

Social Networks and the Dynamics of Labor Market Outcomes: Evidence from Refugees *

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Abstract

This paper examines the dynamic implications of social networks for the labor market outcomes of political refugees resettled in the U.S. Using a theoretical model of job information transmission within social networks, the paper shows that the relationship between the size of a social network, the vintage of network members and labor market outcomes is non-monotonic. To test this prediction, I use an empirical strategy which exploits the fact that resettlement agencies distribute refugees across cities, precluding individuals from sorting into locations. The results indicate that an increase in the number of social network members resettled in the same year or one year prior leads to a deterioration of labor market outcomes, while a greater number of long-tenured network members improves the probability of employment and raises the hourly wage for newly arrived refugees.

1 Introduction

There is now substantial evidence that social networks play an important role in the U.S. labor market. More than half of jobs are reported to be found through informal social network contacts (Ioannides and Loury, 2004). Furthermore, a number of studies provide evidence of network-based job referrals and informational spill-overs in the U.S. labor market (Bayer, Ross, and Topa, 2005;

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Topa, 2001; Laschever, 2005). The broader literature on how social networks affect crime, human capital accumulation and welfare participation highlight additional, indirect channels through which networks affect labor markets (Glaeser, Sacerdote, and Scheinkman, 1996; Kling, Liebman, and Katz, 2007; Sacerdote, 2001; Gould, Lavy, and Paserman, 2004; Bertrand, Luttmer, and Mullainathan, 2000). A larger network, in particular, has been shown to be, on net, advantageous to members of such networks: the seminal work of Munshi (2003) shows that Mexican migrants have a higher probability of employment when their social networks are exogenously larger.¹ This paper focuses instead on how social networks affect the dynamics of labor market outcomes and provides empirical evidence that social networks can instead have heterogeneous affects across network members and over time due to within-network competition.

Relatively little attention has been paid to labor market dynamics and the possibility of within-network competition for job information.² Calvo-Armengol and Jackson (2004) develop a model which suggests that the structure of a social network affects persistence in unemployment levels within and across networks.³ They also show that in the short-run, there can be a negative correlation in employment outcomes between some network members due to competition over a finite number of known jobs. Competition within a network may therefore, in the short run, mitigate the network's ability to overcome labor market imperfections. In this paper, I extend their approach to analyze the short-run labor market implications of this competition effect when social network size changes over time.

The theoretical framework in this paper embeds the structure of Calvo-Armengol and Jack-

¹Edin et al. (2003) also find a positive relationship between the number of network members and earnings among refugees in Sweden.

²Wabha and Zenou (2005) provide evidence which suggests competition by showing that among the employed, the probability of finding a job through a social network is concave with respect to population density. Using a model of employer referrals similar to that of Montgomery (1991) as motivation, Munshi (2003) also finds that the positive effect is driven by the number of senior network members and an insignificant, but positive, effect for those who arrived in the previous 3 years. This serves as further motivation for investigating the empirical importance of within-network competition.

³By endogenizing the labor force participation decision, they show the striking result that initial differences in employment levels across networks can lead to long-run inequality between groups.

son (2004), where individuals can share job information with social network members, within an overlapping generations model. The main prediction is that the relationship between network size, the tenure of network members and labor market outcomes is non-monotonic. Depending on the vintage of other network members, having access to a larger network may actually lead to a deterioration of individuals' labor market outcomes due to competition among unemployed members for job information.⁴ However, this is a dynamic relationship: an increase in the size of a given cohort will first decrease the employment rate and average hourly wage of cohorts who arrive close in time to the large cohort, but will improve outcomes for those cohorts that arrive sufficiently later. This implies a non-monotonic and dynamic relationship between the size of a social network and labor market outcomes.

The theoretical and empirical literatures on networks show mixed results for wages (Ioannides and Loury, 2004; Mortensen and Vishwanath, 1994; Bentolila et al., 2004). The job information transmission model presented in this paper highlights an additional subtlety: networks can affect both the number of offers a person receives but also the wage conditional on an offer.⁵ As a result, the relationship between network size and wages conditional on employment is theoretically ambiguous since these two mechanisms may act to offset one another. The empirical analysis therefore evaluates wages both unconditional and conditional on employment.

In order to test these predictions empirically, I compiled a data-set on refugees resettled in the U.S. between 2001 and 2005 using administrative records from the International Rescue Committee (IRC), a large resettlement agency. The main challenge in identifying network effects is separating the causal impact of the network from the role of unobservable characteristics shared by network members, especially as individuals potentially sort themselves into localities and networks

⁴The competition effect arises not because of an increase in labor supply in the face of fixed demand: this effect occurs even when the probability of receiving job information is constant irrespective of network size.

⁵In the model in this paper, passed job information are previously rejected offers, and therefore wage offers are lower on average if received from a fellow network member.

based on these factors.⁶

Refugees are of interest since social networks may play a particularly important role among migrant communities (Borjas, 1992; Munshi, 2003). The unique institutional features of the resettlement process also facilitates an empirical strategy which removes the bias from individuals sorting into networks. In particular, refugees resettled by the IRC without family in the U.S. do not choose their destination city. Instead, the IRC selects the geographic location for this set of refugees using individual characteristics which are all available to the econometrician. By defining a refugee's social network as refugees from the same country of origin in the same city, network size is uncorrelated with unobserved individual characteristics as they are unobserved to both the econometrician and the IRC at the time of placement.

Variation in the relative size and structure of refugee social networks across cities and ethnic groups over time is used to examine the dynamic relationship between social networks and labor market outcomes. By focusing on dynamics, the empirical analysis isolates both the competition and positive information effect from an increase in network size. This variation also facilitates a flexible econometric specification, allowing for ethnic group, city and time heterogeneity, in case the agency's placement decisions are based on unobserved ethnic group and city level factors.

The empirical analysis using refugees resettled in the U.S. shows that an increase in network size has heterogeneous effects across network members, creating both negative and positive ramifications for employment outcomes. I find that a one standard deviation increase in the number of network members who arrive in the U.S. one year prior lowers the probability of employment for a new arrival by 4.8 percentage points. Conversely, as predicted by the model, an increase in the number of tenured network members improves the labor market outcomes for recently arrived refugees. An analogous increase in the number of network members who have two years tenure in

⁶This is one of the "Reflection" problems articulated by Manski (1993).

the U.S. increases the employment probability by 4.6 percentage points. The analysis also shows that average hourly wages follow the model's prediction. Among those who are employed, there is a strong positive effect from an increase in the number of senior network members on wages but an insignificant impact from changes in the number of network members who arrived in the current or previous year. This suggests that by providing job information, networks affect wages both through the employment rate but also by affecting job quality once jobs are found.

This paper argues from a methodological standpoint that evaluating the composition of a social network within a dynamic context is necessary to accurately assess the role of social networks in the labor market. A static analysis of network effects, using the stock of immigrants as the relevant network measure, is likely to miss important heterogeneity in the way network-based job information flows influence outcomes. In some cases, as demonstrated in this paper, estimating the static effect of an increase in the total size of the network, inclusive of all cohorts, will mask the presence of network effects completely.

In the following section, I present a theoretical framework of job information transmission within social networks. Details on the institutional background and data are provided in Section 4, and Section 5 discusses the empirical strategy. The empirical results for both employment and wages are presented in section 6. Section 7 addresses alternative explanations for the empirical findings, and the paper concludes in section 8 with a brief discussion on policy implications for the refugee resettlement process.

2 Theoretical Framework

2.1 A Model of Employment Rates

The theoretical framework builds on the model developed by Calvo-Armengol and Jackson (2004) and Boorman (1975), incorporated into an overlapping generations setting. By embedding this

model into an overlapping generations framework and analyzing the short-run dynamics from changes in cohort size, I generate concrete predictions which can be tested empirically. To do this, I make the simplifying assumption that all individuals within a network are connected, which eliminates the distinction made by Calvo-Armengol and Jackson between direct and indirect connections.⁷

The basic structure and timing of the model is as follows: each agent lives and works for S periods, and each cohort c has N_c agents. If agent i in cohort c is employed at the end of period t , then $s_{ic}^t = 1$ and accordingly $s_{ic}^t = 0$ if agent i is unemployed. Since all agents within a cohort are identical, I work with the employment rate within the cohort at time t , denoted as s_c^t . There is a positive probability that any employed agent will lose his job at the very beginning of the period at the exogenous breakup rate b . Information about job openings then arrive: any agent hears about a job opening with probability a , and the job arrival process is assumed to be independent across agents. If an agent is unemployed and receives job information, he will fill the position. However, if the agent is already employed, he will pass along the information to a randomly selected network member who is unemployed. Once job information arrives and is referred to unemployed members where suitable, jobs are immediately accepted.

Since each individual receives information directly with probability a , the total number of jobs available in the economy is scaled up as the size of the network increases. The assumption therefore is that the size of the network is small compared to the entire economy. The advantage of this approach is that it enables the model to isolate the network effect directly. This assumption also reflects the empirical setting in which the predictions will be tested.⁸

⁷This paper therefore also abstracts away from the distinction made by Granovetter (1973) on weak versus strong ties.

⁸As shown in table 1, the average cohort size in the sample of refugees used in this paper is less than 30. Since the resettlement locations are medium-sized cities, including cities such as Phoenix, a change in the number of refugees arriving in each city in a given year is unlikely to have a general equilibrium effect on the job arrival rate or the distribution of wages. This validity of this assumption will be discussed further in the empirical sections.

This structure can be formalized in the following way:

$$s_c^t = a + r^t \quad \text{if } c = t \quad (1)$$

$$s_c^t = (1 - b)s_c^{t-1} + (1 - (1 - b)s_c^{t-1})(a + r^t) \quad \text{if } c \leq t \leq c + (S - 1) \quad (2)$$

$$r^t = (1 - b) \frac{\sum_{k=t-S+1}^{t-1} N_k s_k^{t-1} a}{\sum_{k=t-S+1}^t N_k - (1 - b) \sum_{k=t-S+1}^{t-1} N_k s_k^{t-1}} \quad (3)$$

where r^t represents the probability of receiving job information through an employed network member. An individual entering the market can become employed by receiving job information directly, a , or through a network member passing information, captured by the term r^t . The probability of receiving job information from the network, r^t , is the total number of jobs which are available in the network to be passed, determined by the number of employed individuals who receive information in that period, divided by the number of potential recipients. Potential recipients are those who are unemployed at the beginning of that period, after the exogenous break-up has occurred. For cohorts who have previously been in the market, the probability of being employed is the probability of having a job in the previous period and keeping it, at rate $1 - b$, plus s_c^t weighted by the probability of being unemployed. This simple model can be used to show a couple of predictions which can be tested empirically.

Proposition 1 *For all values $0 < a < 1$ and $0 < b < 1$, an increase in cohort size N_j decreases s_c^j for all c .⁹*

Proof: See appendix.

The intuition is that since s_c^{j-1} does not change, increasing N_j only increases the number of unemployed individuals seeking job information from network members while leaving the number of employed members unchanged. The result is a decline in the employment rate for both the cohort

⁹This claim holds for all values of a and b such that $s_c^j \neq 1$ for all c and j .

which is made exogenously larger and all other cohorts in the market in that period. The effect is present despite the fact that any individual in the market has the same probability of hearing about a job directly as before. Since the probability of hearing about a job directly is the same as prior to the change in N_j , this competition effect arises from the dynamics *within* the network.

Proposition 2 *The impact of an increase in N_j on s_k^k is monotonically increasing between $k = j$ and $j + S - 1$.*

Proof: See appendix.

Propositions 1 and 2 show that despite an initial negative effect on all cohorts, cohort j 's negative impact on employment on subsequent cohorts is mitigated over time, as the cohort gains experience in the labor market. Numerical analysis of the model shows $\frac{\partial s_k^k}{\partial N_j} > 0$ for at least $k = j + S - 1$ and usually earlier cohorts. That is, while an increase in the size of cohort j first negatively impacts cohorts who arrive close in time to period j , it eventually increases the employment rate for cohorts who arrive sufficiently later.¹⁰ As cohort j 's employment rate increases over time, its larger size becomes an asset to the entire network.

To illustrate the model's predictions, Figure 1 provides an example where $a = .35$, $b = .2$, and $S = 4$. The graph shows a comparison in the employment rates of a control network with constant cohort size and a treatment network where there is a one-time shock in which the size of cohort j is doubled. Both the treated cohort, j , and the cohort entering in the next period, cohort $j + 1$, experience a lower employment rate in their first period in the market than it would have been in the absence of the cohort size shock. However, the following cohorts, $j + 2$ and $j + 3$, both receive gains in the employment rates in all periods these cohorts are in the market.

In the simple model described above, job information arrives to all agents in the economy

¹⁰The positive effect on later cohorts, according to the numeric analysis, holds for all parameter values even though the analytic results only show a monotonically increasing effect.

at the same rate regardless of their current labor market status. The model can be made more general to allow for the job information arrival rate to depend on employment status: for example, reflecting either that search intensity may be higher for the unemployed or that job information is likely to circulate through employers. Propositions 1 and 2 are robust these alternative assumptions regarding the arrival rate.¹¹

2.2 A Model of Employment Rates and Wages

Subsequent work by Calvo-Armengol and Jackson (2007) analyzes a more general model which includes stochastic wages and finds, despite a short-run competition effect, a positive steady-state correlation for employment rates and wages across network members.

I incorporate wages into the overlapping generations framework used above in the following way: with probability a , an individual receives job information which now also contains a wage. If the individual who receives the job information is unemployed, he takes the job. However, if the individual is employed, he accepts the job if $w_{ict}^o > w_{ict}$, where w_{ict}^o denotes the offer wage from the new job information received by employed individual i . Alternatively if $w_{ict}^o < w_{ict}$, the offer is passed to a randomly selected unemployed network member.¹² Wages are *iid* draws from the uniform distribution $w \sim U[\underline{w}, \bar{w}]$. w_c^e denotes the average wage for employed network members in cohort c in period c .¹³ The analysis of the model is done by simulation.

One pattern that emerges in this model is that wages increase with tenure in the labor

¹¹Details on these alternative formulations are available from the author.

¹²This could produce an incentive for network members to behave strategically. It may be preferable for an unemployed network member to refuse the job offer and wait another period to be eligible for job information from other network members. This assumption can, however, be relaxed so that information is passed randomly to anyone in the network. In this case, the magnitude of the impact from a change in network size decreases rather sharply but still demonstrates the pattern of first increasing competition then improving outcomes for later entering cohorts.

¹³The search literature has argued that either pareto or exponential distributions are appropriate as wage distributions (Lancaster and Chesher, 1983; Lynch, 1983). I therefore tested the sensitivity of the model predictions by assuming wages are exponentially distributed with $w \sim E(\lambda = 3) + 5.15$. Analysis of all other parameter values show consistent results as with the uniform distribution: the prediction holds for the employment for all parameter values, and wages conditional on employment continue to be ambiguous for certain values, despite the support of the wage distribution being much smaller.

market. This is not driven by an explicit return to experience: instead, wages improve as individuals receive more draws from the wage distribution the longer they are in the market, discarding low wage offers.

There are two ways through which a change in network size affects the wage in this model. First, a change in N_j affects the number of job offers an individual receives and therefore the wage. Second, it affects the proportion of the employed in the network who received job information directly versus indirectly. This is important since the only job offers available to the unemployed from within the network are those with wages which are sufficiently low that the employed network member who initially receives the job information rejects the offer. This implies that the average wage from an offer received indirectly is lower than an offer received directly, and a change in the proportion of the network becoming employed through the indirect channel will also affect average wages within the cohort.

These two different channels, in fact, work in opposite directions, creating an ambiguity in the model. Wages conditional on employment do not necessarily follow the same pattern as in section 2.1. For example, an increase in N_j will lead to a smaller number of offers available to cohort j in period j , lowering wages. However, it also reduces the proportion of jobs being attained through the network. Since these jobs have lower wages on average, the average wage of those who are employed may actually increase. It is therefore possible to have within-period increases in average wages among the employed due to an increase in N_j , despite the decline in the employment rate.

There is accordingly no general prediction with regards to wages conditional on employment. An analogous Claim to the Propositions shown in section 2.1, however, for employment rates and wages in the entire network.

Claim 1 *For some values of (a,b) and an increase in N_j , there exists \tilde{k} such that $\forall k \leq \tilde{k}, \frac{\partial w_k^k}{\partial N_j} < 0$*

and $\frac{\partial s_k^k}{\partial N_j} < 0$. For $p > \tilde{k}$, $\frac{\partial w_p^p}{\partial N_j} > 0$ and $\frac{\partial s_p^p}{\partial N_j} > 0$.

where here w_j^j represents the average hourly wage of the entire network, including a wage of 0 for those who are employed. The offsetting effect from changes in the composition of network members obtaining jobs through direct versus indirect channels is not strong enough to change the prediction regarding wages of the entire network.

The model therefore predicts that employment and wage rates will be inversely correlated with the number of recently arrived refugees, but positively correlated with the number of senior network members.¹⁴ The striking part of the prediction is that the deleterious effect from an increase in network size does not come from an increase in labor supply with a fixed labor demand. Instead, the negative effect comes from competition between network members for information provided by already employed individuals. It is a within-network information competition effect and not a result of an increase in labor supply driving down wages or employment rates in equilibrium. The assumption that each individual faces a constant rate a of hearing about a job directly ensures that labor demand is held fixed, so that the latter effect is not driving the model prediction.

3 Institutional Environment and Data

3.1 Refugee Resettlement Process

The United States has a long history of refugee resettlement, having accepted around 2.4 million refugees and asylees since 1975. In 2005, 70,000 refugees were authorized for admission to the U.S. compared with the 55,000 immigrants who were permitted entry in 2005 through the diversity

¹⁴A key difference between the theoretical model presented in section 2.1 and this model is how efficient the network is in passing along job information. The main prediction for employment rates holds in the two extreme cases where: information is passed until it arrives at an unemployed individual (section 2.1) and when information is only passed once and discarded immediately if unused (as described here). The model predictions also hold in a model with a moderate level of efficiency, where individuals who are already employed and receive an offer with a higher wage will pass on their discarded jobs to unemployed network members. The key difference with this formulation is an increase in the average employment rate.

lottery system. Refugees come from a wide variety of countries and flee their homes for different reasons, from war-related violence to religious persecution to retribution for political views. The process through which refugees gain access to the U.S. creates a unique opportunity to look at the role of ethnic networks. Limited research has looked at the economic performance of refugees in the U.S., largely due to data constraints.¹⁵ Refugees are a well-defined group: according to Immigration and Nationality Act (INA) Section 101, they are individuals living abroad who have a well-founded fear of persecution based on race, religion, nationality, social group status or political opinion in their home country. This study does not look at asylees, defined as those who travel by their own means to the United States and then apply for protected status upon arrival.

How does one become a refugee? Total refugee admissions levels and processing priorities are set each year by the president, in consultation with Congress. INS (currently USCIS) officers adjudicate individual cases in refugee processing centers around the world.¹⁶ Once the INS designates an individual as having refugee status, the Bureau of Population, Refugees, and Migration (PRM) is responsible for overseas processing and transportation to the U.S.

The PRM's final role in the resettlement process is to allocate all accepted cases to one of ten contracted voluntary resettlement agencies. The resettlement agencies are responsible for acquiring housing, providing initial benefits including cash assistance and in-kind support, as well as providing access to resources such as ESL training and job assistance. I use data from one voluntary resettlement agency: the International Rescue Committee (IRC). In this paper I look specifically at refugees who did attain admittance via family reunification. For these individuals, the IRC has the sole discretion in determining where the refugee will be resettled among its 16 regional offices. The IRC receives information from the State Department about each refugee's

¹⁵Two exceptions are Cortes (2004) and Borjas (2000). Cortes (2004) argues that refugees perform worse relative to other immigrant groups in the short-run but eventually surpass the other groups.

¹⁶These centers are most often within refugee camps, but individuals can also apply for refugee status in local U.S. embassies.

characteristics, such as country of origin and demographic information. With this information, the IRC decides to send each refugee or refugee family to one of its 16 regional offices. It is important to note that no IRC employee meets the refugee or his family members until the allocation process has been completed, which is generally within one week of the State Department contacting the agency. The refugee travels directly from his place of residence overseas to the chosen IRC regional office within the U.S.

3.2 Placement Policy

The IRC does not have an explicit placement rule when distributing refugees across regional offices, although they do follow a few general guidelines. First, the IRC seeks to place refugees in locations where there is some pre-existing ethnic or nationality-based community. They also attempt to send each refugee to an office which has either a staff member or a volunteer who speaks the same language as the refugee. Individual refugees or refugee families who have special medical problems, such as HIV, are only sent to particular offices which specialize in such cases.

In addition to policies oriented towards achieving a good match between an individual refugee and a city, the IRC also budgets for the total number of refugees expected to arrive in each regional office. To do this, each regional office is budgeted a total number of people per year plus a target for refugees who do not have family already in the U.S. at the time of arrival, designated as non-family reunification refugees. These numbers are estimated using projected numbers from the State Department on how many refugees are expected to be admitted to the U.S. from each region of the world. Often the actual numbers can differ substantially from those anticipated, as the actual number of refugees who arrive from a region can be volatile. There is also a great deal of uncertainty about the number of family reunification cases arriving each year. Since family reunification cases are predestined for particular offices, this shifts the allocation of non-family

reunification cases and often the total number of refugees sent to each city away from budgeted numbers. Finally, the overall number of refugees sent to a particular office is also a function of overall employment statistics at the regional office level.

As for the remaining information provided to the IRC by the PRM, the IRC reports using a limited amount of this information in the allocation process. Given that this is difficult to verify, the data set used in this analysis fortunately includes all information given to the IRC prior to each refugee's arrival since the data was constructed from the forms provided to the IRC from the PRM. Individual characteristics which the IRC uses in the allocation process are therefore also available to the econometrician.

3.3 Data

The data from the IRC comprises of over 1,700 male adults who arrived in the U.S. between 2001 and 2005.¹⁷ All sample respondents did not have family members already in the U.S. to assist in their resettlement, and the IRC therefore placed all of these individuals using the placement policy described above. There are three components to this data. First, a fairly rich set of demographic variables were compiled by the INS and the PRM prior to the refugee's arrival in the U.S., including ethnicity, date of birth, country of first asylum, the size of the family being resettled, initial English language level and education received in the home country. Labor market outcomes, in particular employment status and hourly wage, were collected by the IRC at 90 days after each refugee's arrival. Finally, data on the total number of individuals (inclusive of all ages) placed in each IRC regional office by nationality from 1997 through 2004 were retrieved from archived aggregate reports. Unfortunately, individual-level data prior to 2001 are currently unavailable.

There is a wide variety of ethnic groups and nationalities in the data. The largest groups are

¹⁷There are three groups whose placement do not follow the above guidelines due to special circumstances, the Meskhetian Turks, the Somali Bantu and the Kakuma Youth, and are therefore excluded from the sample.

from Afghanistan, Bosnia, Liberia, Somalia, and the Sudan, although there are in total 38 different ethnic groups represented. The IRC has 16 offices where they resettle non-family reunification cases.¹⁸ The sample excludes those refugees who are HIV positive, which are less than 1% of the sample, since these refugees spend a substantial portion of their initial 90 days under medical supervision.

In order to get an estimate of the size of each ethnic group's network in a given geographic space, I define the social network as non-family reunification refugees from the same nationality who were resettled in the same regional office. Since the aggregate data is available from 1997 onwards, this measure of network size for an individual will include fellow refugees resettled in the four years prior to that individual's arrival. The reason the network is restricted to refugees without family already in the U.S. is twofold. First, while not modelled explicitly, an incentive for participation in the network is insurance: even if an individual is employed now, there is a positive probability of becoming unemployed in future periods and may then rely on the network to gain a job. Refugees with family members who are already established in the U.S. would need to depend less on the social network formed by refugees who largely have not known each other for more than 90 days. The second reason is that the resettlement experience is different across these two groups. Family reunification refugees can be located far away from the regional office but still "resettled" by the IRC. By contrast, since the IRC rents an apartment for each non-family reunification refugee, they tend to be clustered together spatially. Moreover, the two types of refugees are less likely to interact since family reunification refugees receive less resettlement services from the IRC and are accordingly less likely to meet fellow refugees in the office or at IRC-sponsored events. The data on the number of family reunification refugees resettled during this time period will also be used in the econometric analysis, as discussed in section 5.1.2.

¹⁸The offices are: Abilene, TX, Atlanta, Baltimore, Boston, Charlottesville, Dallas, New York, New Jersey, Phoenix, Salt Lake City, San Diego, Seattle, Tucson, Washington DC, and Worcester, MA. Atlanta, Baltimore, Dallas, Phoenix and Salt Lake City are the largest.

Two additional data sources will be used: the 2000 Census available through IPUMs is used to construct an alternative network measure as discussed in the Appendix. Also, supplemental information is also available from a survey of refugees and asylees collected by the Department of Health and Human Services' Office of Refugee Resettlement (ORR) between 1993 and 2004. There is no information available in the data indicating which refugees were family reunification cases, however, so this sample may therefore not be precisely comparable to the IRC sample.

4 Empirical Strategy

The primary objective of this paper is to empirically test the predictions of a simple model of job-related information flows in social networks. Using labor market outcomes as of 90 days after arrival and the aggregate data on IRC placements from 1997-2005, the model predictions will be tested using the following econometric specification:

$$Y_{ijkt} = \alpha + \gamma_1 N_{ijk(t)} + \gamma_2 N_{jk(t-1)} + \gamma_3 N_{jk(t-2)} + \gamma_4 N_{jk(t-3/t-4)} + X_{ijkt}\beta + \delta_{jt} + \phi_k + \epsilon_{ijkt} \quad (4)$$

for individual i in country of origin j in city k who arrived at time t . Y_{ijkt} represents either employment status or wages for individual i . $N_{jk(t-1)}$ and $N_{jk(t-2)}$ are the number of refugees who arrived during the fiscal year one year and two years prior to refugee i 's arrival respectively. $N_{jk(t-3/t-4)}$ is analogously the number who arrived three and four years prior. The network variables are therefore the same for all refugees who arrive in the same fiscal year, are resettled in the same regional office and share the same country of origin/ethnicity.¹⁹ $N_{ijk(t)}$ is the number of refugees from country of origin j resettled by the IRC in regional office k who arrived in fiscal year t up to i 's specific date of arrival. Those individuals who arrived after i are excluded from $N_{ijk(t)}$ since they would be not

¹⁹Since network size comes from aggregate data, this measure is the total number of refugees by nationality including children. Unfortunately, without individual records prior to 2001, this is as precise measure as available.

be acting as competitors nor providing job information to individual i .²⁰

Propositions 1 and 2 of the model predict that having a larger number of network members who arrived in the same year will decrease the probability of a new refugee obtaining employment and his wage. The competition effect diminishes with the length of time elapsed between two cohorts' arrivals, with the positive information effect eventually dominating. Therefore, negative point estimates of γ_1 and γ_2 and positive estimates of γ_3 and γ_4 would be consistent with the model.

Networks which are defined by group identity and geography are particularly susceptible to bias from sorting. If individuals choose their locations based on factors which are not observable to the econometrician, and these factors are common among group members, then it is difficult to separate the effect of having a larger network from the correlation between common characteristics network members share and labor market outcomes. In the case of refugee resettlement, the institutional environment provides a strategy to mitigate this problem of correlated unobservables.

There are two main threats to identification in this environment: the first originates from sorting along unobservable individual characteristics, and the second is omitted city and ethnic group characteristics correlated with network size because of the IRC's placement strategy. The former is addressed by including a flexible functional form to span the information set available to the IRC at the time of placement. X_{ijkt} then captures the individual characteristics which are correlated with network size. The remaining individual attributes in ϵ_{ijkt} are uncorrelated with N_{jk} since they are not known by the IRC at the time of placement.

Since the IRC resettles multiple ethnic groups across multiple cities during many years, there is variation in social network size across cities, ethnic groups and over time. This facilitates a fixed effects strategy to minimize the second concern of unobservable factors at the city and nationality group level. In my preferred specification, I include only δ_{jt} and ϕ_k controls. Time

²⁰For example, an individual who arrived in December could not influence the 90 day labor market outcomes of a refugee who arrived in January. An alternative measure would be the number of refugees who arrived during same year of arrival up until i 's date of arrival plus 90 days.

variant heterogeneity at the nationality group level is captured by δ_{jt} . This captures differences across groups: for example, one nationality group may have lower human capital on average or the types of people who become refugees vary across sending countries. Since this term varies across years of arrival, it also allows there to be unobservable differences, such as quality, within a group across cohorts. There are also unobservable factors at the city level, such as variation in labor demand, which affect all ethnic groups equally and may influence IRC’s placement decisions. Metropolitan-area fixed effects, ϕ_k , are therefore included. There are, however, three additional potential sources of bias. There may be shocks at the city level, denoted as ξ_{kt} , a match quality between ethnic groups and cities, τ_{jk} , and finally shocks to match quality, ν_{jkt} . The first two can also be addressed through fixed effects since the econometric strategy exploits time variation to test the predictions of the dynamic model. Finally, I will argue in section 5.1.1 that time varying shocks to an ethnicity-city pair can not explain the pattern observed.

5 Empirical Results

5.1 Probability of Employment

5.1.1 Main Results

Table 3 shows the results of analyzing employment in a dynamic context. The preferred specification are in Columns 1 and 2 and include city and nationality group-year fixed effects. Column 1 shows that a larger number of network members who arrived in the current and prior year strongly decreases the probability of employment for a new entrant.²¹ A one standard deviation increase in $t - 1$ network size decreases the probability of employment by 4.8 percentage points. Given that the mean level of employment in the sample is 64%, this constitutes a decline of over 7%.

²¹The employment analysis will be done using a linear probability model (LPM). Since the mean employment rate is 64%, the LPM should perform well and is easier to estimate with the large number of categorical control variables. The error term is clustered at the nationality group/regional office level.

Analysis done with the ORR data shows that an additional year in the U.S. lead to an increase in the employment rate of 3.4%. Therefore this negative network effect is an economically significant factor in determining refugee labor market unemployment.

As is consistent with the model, however, a larger number of refugees with two to four years of experience living in the U.S. prior to a new refugee's arrival has a positive and statistically significant effect on employment. The number of refugees resettled in year $t - 2$ has the largest effect on the probability of employment. In this case a one standard deviation increase in $t - 2$ network size raises the probability of employment by 4.6 percentage points. In this specification, the number of refugees who arrived in the prior 3 and 4 years are combined, and the estimates of γ_3 and γ_4 are jointly significant at the 5% level. One-sided tests indicate that while $\hat{\gamma}_1$ is not statistically more negative than $\hat{\gamma}_2$, $\hat{\gamma}_2 < \hat{\gamma}_3$ as predicted by the model. It is fairly surprising that the coefficient on the number of refugees who arrived in years $t - 3$ and $t - 4$ is smaller than that of the $t - 2$ network, although it is still positive and statistically significant. One reason for this is that out migration is likely to be higher for refugees who had been resettled 3 or more years prior to the new arrival.²² Out migration within the first 90 days is 6.96%, and therefore it is quite plausible that the smaller coefficient reflects the fact that this variable has more measurement error in representing the true number of network members currently available to the new arrival. Attenuation bias would then push down the size of the coefficient compared to that of the $t - 2$ cohort. The possibility of selective out-migration is discussed more extensively in section 6.2.

The coefficients on the control variables are as expected, although the interpretation is unclear given that the coefficients are a mixture of the causal relationship and the selection rule used by the IRC. The specification estimated in column 1 contains a limited number of demographic covariates. To ensure that individual characteristics known by IRC at the time of placement are

²²The data used to measure network size is the total number of refugees who were placed in a given city in a given year, and I do not observe whether those individuals continue to live in their initial location.

sufficiently controlled for, Column 2 includes a wide range of control variables. The estimates of $N_{jk(t)}$ for all t are robust to the inclusion of these variables as can be seen in column 4 of table 3. The coefficients are largely unchanged and continue to be significant.²³

Could systematic variation in factors which affect particular ethnic groups in certain cities generate a relationship between network size and labor market outcomes as predicted by the model? First, the negative relationship between cohort size in time t and outcomes is inconsistent with this hypothesis. If the IRC used information on shocks to match quality, thereby creating a correlation between network size and unobservable factors, there would be a positive relationship between network size in time t and outcomes. Furthermore, it is unlikely that these shocks are known and anticipated by the IRC based on self reports and the timing of the resettlement process.²⁴ Finally, in this case we would observe the flows of refugees from a particular group to exhibit an oscillating pattern. Table 2 shows that the number of refugees from a nationality group who are resettled in the same city are positively correlated across all four year time periods. The table presents the correlation matrix of the number of people the IRC allocated to each nationality/regional office pair, i.e. the size of each cohort across 4 year periods from 1997-2005. The strongest correlated is between time t and $t - 1$ and is thereafter monotonically decreasing in the time elapsed between cohorts. A correlation between ν_{jkt} and network size therefore unlikely to generate estimates of γ_1 , and γ_2 which are negative and positive estimates of γ_3 and γ_4 under the null hypothesis of no network effects.

An alternative hypothesis and a common problem in identifying network effects based on

²³Another placement criteria used by the IRC is to send each refugee to an office where someone can speak the same language as the refugee. Including two discrete variables indicating whether the refugee was placed in an office with either a staff member or a volunteer who speaks at least one of the languages spoken by the refugee does not result in significant changes to the coefficients of interest. Having a volunteer who speaks the same language positively impacts employment while there is no impact from staff members.

²⁴The IRC employee who oversees placement decisions states they do not use this information, and there is also a stochastic time lag between when a refugee is assigned to the IRC by the State Department and the actual arrival date, making it very difficult for the IRC to exploit time varying shocks.

geographic variation is that there may be city-ethnic group specific matches which are both unobserved and correlated with network size. This “comparative advantage” would arise if, for example, there are characteristics or skills which are common to all individuals in ethnic group j which receive a higher return in particular cities k . Of course, if the IRC were to use this information while making placement decisions, network size would be endogenous. However, this alternative hypothesis alone would not generate a negative $\hat{\gamma}_1$ and $\hat{\gamma}_2$ and positive $\hat{\gamma}_3$ and $\hat{\gamma}_4$. It would create a uniformly upward bias, not a differential effect between recently arrived refugees and tenured refugees. The structure of the data also allows a richer set of fixed effects than used in columns 1 and 2 of table 3. Specifically I can include nationality-city, nationality-year and city-year controls since the network variables varies at the nationality-city-year level. The inclusion of the nationality group-city fixed effects should rule out this alternative hypothesis directly.

The results of this specification are shown in columns 5 and 6 of table 3. Despite the large number of additional controls this requires, column 3 shows that the results are robust to this richer specification.²⁵ The estimates are in fact larger than in the specification used in columns 1 and 2, although only the coefficient on $N_{jk(t)}$ is statistically different. One reason for this change is that controlling for city-year and nationality-city year better capture group and city-specific resources available to refugees from the IRC during their first 6 months in the U.S. Column 6 includes the full set of control dummies plus a wider set of individual characteristics. In this case, $\hat{\gamma}_4$ is statistically insignificant but qualitatively similar in size. $\hat{\gamma}_3$, $\hat{\gamma}_1$ and $\hat{\gamma}_2$ remain strongly significant and of the same sign and magnitude. The city-year dummy variables also remove the possibility that city-level employment shocks are influencing the estimates. These additional controls help to identify the causal effect of network size on employment under the maintained assumption that there are not year-specific shocks which vary at the city-ethnicity level and are used by the IRC to determine

²⁵There are 198 nationality-city, 72 city-year and 115 nationality-year pairs.

placement.

To contrast the econometric strategy focusing on dynamics with the static approach, I estimate the effect of the stock of network members on the probability of employment. Columns 5 and 6 of table 3 show that this analysis leads to contradictory results. An increase in the number of refugees from country j resettled in city k from years t through $t - 4$ increases the probability of employment for a new arrival. This specification includes nationality-year, and city controls. However, once city-nationality and city-year controls are included as in Column 6, the effect becomes insignificant and the point estimates are negative. In this case, the analysis would be inconclusive regarding the existence of social networks providing job information to newly arrived refugees. This highlights the importance of considering dynamics when analyzing the role of social networks in labor markets. By properly structuring the network variables to reflect the dynamic relationship between network size and labor market outcomes, the presence of network-based job information transmission is shown to be easily detected and not sensitive to the specification used. Furthermore, the static approach fails to identify the presence of the short-run competition effect. The approach used in this paper therefore sheds new light on how networks function and can affect the labor market outcomes of network members.

5.1.2 Robustness Analysis

Falsification Test

The structure of the data also facilitates a falsification test using the 2001-2004 sample.²⁶ I test whether the number of refugees who arrive in year $t + 1$ impact the probability of employment. Since there is no possible interaction between sample refugees and $t + 1$ refugees, there should be no significant relationship. This exercise therefore serves to test whether there is a cyclical pattern to

²⁶Refugees who arrived in 2005 must be excluded since I do not observe the number of refugees who arrived in 2006.

IRC placement of refugees which may be confounded with the social network mechanism of interest.

Columns 1 through 4 in table 4 are consistent with the maintained identification assumption. Columns 1 and 3 show the baseline results for the sub-sample of refugees who arrived between 2001 and 2004 using nationality-year and city and then the full set of fixed effects, respectively. The results are quite similar to those in columns 3 through 6 in table 3. Columns 2 and 4 show the relationship between y_{ijkt} and $N_{jk(t+1)}$. In neither specification is there a significant relationship and the most flexible specification in Column 4 shows a very small, positive, point estimate. This evidence is inconsistent with the idea of time-variant match quality shocks which are correlated with network size driving the results. It also casts doubt on the concern that there is a dynamic relationship between IRC staffing resources and the number of refugee arrivals.²⁷

Heterogeneous Effects by Initial English Level

Social networks play an important role in many aspects of a refugee's life, including providing translation services. Does the network effect estimated in this paper reflect simply the ability of network members to translate for network members at the work site, thereby raising the probability of employment particularly for refugees with no or limited English? Column 5 of table 4 shows results of testing for heterogeneous network effects by including $N_{jk(t)}$ for all t interacted with initial English ability. The level effects are consistent with the previous analysis and the interaction terms are insignificant. This indicates that the coefficients on $N_{jk(t)}$ for all t are unlikely to only reflect the ability of social networks to provide English language services.

Definition of Social Network

The above analysis defines the relevant social network as the number of non-family reunification refugees resettled in a city from the same country of origin. This section checks the sensitivity of

²⁷The number of staff members and volunteers at the office and an indicator for whether the case workers speaks a common language with the refugee is additional information available to address this concern. The relationship between network size and outcomes are robust to the inclusion of these variables as well.

the analysis to this assumption. I argued in section 3.3 that family reunification networks do not participate in the same social networks as those who arrive without family. However, do family reunification refugees also influence labor market outcomes? Also, are there other immigrants from the same country of origin in the city who are not refugees who participate in the same network?

Analysis using the Census, which incorporates all immigrant types, also shows evidence consistent with the model. These results are presented and discussed in the Appendix. Finally, the inclusion of the number of family reunification refugees with the number of social network members does not alter the main findings, as seen in column 6 of table 4. The number of family reunification refugees does not significantly affect sample refugees' outcomes nor alters significantly the estimates of the coefficients of interest.

5.2 Job Quality: Wages

Both measures of network size provide complementary evidence on the importance of job information flows for employment within social networks. I now turn to the role of networks in determining hourly wages. Columns 1 and 2 of table 5 show the effect of network size on wages for the employed sample. Recall that the theoretical predictions regarding these effects were ambiguous. There are two offsetting factors: on one hand, an increase in $N_{jk(t)}$ will decrease wages since an individual will receive less job offers, thereby reducing the ability to choose the highest paying offer. However, the proportion of individuals who receive job information indirectly, through other employed network members, will decline. Since these wages are lower on average, the average wages of those who are employed rises. Columns 1 and 2 of table 5 are broadly consistent with the model's prediction. The size of the network in periods $t - 2$ and $t - 3/t - 4$ are positive and statistically significant. There is no evidence that junior network members, those who arrived in years t and $t - 1$, impact average hourly wages. These results constitute weak evidence of the information transmission model. The

more senior network members are having a strong, positive effect on hourly wages while those network members who arrived more recently have no discernable effect. This is also suggestive that the effect of the network in changing the number of wage offers an individual receives is stronger than the compositional effect.

The inclusion of additional demographic information on individual refugees in column 2 does not have a large effect on the estimates. The initial English level has a large impact on the average hourly wage. Again, this must be interpreted with caution since the estimate may not reflect the causal relationship between English level and wages since the IRC may use this information when making geographic placement decisions.

In order to test Claim 1, I estimate equation 4 with the full male sample and impute wage offers for the unemployed as zero. Claim 1 argues that variation in network size will have heterogeneous effects on hourly wages (unconditional on employment) due to the dynamic relationship between network size and wages. An increase in the number of network members who arrive in the same period will have a negative impact on wages. The impact from an increase in the number of more senior members on a new arrival i 's wages will be monotonically increasing in the time elapsed between the additional network member's arrival in the U.S. and individual i . The estimates are consistent with the model's prediction. As shown in column 3 of table 5, one standard deviation increase in the number of network members who arrived in time $t - 1$ decreases the wage by \$.70. An increase of one standard deviation in $N_{jk(t-2)}$ increases hourly wage by \$.50. Using this measure of wages, these results reflect both the effect of the network on employment and the direct effect on wages. These results support the intuitive notion that network members become increasingly valuable to new arrivals as their exposure in the labor market in the U.S. increases. Including a wider range of demographic and other control variables as in column 4 of table 5 leads to little change in the network coefficients. An alternative estimator, least absolute deviations (LAD), also

produces similar results, as shown by columns 5 and 6 of table 5. LAD alleviates the concern of censored wage offers under the assumption that unemployed individuals receive wage offers below the median offer made to employed workers with comparable skills.²⁸

6 Alternative Explanations

This section consider two alternative explanations of the empirical findings than the model of network-based job information transmission demonstrated in section 2: labor market competition with fixed labor demand (6.1) and measurement error in relation to secondary migration (6.2).

6.1 Labor Market Competition

The theoretical framework and empirical evidence sections have both argued that an increase in the number of network members who arrived recently in the U.S. exacerbates *within-network* competition within the social network. This section considers whether an increase in labor supply in the face of fixed labor demand is an alternative explanation for these estimates.

First, the number of new arrivals in a given ethnic network is small in each year, around 30 people on average. I argue that it is therefore unlikely that such a small addition to the total labor market in cities such as Atlanta and Salt Lake City will influence the unemployment rate or equilibrium wage level. However, segmented labor markets may make these numbers non-trivial.

A more formal way to separate these two different “competition” effects is a test using September 11, 2001. Anecdotal evidence from the International Rescue Committee suggests that the terrorist attacks on September 11, 2001 had a large, negative impact on refugees’ labor market

²⁸The model predictions imply that the effect of network size should have an effect on *offer* wages, but wage offers to an unemployed individual below his reservation wage are unobserved, creating a censoring problem. Without a suitable exclusion restriction to use a classic selection model, I follow Neal and Johnson (1996) and Johnson, Kitamura, and Neal (2000) by imputing unemployed individuals as having a wage of zero and use LAD estimation (Heckman, 1974). The analysis does not include the full set of control variables for city-time, nationality-time and city-nationality since LAD estimation is difficult with large numbers of dummy variables.

outcomes. Two potential channels for the negative 9/11 shock: an increase in xenophobia that decreased employment opportunities and a negative shock to the tourism industry, where many refugees were employed.²⁹ The effect of this shock, however, differs in the two models. The *network model* will predict, as will be explained below, a diminished competition effect after 9/11. Conversely, the *fixed labor demand model* would lead to exacerbated competition after a negative shock in labor demand due to the terrorist attacks. This natural experiment also tests more generally how refugee social networks respond to an exogenous negative shock in the context of the job information transmission model.

In terms of the model presented in section 2, the 9/11 shock can most simply be analyzed in the model as a shock to the arrival rate, a . An decline in a dampens the effect of a change in the size of a cohort: both the initial competition effect and the positive information effects are muted. Figure 2 provides a graphical example of this. The first panel shows how an increase in cohort c affects employment in that period, i.e. $\frac{\partial s_c^c}{\partial N_c}$. The treatment effect becomes stronger, i.e. more negative, as a increases. Therefore, for a given change in network size, an increase in a will exacerbate the competition effect, making $\frac{\partial s_c^c}{\partial N_c}$ more negative. The second panel depicts the model's prediction for the corresponding scenario where an increase in N_c raises the employment rate of a younger cohort. In the example presented here, the impact on the employment rate of cohort $c+2$ is positive for all values of a , b and N_c , and an increase in a strengthens this effect.³⁰

$$Y_{ijkt} = \alpha + \sum_{p=1}^4 (\gamma_p N_{ijk(t-p+1)} + \pi_p N_{ijk(t-p+1)} * Post9/11) + X_{ijkt}\beta + \delta_{jt} + \phi_k + \epsilon_{ijkt} \quad (5)$$

is the econometric specification used for the test. The hypothesis is that π_p should be of

²⁹A table with the distribution of industries from 2001-2003 is available from the author upon request.

³⁰However, the relationship between a and $\frac{\partial s_c^c}{\partial N_c}$ is nonlinear: the treatment effect quickly converges to zero when the network is close to full employment. The intuition is that for low levels of a , there are few referrals available in the network; as a rises, more information is available to compete over. However, for high levels of a such that employment is near 100%, there is little competition since all are likely to become employed directly. Since the average employment rate in the sample is 66%, however, it is unlikely that the portion of the model in which an increase in a lowers competition is relevant empirically.

the opposite sign of γ_p for all p reflecting the dampening of network effects after a decline in a . Table 6 shows the results of estimating equation 5 using two different functional forms.

Columns 1 and 2 test for a differential network effect after 9/11 from an increase in the number of network members who arrived in the same period, N_{jkt} , and two or more years prior, $N_{jk(t-2/t-3/t-4)}$.³¹ While the negative competition effect is still present, there is a clear reduction in the magnitude of the competition effect after 9/11. This is in opposition to the prediction of the *fixed labor demand* model.

Columns 1 through 4 also suggest that the effect from an increase in $N_{jk(t-2/t-3/t-4)}$ is more muted after September 11, 2001. The standard errors are overall fairly large for the coefficients on both $N_{jk(t-2/t-3/t-4)}$ and $N_{jk(t-2/t-3/t-4)} * Post9/11$, only significant at traditional levels in some specifications, but the point estimates consistently show a positive level effect and negative interaction effect. The analysis therefore suggests that after September 11, 2001, the influence of social networks on newly arrived refugees' employment outcomes diminished as suggested by the model.

6.2 Measurement Error and Secondary Migration

A limitation of the data is that each refugee is observed at only one point in time. The empirical analysis relies on the assumption that refugees remain in their placement city for four years after arrival. As already discussed in section 5, the imprecision in the estimates of $N_{jk(t-3/t-4)}$ may be due to classical measurement error induced by secondary migration. This section therefore assesses whether non-random out-migration can generate a pattern as observed in section 5.

Consider first a theoretical framework where there are no social networks, but refugees

³¹The effect of an increase in $N_{jk(t-1)}$ is theoretically ambiguous since, in the model, a change in a can lead to a change in where the treatment effect flips from negative to positive. For this reason the interaction between post 9/11 and network size in year t is the easiest to interpret. Columns 3 and 4 combine N_{jkt} and $N_{jk(t-1)}$ together: in this case the differential effect post 9/11 is much smaller and imprecisely estimated.

can choose to leave their initial resettlement city at any time. The number of jobs available to refugees from a particular country is fixed and there is no sharing of information: the probability of becoming employed is then simply the number of jobs available divided by the total number of refugees in the city in that year. In this simple model, a nonlinear pattern does emerge if a fraction of refugees out-migrate each year. Using the notation from the empirical analysis, the effect of an increase in N_{jkt} is negative due to labor market competition, irrespective of the network, and the negative effect will be mitigated over time as individuals leave the city. This implies that the effect of an increase in $N_{jk(t-2)}$ will be less negative than an increase in $N_{jk(t-1)}$ or N_{jkt} . This prediction is distinct, however, from both the empirical results and the network model's simulation results. In particular, out-migration can not explain how the impact of $N_{jk(t-2)}$ is positive.

The above thought experiment is one where out-migration is randomly distributed across refugees. However, it may be the case that current employment status affects secondary migration decisions. I also consider models where $p\%$ of either the employed or unemployed network out-migrate each period. Simulation of such models show that the same pattern emerges as when randomly selected network members move out of the labor market. Recall S is the number of periods an individual is in the market. During at least the S periods following the entry of the exogenously larger cohort, the average employment rate for the entering cohort is less than or equal to the rate when cohort size is constant.³²

The only direct evidence relating the decision to out-migrate as a function of network size has to be restricted to decisions made during first 90 days after arrival due to data limitations. While this is imperfect, such analysis shows no significant relationship between $N_{jk(t)}$ through

³²When the unemployed are more likely to out-migrate, there are a few parameter values in which an increase in the size of an arriving cohort leads to a higher employment rate for a cohort entering the market $S + 1$ periods after the exogenously large cohort. Note, however, that this is strikingly different than the network model, which generates a positive impact on employment for cohorts who are in the market simultaneously with cohort c . Since refugees work for more than two years in the U.S., it is also inconsistent with the empirical findings since the coefficient on $N_{jk(t-2)}$ is positive.

$N_{jk(t-3/t-4)}$ and binary variable indicating out-migration.³³

7 Conclusion

This paper presents evidence on the importance of ethnic networks in influencing access to local labor markets for refugees recently resettled in the U.S. The empirical results support a model of job information transmission within a social network. Both the size and the structure of the network, as measured by length of tenure of network members in the U.S., influence the labor market outcomes of newly arrived refugees. This provides an insight into the functioning of social networks and provides empirical evidence that within-network competition over job information can lead to an economically sizable negative impact on labor market outcomes. This result tempers the previous findings in the empirical literature on social networks which show that networks play a beneficial role in overcoming market frictions.

A static analysis of the effect of total network size on labor market outcomes conflates these two opposite effects. This paper highlights that ignoring the dynamic relationship between employment, wages and social network structure can erroneously create inconclusive results. This may shed light on the contradictory conclusions found by Edin et al. (2003), who find a positive relationship between the stock of immigrants and labor market outcomes, in contrast to Borjas (2000), who finds a negative relationship between proportion of individuals within a city from the same country and assimilation for refugees in the U.S. This paper suggests that the tenure composition of social networks and other dimensions of structure are important in assessing the full network effect.

Evidence of social networks providing labor market information suggests that there are spill-overs from policy interventions. According to the model, such an intervention would increase

³³The table is available from the author upon request.

available job information, by diminishing competition and increasing information, to unemployed network members who were not directly exposed by the program. Therefore, a job training program which increases the employment rate of some individuals in a social network will generate a positive externality to other network members. This makes the returns to programs providing employment and training services to refugees even higher than otherwise measured by program participants alone. The model's prediction is general to any social network providing job information to its members. Accordingly, we would expect there to be spill-overs in policy interventions which improve labor market performance more generally, particularly for other immigrant groups.

The evidence in this paper sheds some light onto the debate over the optimal resettlement of refugees. Large numbers of refugees and asylum seekers are permanently resettled in Europe and North America due to prolonged and protracted conflicts around the world.³⁴ However, there is no consensus on the optimal method of resettlement within the new destination country. Policies vary widely from the dispersal policies in some European countries to the clustering method used by at least some American resettlement agencies (Edin et al., 2004).

By showing empirical evidence that refugee social networks provide labor market information to its members, this paper suggests a drawback to immigrant dispersal policies. Sending refugees to areas with a community of tenured network members, who have achieved relatively high employment rates, could improve short-run labor market outcomes and ease the fiscal burden refugees put on local municipalities. However, this analysis looks only at short-run outcomes and therefore can not provide an estimate of the total costs of dispersal policies. In the long-run, there are additional considerations such as the way the network affects individuals' incentives to invest in learning the host country language or other types of human capital. While identifying one mechanism through which networks affect labor market outcomes, job information transmission, provides

³⁴During 2004, for example, 676,400 people applied for asylum and over 83,000 refugees were permanently resettled to third countries through UNHCR resettlement programs (UNHCR, 2005)

one piece of the puzzle, the long run role of social networks in creating incentives or disincentives for integration and investments in host country-specific human capital remains an area of future research.

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8 Tables

Table 1: Summary Statistics

	Mean	Std. Dev.	No. Obs
IRC Data:			
Age	33.99	11.05	1720
HH Size	2.76	2.04	1720
Employment rate	0.66		1720
Wage (conditional on employment)	7.48	1.36	1125
Spoke No English Upon Arrival	0.466		1453
Primary School	0.180		1720
Secondary School	0.464		1720
University or Above	0.202		1720
None, vocational or adult education	0.153		1720
Muslim	0.251		1720
IRC Exemption from Employment	0.059		1720
# Refugees Resettled in Year t	10.32	13.47	1720
# Refugees Resettled in Year $t - 1$	29.47	34.13	1720
# Refugees Resettled Year $t - 2$	25.16	43.82	1720
# Refugees Resettled Years $t - 3$ and $t - 4$	65.80	102.63	1720
# Family Reunification Refugees Resettled in Year t	15.45	27.24	1720
# Family Reunification Refugees Resettled in Year $t - 1$	18.77	48.25	1720
# Family Reunification Refugees Resettled in Year $t - 2$	19.50	58.55	1720
# Family Reunification Refugees Resettled in Years $t - 3$ & $t - 4$	48.89	149.99	1720
2000 Census Data:			
Network Members who Arrived in 1999	150.83	267.84	753

Table 2: Correlation Coefficients of Refugee Cohort Sizes: 1997-2005

	Current Year	Prior Year	2 Years Prior	3 Years Prior
Num Refugees Resettled in Current Year	1			
Num Refugees Resettled in Prior Year	0.5394	1		
Num Refugees Resettled in 2 Years before	0.2859	0.4744	1	
Num Refugees Resettled in 3 Years before	0.2711	0.3794	0.5892	1
Num Refugees Resettled in 4 Years before	0.2399	0.3473	0.3971	0.5815

Table 3: Employment Probability on Network Size

	1	2	3	4	5	6
# Refugees Resettled in Year t^e	-0.236 ** (0.118)	-0.245 ** (0.124)	-0.340 ** (0.164)	-0.345 ** (0.173)		
# Refugees Resettled in Year $t - 1^e$	-0.140 ** (0.069)	-0.117 * (0.070)	-0.257 *** (0.100)	-0.232 ** (0.100)		
# Refugees Resettled in Year $t - 2^e$	0.104 *** (0.039)	0.100 *** (0.039)	0.113 ** (0.054)	0.105 ** (0.054)		
# Refugees Resettled in Years $t - 3$ and $t - 4^e$	0.037 ** (0.017)	0.034 ** (0.017)	0.056 (0.043)	0.044 (0.042)		
# Refugees Resettled Years t to $t - 4^e$					0.028 *** (0.011)	-0.035 (0.047)
Age	0.023 *** (0.005)	0.022 *** (0.006)	0.026 *** (0.006)	0.025 *** (0.007)	0.022 *** (0.006)	0.025 *** (0.006)
Age Sq	-0.0003 *** (0.0001)	-0.0003 *** (0.0001)	-0.0004 *** (0.0001)	-0.0004 *** (0.0001)	0.000 *** (0.000)	0.000 *** (0.000)
HH Size	-0.015 ** (0.007)	-0.013 ** (0.007)	-0.021 *** (0.007)	-0.019 *** (0.008)	-0.015 ** (0.007)	-0.020 *** (0.007)
IRC Exemption from Employment	-0.540 *** (0.051)	-0.543 *** (0.050)	-0.557 *** (0.056)	-0.557 *** (0.054)	-0.540 *** (0.051)	-0.552 *** (0.057)
P-value of education variables		0.449		0.250		
P-value of initial English level variables		0.002		0.000		
P-value of religion variable		0.318		0.581		
No obs	1720	1720	1720	1720	1720	1720
Adjusted R squared	0.231	0.236	0.282	0.288	0.224	0.273

a SE are in parentheses & clustered by city-ethnicity.

b Columns 1, 2 and 5 include fixed effects for nationality-year and regional office.

c Columns 3, 4 and 6 include fixed effects for nationality-year, regional office-year and nationality-city.

d Columns 2 and 4 include additional individual covariates including: education, initial English level, religion.

e Rows 1-4 are multiplied by 100.

Table 4: Employment: Falsification, Heterogeneous English Effects, and Family Refugees

	1	2	3	4	5	6
# Refugees Resettled in Year $t + 1$		0.096 (0.099)		0.030 (0.179)		
# Refugees Resettled in Year t	-0.279 ** (0.125)	-0.306 ** (0.128)	-0.551 *** (0.156)	-0.551 *** (0.156)	-0.203 (0.164)	-0.245 ** (0.118)
# Refugees Resettled in Year $t - 1$	-0.163 ** (0.076)	-0.158 ** (0.078)	-0.253 ** (0.126)	-0.248 ** (0.124)	-0.219 ** (0.094)	-0.159 ** (0.074)
# Refugees Resettled Year $t - 2$	0.072 * (0.038)	0.074 ** (0.037)	0.147 ** (0.060)	0.148 ** (0.061)	0.111 (0.075)	0.101 ** (0.051)
# Refugees Resettled Years $t - 3$ & $t - 4$	0.037 ** (0.016)	0.038 ** (0.015)	0.085 (0.058)	0.087 (0.061)	0.077 ** (0.033)	0.053 ** (0.023)
# Refugees Resettled in Year t * No English					-0.005 (0.235)	
# Refugees Resettled in Year $t - 1$ * No English					0.135 (0.087)	
# Refugees Resettled Year $t - 2$ * No English					-0.067 (0.096)	
# Refugees Resettled Yrs $t - 3$ and $t - 4$ * No English					-0.027 (0.031)	
# Family Reunification Refugees in Year t						0.075 (0.105)
# Family Reunification Refugees in Year $t - 1$						0.001 (0.063)
# Family Reunification Refugees in Year $t - 2$						-0.040 (0.073)
# Family Reunification Refugees Yrs $t - 3$ and $t - 4$						-0.008 (0.025)
P-value of F test for No English Interactions					0.320	
No obs	1340	1340	1340	1340	1471	1720

a SE are in parentheses & clustered by city-ethnicity. Basic demographic controls include: age, age squared, HH size, IRC exemption from employment.

b Columns 1-4 only contain years 2001-2004.

c Columns 1, 2, 5 and 6 include fixed effects for nationality-year and city. Column 5 includes a dummy for No English.

d Columns 3 and 4 include fixed effects for nationality-year, city-year and nationality-city.

Table 5: Wages on Network Size: Conditional, Full Sample and LAD

	1	2	3	4	5	6
# Refugees Resettled in Year t ^b	0.161 (0.372)	0.230 (0.369)	-0.024 ** (0.012)	-0.023 * (0.013)	-0.451 (0.469)	-0.644 (0.589)
# Refugees Resettled in Year $t - 1$ ^b	0.000 (0.246)	0.034 (0.256)	-0.021 *** (0.008)	-0.018 ** (0.008)	-0.453 ** (0.220)	-0.396 (0.279)
# Refugees Resettled Year $t - 2$ ^b	0.576 *** (0.214)	0.537 *** (0.211)	0.011 ** (0.005)	0.010 ** (0.005)	0.488 *** (0.191)	0.556 ** (0.237)
# Refugees Resettled Years $t - 3$ & $t - 4$ ^b	0.440 *** (0.137)	0.394 *** (0.134)	0.006 * (0.004)	0.005 (0.003)	0.113 (0.087)	0.132 (0.109)
Age	0.083 *** (0.021)	0.078 *** (0.021)	0.245 *** (0.039)	0.231 *** (0.046)	0.133 *** (0.029)	0.095 *** (0.038)
Age Sq	-0.001 *** (0.000)	-0.001 *** (0.000)	-0.004 *** (0.001)	-0.003 *** (0.001)	-0.002 *** (0.000)	-0.001 *** (0.001)
Case Size	0.032 (0.020)	0.033 (0.021)	-0.130 *** (0.053)	-0.114 ** (0.056)	-0.045 (0.028)	-0.034 (0.036)
IRC Exemption from Employment	0.708 (0.645)	0.708 (0.578)	-4.11 *** (0.423)	-4.09 *** (0.407)	-6.15 *** (0.229)	-6.04 *** (0.294)
P-value of education variables		0.000		0.207		0.000
P-value of initial English level variables		0.097		0.000		0.030
P-value of religion variables		0.516		0.463		0.084
No obs	1127	1127	1706	1706	1706	1706
Adjusted R squared	0.311	0.328	0.300	0.309	0.183	0.190

a SE are in parentheses and clustered by city-ethnicity.

b Rows 1, 2, 5 and 6 are multiplied by 100.

c Columns 1 and 2 are conditional on employment while Columns 3-6 use the full sample.

d Columns 1-4 include fixed effects for nationality-year, regional office-year and nationality-city.

e Columns 2, 4 and 6 include additional individual covariates including: education, initial English level, religion.

f Columns 3 and 4 are LAD estimates with FE for nationality group, year of arrival, and city.

Table 6: Employment: Shock of 9/11

	1	2	3	4
# Network Members Resettled in Year t ^a	-0.708 *** (0.183)	-0.720 *** (0.183)		
# Network Members Resettled in Year t * Post 911 ^a	0.530 ** (0.256)	0.536 ** (0.258)		
# Network Members Resettled in Year t and $t - 1$ ^a			-0.326 ** (0.136)	-0.315 ** (0.139)
# Network Members Resettled in Year t and $t - 1$ * Post 911 ^a			0.023 (0.143)	0.020 (0.144)
# Network Members Resettled in Year $t - 1$ ^a	-0.289 *** (0.105)	-0.265 *** (0.105)		
# Network Members Resettled Yrs $t - 2$, $t - 3$ and $t - 4$ ^a	0.077 * (0.043)	0.066 (0.041)	0.080 * (0.046)	0.069 (0.044)
# Network Members Resettled in Years $t - 2$, $t - 3$ and $t - 4$ * Post 911 ^a	-0.039 (0.026)	-0.041 (0.026)	-0.043 (0.028)	-0.046 * (0.028)
Post 911	0.059 (0.174)	0.083 (0.177)	0.069 (0.201)	0.093 (0.202)
No obs	1720	1720	1720	1720

a SE are in parentheses and clustered by city-ethnicity. Coefficients in row are multiplied by 100.

b All columns include fixed effects for nationality-year, city-year and nationality-city.

c Columns 2 and 4 include additional individual covariates including: education, initial English level, religion.

9 Figures

Figure 1: Graphical Example of Model with Constant Wages

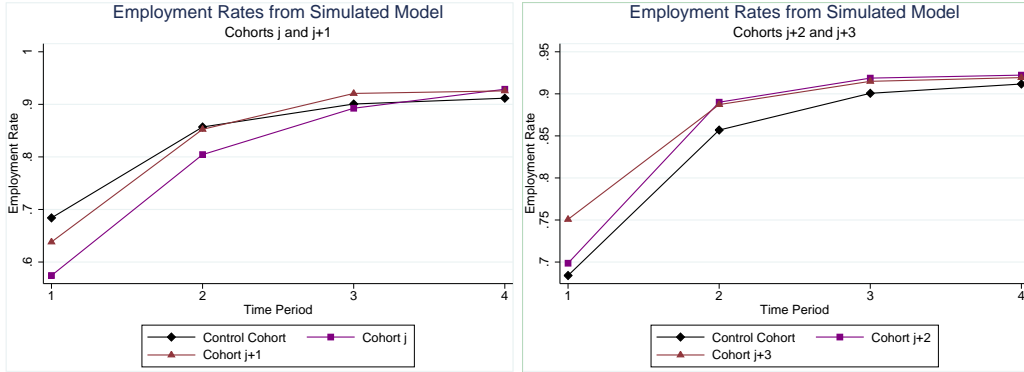
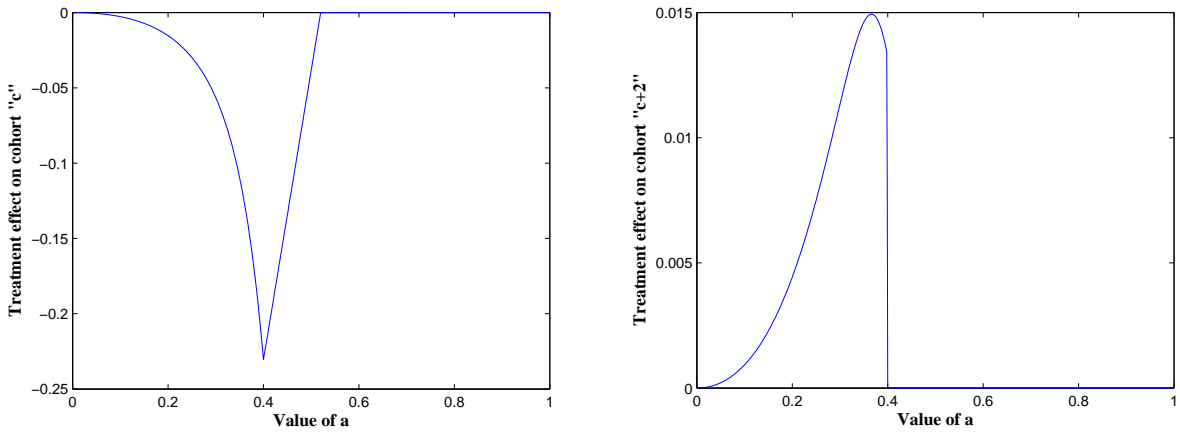


Figure 2: Graphical Example of Model Varying a when $S = 4$ and Cohort c doubled



A Appendix

A.1 Proposition 1

Proposition 1 For all values $0 < a < 1$ and $0 < b < 1$, an increase in cohort size N_j decreases s_c^j for all c .³⁵

Proof:

For cohort j : If N_j increases, s_j^j decreases. This is simple since the previous periods' employment rate, s_c^{j-1} , will be unchanged for all c . Since $s_j^{j-1} = 0$, s_j^j can be written as:

$$s_j^j = \frac{a(N_j + \sum_{c' \neq j} N_{c'})}{N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})}$$

Differentiating with respect to N_j gives:

$$\begin{aligned} \frac{\partial s_j^j}{\partial N_j} &= \frac{a}{N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})} - \frac{a(N_j + \sum_{c' \neq j} N_{c'})}{[N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})]^2} \\ &= \frac{-a(1 - b) \sum_{c' \neq j} s_{c'}^{j-1}}{[N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})]^2} < 0 \end{aligned}$$

For cohorts $c < j$: Similarly, if N_j changes, the employment rate for all other cohorts in time period j , s_c^j , decreases as well. Consider cohort $j - 1$, although this holds for all other cohorts in the market at time j :

$$s_{j-1}^j = (1 - b)s_{j-1}^{j-1} + (1 - (1 - b)s_{j-1}^{j-1}) \frac{a(N_j + \sum_{c' \neq j} N_{c'})}{N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})}$$

Since s_c^{j-1} is unaffected by change in N_j for all c ,

$$\begin{aligned} \frac{\partial s_{j-1}^j}{\partial N_j} &= \frac{(1 - (1 - b)s_{j-1}^{j-1})a}{N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})} - \frac{a(1 - (1 - b)s_{j-1}^{j-1})(N_j + \sum_{c' \neq j} N_{c'})}{[N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})]^2} \\ &= \frac{-a(1 - (1 - b)s_{j-1}^{j-1})(1 - b) \sum_{c' \neq j} s_{c'}^{j-1}}{[N_j + \sum_{c' \neq j} N_{c'}(1 - (1 - b)s_{c'}^{j-1})]^2} < 0 \end{aligned}$$

since $(1 - (1 - b)s_{j-1}^{j-1}) > 0$.

A.2 Proposition 2

Proposition 2 The impact of an increase in N_j on s_k^k is monotonically increasing between $k = j$ and $j + S - 1$.

Proof:

Assume $S = 3$ and $N_k = 1 \forall k \neq j$.

Step 1: $s_{j+1}^{j+1}(N_j) > s_j^j(N_j)$

$$s_j^j(N_j) = \frac{a(2 + N_j)}{2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})}$$

³⁵This claim holds for all values of a and b such that $s_c^j \neq 1$ for all c and j .

$$s_{j+1}^{j+1}(N_j) = \frac{a(2 + N_j)}{2 + N_j - (1 - b)(N_j s_j^j + s_{j-1}^j)}$$

Therefore, need to show: $N_j s_j^j + s_{j-1}^j > s_{j-1}^{j-1} + s_{j-2}^{j-1}$

$$\frac{aN_j(2 + N_j)}{2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})} + (1 - b)s_{j-1}^{j-1} + \frac{a(2 + N_j)(1 - (1 - b)s_{j-1}^{j-1})}{2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})} > s_{j-1}^{j-1} + s_{j-2}^{j-1} \quad (6)$$

Using the steady-state properties of the economy,³⁶ equation (6) will hold with equality if $N_j = 1$.

Since (6) holds with equality when $N_j = 1$, inequality holds if expression is increasing in N_j .

$$\frac{a(2 + N_j)(1 + N_j - (1 - b)s_{j-1}^{j-1})}{2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})} + (1 - b)s_{j-1}^{j-1} \quad (7)$$

Differentiating equation (7) with respect to N_j gives:

$$\begin{aligned} \frac{\partial}{\partial N_j} &= \frac{a(3 + 2N_j - (1 - b)s_{j-1}^{j-1})}{2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})} - \frac{a(2 + N_j)(1 + N_j - (1 - b)s_{j-1}^{j-1})}{[2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})]^2} \\ &= \frac{a(3 + 2N_j - (1 - b)s_{j-1}^{j-1})(2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1}) - a(2 + N_j)(1 + N_j - (1 - b)s_{j-1}^{j-1}))}{[2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})]^2} \end{aligned}$$

$$= a[(2 + N_j)(1 - (1 - b)s_{j-2}^{j-1}) + (1 + N_j)(2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1})) - (1 - b)s_{j-1}^{j-1}(2 + N_j - (1 - b)(s_{j-1}^{j-1} + s_{j-2}^{j-1}))] > 0$$

since $1 + N_j - (1 - b)s_{j-1}^{j-1} > 0$

Since denominator is greater than zero, if numerator is greater than zero, then equation (6) holds.

Step 2: $s_{j+2}^{j+2}(N_j) > s_{j+1}^{j+1}(N_j)$

$$\begin{aligned} s_{j+2}^{j+2}(N_j) &= \frac{a(2 + N_j)}{2 + N_j + (1 - b)(s_{j+1}^{j+1} + N_j s_j^{j+1})} \\ s_j^{j+1}(N_j) &= (1 - b)s_j^j + (1 - (1 - b)s_j^j) \frac{a(2 + N_j)}{2 + N_j + (1 - b)(s_{j+1}^{j+1} + N_j s_j^{j+1})} \end{aligned}$$

Need to show:

$$s_{j+1}^{j+1} + N_j s_j^{j+1} > N_j^j s_j^j + s_{j-1}^j$$

Let $N_j = 1 + x$. Rearranging equation (7) gives:

$$(s_{j+1}^{j+1} - s_j^j) + (s_j^{j+1} - s_{j-1}^j) + x(s_j^{j+1} - s_j^j) > 0 \quad (8)$$

We can write s_j^{j+1} , s_{j-1}^j and s_{j-2}^{j-1} in the following way:

³⁶Employment status reflect a finite-state irreducible and aperiodic Markov process as in Calvo-Armengol and Jackson (2004). Then by Freidlin and Wentzell (1984) and Young (1993), there exists a unique steady-state distribution associated with this process.

$$\begin{aligned}
s_j^{j+1} &= (1-b)s_j^j + [1 - (1-b)s_j^j]s_{j+1}^{j+1} \\
s_{j-1}^j &= (1-b)s_{j-1}^{j-1} + [1 - (1-b)s_{j-1}^{j-1}]s_j^j \\
s_{j-2}^{j-1} &= (1-b)s_{j-1}^{j-1} + [1 - (1-b)s_{j-1}^{j-1}]s_{j-1}^{j-1}
\end{aligned}$$

The left hand side (LHS) of equation (8) is then:

$$LHS = (s_{j+1}^{j+1} - s_j^j)(2 - (1-b)s_j^j) + x(s_j^{j+1} - s_j^j) + (1-b)(s_j^j - s_{j-1}^{j-1})(1 - s_j^j)$$

Using the fact that $N_j s_j^j + s_{j-1}^j > s_{j-1}^{j-1} + s_{j-2}^{j-1}$ as shown above, this implies

$$s_j^j - s_{j-1}^{j-1} > +s_{j-2}^{j-1} - s_{j-1}^j - x s_j^j > (s_{j-1}^{j-1} - s_j^j)(1 - (1-b)s_{j-1}^{j-1}) - x s_j^j$$

Substituting the above gives:

$$\begin{aligned}
LHS &> (s_{j+1}^{j+1} - s_j^j)(2 - (1-b)s_j^j) + x(s_j^{j+1} - s_j^j) + (1-b)(1 - s_j^j)[(1 - (1-b)s_{j-1}^{j-1})(s_{j-1}^{j-1} - s_j^j) - x s_j^j] \\
&= (s_{j+1}^{j+1} - s_j^j)(2 - (1-b)s_j^j) + (1-b)(1 - s_j^j)(1 - (1-b)s_{j-1}^{j-1})(s_{j-1}^{j-1} - s_j^j) + x[(1 - (1-b)s_j^j)(s_{j+1}^{j+1} - s_j^j)] > 0
\end{aligned}$$

since $s_{j+1}^{j+1} > s_j^j$ as shown above and $s_{j-1}^{j-1} > s_j^j$ as in Claim 1.

A.3 Alternative Network Measure: Census Data

The main analysis assumes the social network is comprised only of non-family reunification refugees from the same country of origin in the same city. However, to relax that assumption I also use the 2000 Census data available through IPUMS to construct a measure of network size which includes all individuals from a country of origin group in a given metropolitan area. This measure will include all immigrants groups, not only refugees.³⁷

Since the data structure differs from the network measure used above, the empirical specification varies as well. In order to test the hypothesis using the 2000 Census data, the size of the network is restricted to those who arrived most recently in the U.S., specifically those who arrived in 1999. I then look for a differential effect of this network for refugees who arrived in 2001 and 2002.

$$Y_{ijkt} = \alpha + \phi_1 N_{jk(t=1999)} + \phi_2 N_{jk(t=1999)} * \lambda_{2001} + X_{ijkt}\beta + \delta_j + \phi_k + \lambda_{2001} + \epsilon_{ijkt} \quad (9)$$

Y_{ijkt} , X_{ijkt} , δ_j , ϕ_k , and ϵ_{ijkt} are defined as above. As described above, $N_{jk(t=1999)}$ is the size of the network for those immigrants who arrived in 1999 according to the Census, and λ_{2001} is an indicator for those refugees who arrived in 2001. Estimates showing ϕ_1 to be positive and ϕ_2 to be negative would be consistent with the model. The differential

³⁷I calculate the size of the network at level of the metropolitan statistical area (MSA); most are defined by a single MSA but some networks are defined using multiple MSAs, such as New York. I define a social network by either nationality or ethnicity, depending on the availability of the relevant code in IPUMS. IPUMS data also provides the age of each network member as well as the year of arrival in the U.S. Therefore I can create a network size variable which is specific to the year of arrival of the network members. The information on age also allows me to restrict the network to only prime age adults. Since the Census does not obtain information on the foreign born's visa type or residency status/citizenship, this measure will include all immigrant types, ranging from illegal immigrants to permanent residents and naturalized citizens.

network effect across the two cohorts is therefore captured by ϕ_2 : an increase in the number of network members who arrived in 1999 would have a smaller or negative impact on labor market outcomes for those who arrived in 2001 than for those who arrived in 2002. Network members who arrived in 1999 would be more likely to be competitors for job information with those who arrived in 2001. However, by 2002 they would be better able to provide referrals to the newly resettled refugees having acquired additional job information over time.

Probability of Employment

Using the 2000 Census to create a second network measure allows for flexibility in the definition of the social network. This measure expands the potential network members to those who come from the same country of origin or ethnic group but who may have different immigration status. In this case, individual network members have self-selected into their preferred location based on a number of unobserved factors. So while this measure of the network is more susceptible to selection bias due to comparative advantage, it does test the generality of the job information sharing effect across two independently constructed network measures. Columns 1 and 2 in table 7 show that the estimates are as expected from the model. The effect of a larger number of network members from 1999 increases the probability of employment for those refugees who arrived in 2002. More specifically, increasing network size by one standard deviation increases the probability of employment for the 2002 cohort by 6.7%. The interaction term between network size and the indicator for arrival in 2001 is negative. This shows that relative to those refugees who arrived in 2002, an increase in the network size has a smaller effect on the probability of employment. The sum of the two coefficients is negative but small and statistically insignificant. This is consistent with the information transmission model: those refugees who arrive less than 2 years after the network members do not gain from an increase in network size while those who arrived sufficiently later do experience the positive influence of the network in terms of job information. While not shown in table 7, these results are also robust to the inclusion of a richer set of demographic variables.

Wages

Changing the estimation approach to use Census data as in equation 9 provides qualitatively similar results. Column 3 of table 7 indicates that the OLS estimates show no significant effect of network size on wages of those employed although the signs of the point estimates are as expected from the model. The coefficients in columns 4 and 5 from using the full sample with LAD estimation are more informative. The network effect for refugees who arrived in 2002 is positive and statistically strong. A one standard deviation in network size increases wages by \$0.56. The interaction of network size with the dummy indicating arrival in 2001 is negative and statistically significant as in the employment regression. The sum of the two network coefficients is negative but statistically insignificant. This closely parallels the results found in the employment results and the theoretical model's predictions.

Table 7: Employment and Wage Effects Using Census Data for Network Measure

	Employment		Wages		
	1	2	3	4	5
Network size which arrived in 1999 ^g	0.0284 ** (0.0121)	0.0220 * (0.0126)	0.013 (0.055)	0.249 *** (0.088)	0.172 * (0.091)
Network size which arrived in 1999 * Refugee arrived in 2001 ^g	-0.0275 ** (0.0114)	-0.0253 ** (0.0121)	-0.043 (0.058)	-0.238 *** (0.095)	-0.201 ** (0.097)
Age	3.388 *** (0.912)	3.020 *** (1.002)	0.073 ** (0.034)	0.270 *** (0.068)	0.229 *** (0.072)
Age Sq	-0.0530 *** (0.0122)	-0.0482 *** (0.0129)	-0.0009 ** (0.0005)	-0.0042 *** (0.0009)	-0.0037 *** (0.0009)
HH Size	-1.789 * (1.093)	-1.474 (1.046)	-0.017 (0.028)	-0.162 ** (0.078)	-0.122 (0.076)
p-value of education variables		0.014			0.038
p-value of initial English level variables		0.066			0.003
p-value of religion variables		0.027			0.002
p-value of occupation variables		0.757			0.736
No obs	753	753	523	742	742
Adjusted R squared	0.187	0.199	0.300	0.183	0.207

a Standard errors are in parentheses and clustered by city-ethnicity.
b Sample restricted to refugees who arrived in 2001 and 2002.
c All columns include fixed effects for nationality-year and regional office.
d Column 3 uses only the employed sample. Columns 4 and 5 use the full sample.
e Columns 2 and 5 also include: education, initial English level, religion and occupation variables.
f Network Size is number of individuals in the 2000 Census who arrived in 1999 by place of birth/MSA.
g Coefficients in row are multiplied by 100.