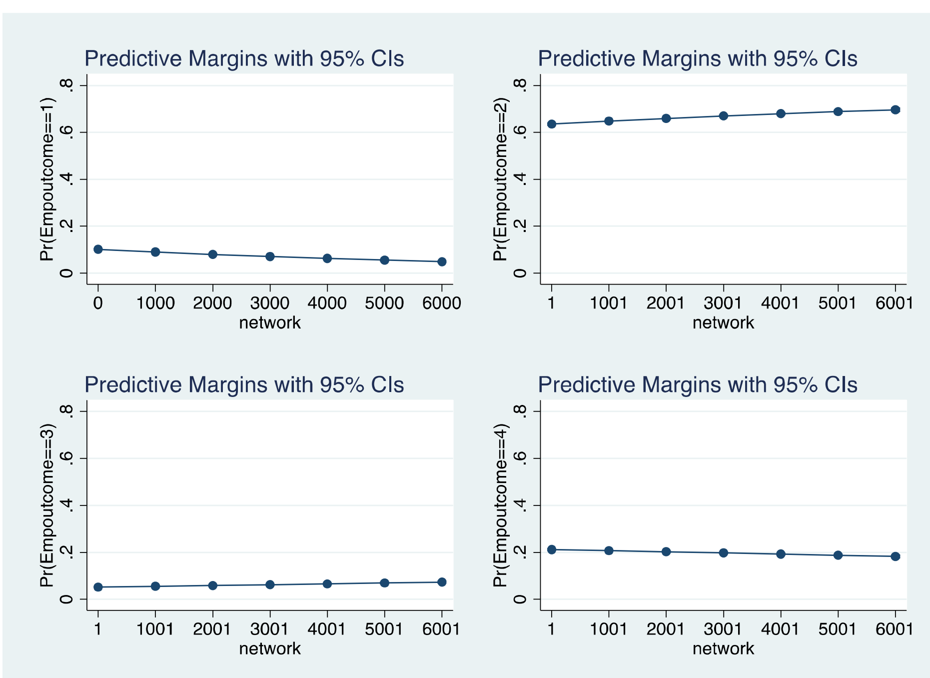

Figure 11: Network's marginal effects on employment outcomes in Houston-Brazoria

(From top-left to bottom-right: self-employment, salaried employment, unemployment, and not in labor force – respectively)

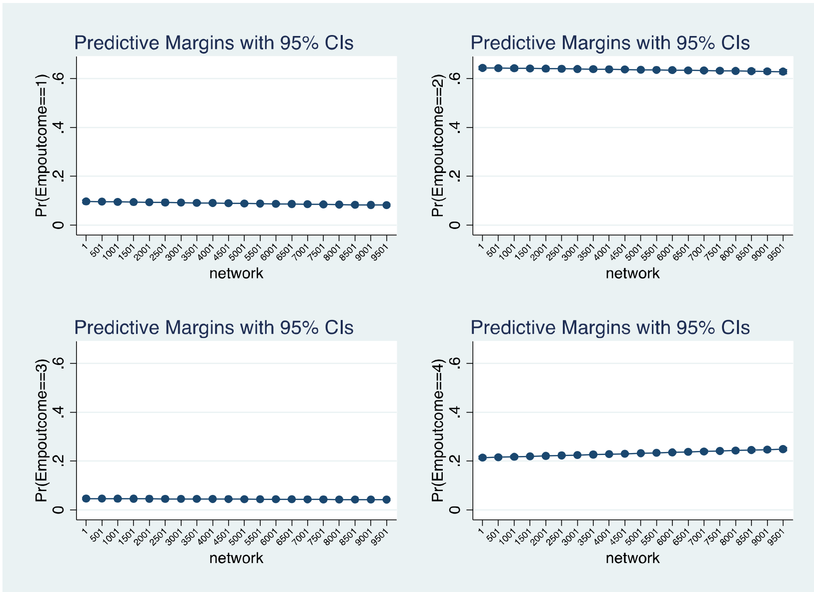

Figure 12: Network's marginal effects on employment outcomes in Minneapolis-Saint Paul

From top-left to bottom-right: self-employment, salaried employment, unemployment, and not in labor force – respectively

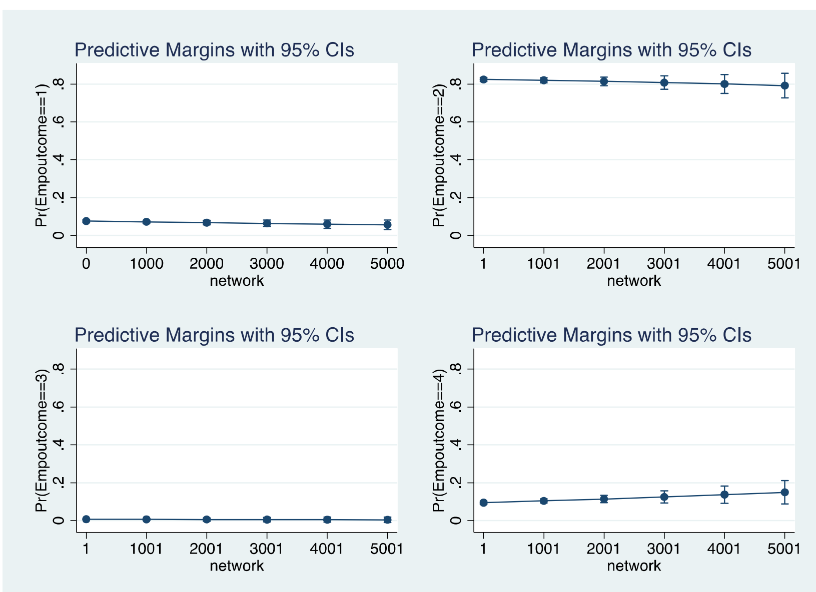

Figure 13: Network’s marginal effects on employment outcome using two-stage logit (HOU)

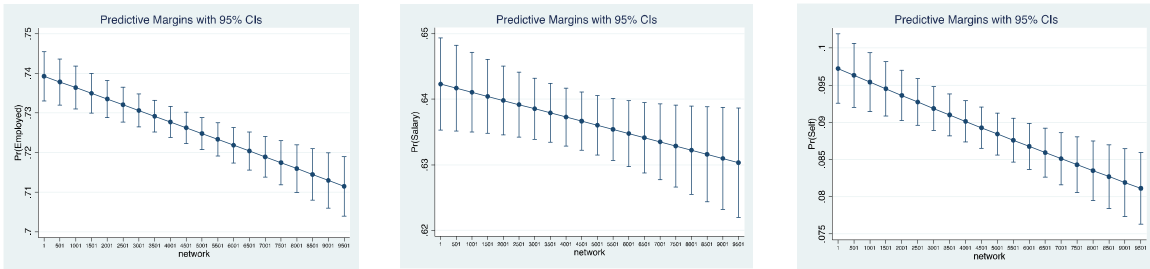

Figure 14: Network’s marginal effects on employment outcome using two-stage logit (NYC)

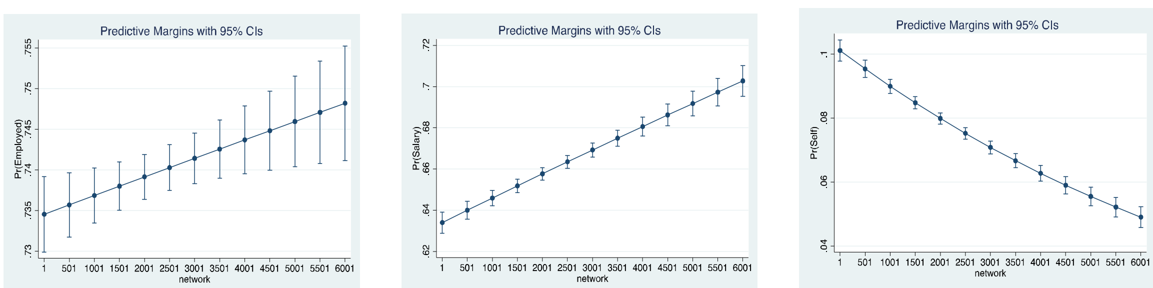

Figure 15: Network’s marginal effects on employment outcome using two-stage logit (LAX)

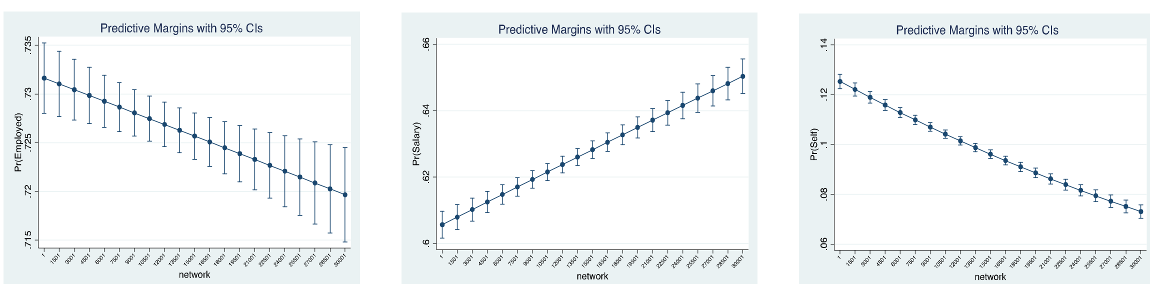

Figure 16: Network’s marginal effects on employment outcome using two-stage logit (MSP)