Social Networks and the Dynamics of Labor Market Outcomes: Evidence from Refugees Resettled in the U.S.

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COMMENTS ARE WELCOME.

Abstract

Recent theoretical work suggests that social networks may play an important role in the dynamics of employment and wages across groups of individuals. This paper provides empirical evidence of job information flows within social networks and the non-linear relationship between social network size and labor market outcomes. An extended version of the model developed by Calvo-Armengol and Jackson (2004) shows that competition can exist between network members for job referrals and investigates the dynamics between the size of a social network, the tenure of network members and labor market outcomes. The predictions of the model are tested empirically using a unique data-set of refugees resettled in the U.S. from 2001-2005. The empirical strategy exploits the special institutional environment of refugee resettlement. I find that a one standard deviation increase in the number of network members who have arrived in the U.S. one year ago lowers the probability of employment by 4.9% and the average hourly wage by $.70. Conversely, as predicted by the model, more tenured network members improve labor market outcomes for recently arrived refugees.

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1 Introduction

A growing literature in recent years has shown that social networks play an important role in the labor market. As economists, social networks are generally viewed to be a partial solution to information problems or other market failures. In fact, their role in the labor market is more difficult to assess. The empirical literature has shown that networks can influence labor market participation with opposite effects, ranging from increasing welfare participation as in Bertrand et al, 2000 to increasing the probability of employment among Mexican migrants to the U.S. (Munshi, 2003). Recent theoretical work by Calvo-Armengol and Jackson (2004) suggests that the structure of social networks is important for the dynamics of employment and wages across groups. This paper looks at one specific mechanism through which networks affect labor market outcomes, job information transmission, and shows that network effects can be heterogenous across agents even within this one mechanism. I use new data on refugees recently resettled in the U.S. to provide empirical evidence on the relationship between the structure of a network, as measured by its size and the tenure of networks members, and labor market outcomes. In particular, the hypothesis is that an increase in network size will improve the labor market outcomes of certain members while negatively impacting others.

In order to test this specific non-monotonic relationship between network size, the tenure of network members and labor market outcomes, I compiled a data-set on refugees resettled in the U.S. between 2001 and 2005 using administrative records from a large resettlement agency. The empirical strategy exploits the special institutional environment of refugee resettlement and uses variation in the relative size and structure of refugee social networks across cities and ethnic groups over time. The key feature of the resettlement process is that refugees without family in the U.S. do not choose their destination city. This addresses the classic problem in identifying social network effects. Since individuals usually select their place of residence, it is difficult to distinguish the role of networks from other common unobservable characteristics. This is one of the "Reflection" problems isolated by Manski (1993).

The resettlement of refugees in the U.S. is implemented by voluntary resettlement agencies who have been contracted by the State Department to provide all initial services such as housing, financial assistance and job training/job referrals. The sample of refugees analyzed in this study are those who do not have family members in the U.S. at the time of their arrival to assist in their resettlement. In this case, it is the sole responsibility of the contracted resettlement agency to choose a geographic location for these individuals. This precludes individuals from sorting into localities based on unobservable individual characteristics. Furthermore, all individual characteristics used by the IRC when placing refugees into particular cities are available in the data. To address the possibility that the resettlement agency makes placement decisions based on unobserved ethnic group and city level factors, I include city-year, ethnic group-year and city-ethnic group fixed effects.

Much of the empirical literature uses the seminal work by Montgomery (1991) to motivate the role of networks in the labor market. In this context, firms use employee referrals in order to better screen the ability of potential new hires in an economy with unobservable types. However, since ability is also unobservable to the econometrician and there is no clear prediction from the model regarding the size of the network, the link between the theoretical work and empirical evidence is not strong. One such example of this is Munshi (2003) who develops a model similar to that of Montgomery and then provides empirical evidence that an increase in network size enchances employment outcomes among Mexican migrants in the U.S.

I instead provide a theoretical framework which extends the work of Calvo-Armengol and Jackson to examine the short-run dynamics of a network-based job information model in an overlapping generations framework. Individuals have a random probability of receiving job information. This information is either used to obtain a job or passed on to an unemployed member in the individual's social network. The model predicts that having a larger network can in some cases lead to a deterioration in labor market outcomes. More specifically, competition can exist between network members for job information, thus creating a non-monotonic relationship between the size of a social network and labor market outcomes depending on the tenure of network members. In fact changes in social network size will differentially influence labor market outcomes over time: 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, while improving outcomes for those cohorts that arrive sufficiently later.

The empirical analysis provides evidence that an increase in network size has heterogenous effects across network members, as predicted by the dynamic job information transmission model. I find that a one standard deviation increase in the number of network members who arrive in the U.S. in one year prior lowers the probability of employment for a new arrival by 4.9 percentage points. This indicates that the within-network competition effect is economically significant. Conversely, as predicted by the model, more tenured network members improve the labor market outcomes for recently arrived refugees. An analogous increase in the number of network members who have two years tenure in the U.S. increases the employment probability by 4.6 percentage points.

It is rare in the empirical literature to examine the effect of networks on hourly wages. For example, Laschever (2005) only has data on employment outcomes, and Munshi (2003) only has coarse information on the occupation in which Mexican migrants were employed.[2] The sample of refugees used in this study is therefore uniquely suited to look at the role social networks in affecting wages. The analysis shows that average hourly wages also follow the model prediction.[3] A one standard deviation increase in the number of refugees who arrived one year prior decreases the average hourly wage of a new arrival by $.70. An analogous increase in the number of refugees who arrived two years prior increases the wage by $.50.

A static analysis of network effects, as in analyzing the stock of immigrants as the relevant network size measure, misses important heterogeneity in the way network-based job information flows influence outcomes. In some cases, as demonstrated in this paper, the composite effect of total network size will mask the presence of network effects completely. Therefore evaluating the composition of a social network within a dynamic context is critical to accurately assessing the role of social networks in the labor market. This contrasts with much of the existing empirical work in the literature. Edin et al. (2003), for example, find that there is a positive association between ethnic concentration, as measured by the stock of immigrants in a municipality, and earnings among refugees in Sweden. This approach is unable, however, to distinguish between numerous mechanisms including job information transmission and human capital externalities and also ignores the possibility of within-network competition.

Munshi (2003), however, does distinguish between senior and junior network members. Using exogenous variation from rainfall shocks in Mexico to predict network size, he finds a larger number of senior network members increases the probability of employment and the probability of being employed in a higher paying occupation for network members. However, the effect of recently arrived network members can not be distinguished from zero but has a positive coefficient. Given that these estimates are noisy, the partition over time is not sufficiently fine and there is no relevant theoretical framework, the author is unable to draw strong conclusions from this particular finding. It is suggestive, however, that size is not the only relevant measure to capture how a network

[2]Edin et al. analyze earnings of refugees in Sweden but do not look at the dynamic relationship between network size and earnings, instead focusing on the effect from the stock of network members.

[3]Average hourly wages for the entire network, including zero wages for those who are employed. This distinction is discussed in Sections 2 and 4.

influences the economic outcomes of its members, and that social networks may influence the labor market differently depending on their structure.

These results have policy implications for 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. During 2004, for example, 676,400 people applied for asylum and in addition over 83,000 refugees were permanently resettled to third countries through UNHCR resettlement programs.[23] 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. The existence of ethnic networks which facilitate labor market access in the short run is one factor to be weighed among many in choosing resettlement locations for refugees.

The results are also relevant for understanding recent research on the impact of immigration on wages. Patricia Cortes (2006) presents a puzzle: according to her structural estimates and theoretical predictions, increased immigration should lead to a depression of wages for other immigrants. However, she does not find direct evidence of this in the data. Neither Card (1990) nor Borjas (2003) find a significant negative effect of an increase in immigration on immigrant wages. My findings provide a potential explanation for this: social networks influence labor market participation and wages by providing job information. This points to a difficulty in estimating the effect of increased labor supply due to immigration on wages in the U.S. An increase in the number of immigrants in a city also implies an increase in the size of the social network for some groups. This can be an offsetting factor to the downward pressure on wages due to the increase in labor supply. The resulting estimate may conflate these two effects.

The paper is organized as follows: Section 2 discusses the framework of the theoretical model of information flows within social networks. Details on the institutional background and data are provided in Section 3 and Section 4 covers the empirical strategy. The results of the empirical analysis will be presented in section 5 and finally section 6 concludes.

2 Theoretical Framework

2.1 A Model of Employment Rates

The theoretical framework is an extension of the model developed by Calvo-Armengol and Jackson (2004) incorporated into an overlapping generations setting. In the original model, information about jobs arrive randomly to agents, and this information leads directly to employment in that job. Thus, if an individual who is unemployed hears about a job, he will take the position. However, if the agent who receives the job information is already employed, then he passes it along to a direct connection within his social network. At the end of each period, there is an exogenous break-up of jobs. The objective of the Calvo and Jackson model is to show that in the steady-state, there is positive correlation of employment outcomes across time and across all agents within a network. The authors also incorporate the possibility of agents dropping out of the labor market, which due to contagion, can lead to persistent levels of inequality across different groups.

I provide empirical evidence of an adapted version of this model which focuses on short-run dynamics. To do this, I first make the simplifying assumption that all individuals within a network are connected, thereby eliminating the distinction made by Calvo and Jackson between direct and indirect connections. Furthermore I extend the model by adding on the structure of an overlapping generations framework which corresponds well to the empirical setting of refugee resettlement.

The basic structure and timing of the model is as follows: each agent works for S periods, so that in the steady-state there are S cohorts in the network at any point in time. Each cohort c has N_c agents. It is this variation in cohort size which will provide estimable predictions from the model. 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, it is preferable to work with the employment rate within the cohort, s_c^t. Period t begins with some agents being employed and others not, so s_c^{t-1} describes employment rate of cohort c from the previous period. 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. 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. 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. Job information can be shared with any unemployed member in the network, irrelevant of which cohort he belongs to. Accordingly, an older network member can receive job information from a younger member if the former is unemployed. Once job information arrives and is referred to unemployed members where suitable, jobs are immediately accepted. Finally, there is a positive probability for any employed agent to lose his job at the very beginning of the next period at the exogenous breakup rate b.

This structure can be formalized in the following way:

For $t \geq S$:

$$s_c^t = a + r^t \qquad \text{if } c = t$$

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

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

where r^t represents the probability of receiving job information through an employed network member. For simplification of notation, the above expressions are equivalent to:

$$s_c^t = \frac{a\sum_{k=t-S+1}^{t} N_k}{\sum_{k=t-S+1}^{t} N_k - \sum_{k=t-S+1}^{t-1}(1-b)s_k^{t-1}} \qquad \text{if } c = t$$

$$s_c^t = (1-b)s_c^{t-1} + (1-(1-b)s_c^{t-1})\left(\frac{a\sum_{k=t-S+1}^{t} N_k}{\sum_{k=t-S+1}^{t} N_k - \sum_{k=t-S+1}^{t-1}(1-b)s_k^{t-1}}\right) \qquad \text{if } c \leq t \leq c + S - 1$$

This simple model can be used to show a couple of predictions which can be tested empirically.

Claim 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*.*[4]

Proof of Claim 1:

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-1} 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:

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

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

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

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,

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

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

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

The intuition is that since s_k^{c-1} does not change, increasing N_c only increases the number of unemployed individuals seeking job information from network members while leaving the number of employed members unchanged.

Claim 2 *For an increase in N_c, there exists $\tilde{k}$ such that $\forall k \leq \tilde{k}$, $\frac{\partial s_k^k}{\partial N_c} < 0$ and $\frac{\partial s_p^p}{\partial N_c} > 0$ for $p > \tilde{k}$*

Differentiating with respect to N_j gives:

$$\frac{\partial s_{j+1}^{j+1}}{\partial N_j} = \frac{a(1-b)}{D}[(\bar{N} - N_j)s_j^j - \sum_{k=j-2}^{j-1} N_k s_k^j + \bar{N}(N_j\frac{\partial s_j^j}{\partial N_j} + \sum_{k=j-2}^{j-1} N_k \frac{\partial s_k^j}{\partial N_j})]$$

where $D = [\sum_{k=j-2}^{j+1} N_k - (1-b)\sum_{k=j-2}^{j} s_k^j]^2$ and $\bar{N} = \sum_k N_k$

The idea is that an increase in N_j creates more competition for job information within the network, decreasing the employment probability for cohort $j+1$. However, as cohort j gains experience in the labor market its employment rate rises, the larger size becomes an asset to the entire network.

To illustrate how the model leads to the predictions outlined in Claims 1 and 2, Figure (**??**) provides an example. The graph shows a comparison in the employment rates of a control network with constant cohort size and that of a treatment network in which the size of cohort j is doubled. All subsequent cohorts after j have the same size as the control cohort. The treated cohort, j, experiences a lower employment rate in their first period in the market, but by period 4, the larger cohort size leads to a slightly higher employment rate. s_{j+1}^{j+1} is represented as "Cohort c+1" in time period 1 in Figure (**??**). Similar to the pattern displayed by cohort j, the initial employment rate is lower than it would have been in the absence of the cohort size shock, but this effect is largely gone by cohort $j+1$'s second period in the market. In fact by time period 3, corresponding to period $j+3$, the cohort reaches a higher employment rate than the counterfactual cohort. The following cohorts, $j+2$ and $j+3$, both receive gains in the employment rates for all 4 periods these cohorts are in the market.

2.2 A Model of Employment Rates and Wages

Subsequent work by Calvo-Armengol and Jackson (forthcoming 2006) analyzes a more general model which includes stochastic wages. In this model, job information that arrives exogenously also includes a wage. This leads to different behavior than in the above model. An employed individual will now switch jobs if he receives job information with an offer wage higher than his current wage. The implications of this more general framework is that in the steady-state, information passing leads to positive correlation between the employment and wage status of agents who are connected by a social network. There is again, though, the possibility of a negative correlation in wages across certain agents due to within network competition.

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. Wages are *iid* draws from the uniform distribution $w \sim U[\underline{w}, \bar{w}]$. w_c^c denotes the average wage for employed network members in cohort c in period c.

While general results for this model are still in progress, I present here one numerical example. Figures (**??**) and (1) reflect the results of simulating the model with $a = .40$, $b = .05$ and agents working in the market for 5 periods, i.e. $S = 5$. Wages are distributed $w \sim U[5.15, 45.15]$, where $\underline{w} = 5.15$ reflects the minimum wage law. The thought experiment here is to triple cohort size N_j and evaluate the effect on employment rates and wages of cohorts j, $j+1$, $j+2$, and $j+3$. All cohorts except j are the same size. The figures present both the results of the simulated model with the shocked cohort j and the counterfactual where cohort j remained the same size as all other cohorts. For cohorts j and $j+1$, both the employment rates and the average wages are lower in the first period than the levels that would have been achieved under the counterfactual. The effect on cohort $j+2$ in its first period in the market, however, is close to zero while cohorts $j+2$ and $j+3$ show initial gains from the increase in cohort j.

In this model the effect on wages and employment is more subtle than in the simpler model without wages. For a given employment rate, the job information available in the network for unemployed members is diminished since employed network members with low wages are unlikely to provide information to the unemployed. This is because the only jobs which are passed are those which have sufficiently low wages such that the employed network member who initially receives the job information rejects the offer. This also implies that individuals who become employed through passed job information will have wages that are lower than the average.

There are therefore two effects working in opposite directions on the average wages of the employed. The primary effect of an increase in network size is to change the number of job offers an individual receives, thereby affecting the wage. However, the offsetting effect is due to changes in the proportion of individuals who receive their jobs directly versus indirectly, i.e. via the network. Since these jobs have wages which are lower on average, this works in the opposite direction as the primary effect.

There is thus the possibility that wages do not follow the same pattern as in the above example for all parameter values. An increase in N_j may lead to a lower 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 possible to have within-period increases in the wage due to an increase in N_j. Based on preliminary simulation results, when a =.35 and b=.20, the average wage for the treated cohort increases during the first period and there is no discernable treatment effect for the subsequent periods.[5]

[5] Figure based on simulating model with 50 time periods 3500 times. $24.70 is the average of cohorts 10-30 over all 3500 simulations. The wage of the shocked cohort is $24.67 in its first period in the market. This is not a large effect but it is higher than the maximum value of $24.70 which was found when N =1 in all periods. Claim 5 therefore does

There is therefore no general prediction with regards to wages of the employed. An analogous Claim to the employment claim does hold, however, for wages in the entire network.

Claim 3 *For some values of (a,b) and an increase in* N_c*, there exists* $\tilde{k}$ *such that* $\forall k \leq \tilde{k}$, $\frac{\partial w_k^k}{\partial N_c} < 0$ *and* $\frac{\partial w_p^p}{\partial N_c} > 0$ *for* $p > \tilde{c}$

where here w_c^c represents the average hourly wage of the entire network, including a wage of 0 for those who are employed.

The model therefore predicts that employment and wage rates will be inversely correlated with the number of recently arrived refugees while positively correlated with the number of senior network members. The negative effect comes from competition between network members for information provided by already employed individuals. It is therefore a within-network competition effect and not a result of an increase in labor supply driving down wages in equilibrium. The assumption that each individual faces a constant rate a of hearing about a job directly ensures 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. Since 1996, over 500,000 refugees and asylees have been admitted. Refugees come from a wide variety of countries and flee their homes for widely varying reasons, from war-related violence to religious persecution to retribution for political views. The process in which refugees gain access to the U.S. creates a unique opportunity to look at the role of ethnic networks. Refugees are a well-defined group. According to Immigration and Nationality Act (INA) Section 101: a refugee is

> any person who is outside any country of such person's nationality...who is unable or unwilling to return to...that country because of persecution or a well-founded fear of persecution on account of race, religion, nationality, membership in a particular social group, or political opinion.

not hold for these parameter values. The subsequent entering cohort had an average wage of $24.66. I am unable to say whether this effect is positive or negative. The following two cohorts have even slightly higher average wages but again, within the range found when simulating the model with N =1.

Refugees are distinct from asylees in that refugees' status determination occurs overseas. Asylees, by contrast, travel by their own means to the United States and then apply for protected status upon arrival.

How does one become a refugee? The president, after consulting Congress, sets designated nationalities and processing priorities each year which fit into the predetermined ceiling for total refugee admissions levels. The Bureau of Population, Refugees, and Migration (PRM) of the State Department develops the application criteria and specific admission levels while INS officers adjudicate individual cases in refugee processing centers around the world. Often these centers are within refugee camps, although individuals can also apply for refugee status in the local U.S. embassy. Once the INS designates an individual as having refugee status, the PRM is responsible for overseas processing and transportation to the U.S.[6]

The PRM's final role in the resettlement process is to allocate all accepted cases to one of twelve 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. This makes estimating the effects of social networks on labor market outcomes among refugees resettled in the U.S. a particularly interesting case since the mechanism through which these networks operate can be pinpointed. Since refugees are provided with housing and some initial financial assistance, the potential intervention by the social network is more limited than the case of Mexican migrants. I use data from one voluntary resettlement agency, the International Rescue Committee (IRC), who resettles approximately 12 percent of all refugees and asylees. In this paper I look specifically at individuals who are granted refugee status directly, excluding both asylum seekers and refugees who attained 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 individual characteristics of each refugee including basic information such as country of citizenship plus demographic information including age, gender, marital status and education. 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 is 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 home country or country of first asylum overseas to the chosen IRC regional

[6] Transportation of refugees to the U.S. is usually contracted out to the International Organization for Migration.

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 the presence of a pre-existing ethnic or nationality-based community. They also attempt to choose a regional office based on language competencies. The goal is to send each refugee to an office which has either a staff member of a volunteer with competency in a language spoken by refugee. Individual refugees or refugee families who have special medical problems, such as HIV or severe mental health concerns, 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 non-family reunification refugees. These numbers are estimated using projected numbers for how many refugees are expected to be admitted to the U.S. from each region of the world as provided by the State Department. The department of the IRC responsible for placing refugees therefore attempts to match these numbers. Often the actual numbers can vary substantially from those anticipated since 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 away from budgeted numbers. Finally, the overall number of refugees sent to a particular office is also a function of 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. In fact, the data was compiled from the very forms provided to the IRC from the PRM. I can therefore control for individual characteristics which the IRC uses in the allocation process.[7] This is important since it removes the problem of sorting based on unobserved

[7] I make the distinction here between individual characteristics and those characteristics which will be shared by an entire ethnic group, for example. This issue will be discussed in the next section.[2]

characteristics which exists in other studies estimating social network effects.[8]

3.3 Data

The data from the IRC comprises of over 1,700 male individuals from "free" cases, where a free case is one where there are no family members in the U.S. to assist in the resettlement of the case. There are three components to this data. A fairly rich set of demographic variables which were compiled by the INS and the PRM prior to the refugee's arrival in the U.S. is available, 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. This data is comprehensive of all individual characteristics known by the IRC at the time of placement and were manually entered from the paper forms the IRC received from PRM. Labor market outcomes, in particular employment status and hourly wage, were collected by the IRC at 90 days after each refugee's arrival. For the period 2001-2003, industry and occupation codes are available for those employed.[9] 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 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 "free" cases.[10] Fortunately this structure creates variation in the size of local networks available to the resettled refugees while enough clustering to produce statistically distinguishable results. The sample excludes those refugees who are not 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. Three special caseload groups, the Somali Bantu, Lost Boys (Sudanese youth from the Kakuma Refugee Camp in Kenya) and Meskhetian Turks, are also excluded since these groups' geographic distribution was dictated

[8] Bertrand et al. (2000), for example, evaluate the role of networks in welfare participation. This study uses a similar empirical strategy with neighborhood and language group fixed effects, but there remains the possibility of differential selection of individuals into metropolitan areas based on unobserved preferences for work and welfare participation.

[9] Unfortunately as of 2004, the IRC changed the 90 day report format and eliminated the field to report employer information.

[10] The 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.

by a consortium of voluntary agencies under very special circumstances.[11]

In order to get an estimate of the size of each ethnic group's network in a given geographic space, I will be using two different measures. The primary analysis will 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 relevant network is defined to include only those individuals without family in the U.S. since those with family are likely to form their own network. 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.

The second measure of the size of the social network comes from the 2000 Census data available through IPUMS. I calculate the size of the network at level of the metropolitan statistical area (MSA). I define a social network by either nationality or ethnicity, depending on the availability of the relevant code in IPUMS.[12] 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. It is important to note that 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.

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). The survey is designed to be a panel study, where each respondent is interviewed for 5 years, and is intended to be representative of all refugees and asylees who were admitted to the U.S. in a given year. I currently have access to this data from 1993-2004. Unfortunately, there is no information available in the data indicating which refugees were family reunification cases. This sample may therefore not be precisely comparable to the IRC sample used in the majority of the analysis.

[11] The decision on which localities would be selected as sites for each of these groups was not made exclusively by the IRC. Particularly for the Somali Bantu and the Lost Boys, there was collaboration between all of the voluntary resettlement agencies leading to a coordinated placement policy. While it is not clear that any additional information was used in selecting the sites (or the distribution of refugees from each group across these sites), there is a particular worry about unobservable characteristics of these groups and how each group matches with city characteristics.

[12] For example,I can identify some ethnic groups which cover multiple countries, such as the Kurds.

4 Econometric Specification

The objective of this paper is to empirically test the predictions of a simple model of job-related information flows in social networks in order to better understand the best way to maximize the labor market success of newly resettled refugees. The model corresponds nicely to the empirical setting. Claim 2 predicts that having a larger number of network members who arrived in the prior year, corresponding to the N_{j-1} cohort, will decrease the probability of a new refugee obtaining employment within the first 90 days. More senior cohorts, conversely, will have a positive effect on employment. Wages should exhibit the same differential pattern across network member cohorts.

I take advantage of two different data sources as described above to create two network measures, one of which comprises exclusively of refugees and the other which includes all adult individuals from the same country of origin/ethnic group. Since the data structure of these two sources differ, the empirical specifications vary as well.

While using the aggregate data on IRC placements from 1997-2005, the empirical specification will be as follows:

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

where Y_{ijkt} represents either employment status or wages for individual i. $N_{jk(t-1)}$, $N_{jk(t-2)}$, and $N_{jk(t-3)}$ are the number of refugees who arrived during the fiscal year one year, two years and three years prior to refugee i's arrival. Therefore the network variables $N_{jk(t)}$, $N_{jk(t-1)}$, $N_{jk(t-2)}$, and $N_{jk(t-3)}$ are 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.[13] N_{jkt} 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_{jkt} since they would be not be acting as competitors nor providing job information to individual i.[14] According to the model, we would anticipate γ_1 and γ_2 to be negative while γ_2 and γ_3 would be positive.

Since the IRC resettles multiple ethnic groups across multiple cities, both geographic and ethnicity-specific factors can be controlled for using fixed effects. Unobservable factors at the city level are controlled for using metropolitan-area fixed effects, ϕ_k. Thus ϕ_k would, for instance,

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

[14]For 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.

control for variations in the local labor market which affect all ethnic groups equally. Additionally δ_j is an ethnic group fixed effect. Thus if one particular ethnicity has lower human capital on average or if the types of people who become refugees vary across sending countries, this effect common to all refugees in a group is captured. λ_t controls for differences across arrival years for all refugees. This is an important control given the large changes in the resettlement process which took place after September 11, 2001. Resources available to the IRC diminished dramatically and according to the IRC, many employers became more reluctant to hire refugees, particularly those from Muslim countries. The additional control variables X_{ijkt} include the individual's age, age squared, gender, and the number of individuals who were resettled together (approximately family size). Additional controls include initial English ability, initial education level, marital status, and religion. The error term is corrected for clustering at the nationality group/regional office/year of arrival level since this is precisely the level at which the network data vary.

To further test for the pattern predicted by the model, I also use Census data to construct a measure of network size which includes all individuals from a country of origin group in a given metropolitan area.[15] This measure will include all immigrants groups, not only refugees. 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.

$$Y_{ijkt} = \alpha + \phi_1 N_{jk(t=1999)} + \phi_2 N_{jk(t=1999)} * \lambda_{2001} + X_{ijkt}\beta + \delta_j + \phi_k + \lambda_{2001} + \epsilon_{ijkt} \qquad (2)$$

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 (as opposed to 2002). We would expect ϕ_1 to be positive and ϕ_2 to be negative. The differential 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. According to the model, by 2002 the network members would have acquired additional job information, becoming employed themselves, such that they would be able to provide referrals to newly resettled refugees. These network members would, however, be more likely to

[15] Most networks are defined at the level of the MSA, however some include multiple MSAs. For example, refugees resettled in the New York office can be resettled in either New York-Northeastern NJ MSA or the Nassau Co., NY MSA. Thus the network size includes both MSAs since there is likely to be contact between individuals across this geographical space.

be competitors for job information with those who arrived more closely to them in time, namely refugees in the 2001 cohort. In this specification, the error term is corrected for clustering at the nationality group/regional office level.

Both of the above equations will be estimated by a linear probability model for the probability of employment.

5 Empirical Results

The current resettlement pattern of IRC refugees is central to the empirical strategy. Table (12) confirms that the IRC is following the clustering strategy they state as policy. 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. Indeed, there is a positive correlation of the numbers of refugees by nationality sent to a given regional office over all time periods. The highest correlation is between the numbers resettled in the current year and the one year prior and thereafter monotonically decreases with the time elapsed between cohorts.

5.1 Probability of Employment

To begin the analysis of the effect of networks on labor market outcomes among refugees resettled in the U.S., I follow much of the existing empirical literature and estimate the effect of the stock of network members on the probability of employment. Table Table (2) shows that this analysis leads to puzzling estimates. In Columns 1 and 2, an increase in the number of refugees from country j resettled in city k from years t though $t-4$ 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, the effect becomes insignificant and the point estimates are negative. In this case, these results would be inconclusive on the existence of social networks providing job information to newly arrived refugees.

The results of the employment analysis confirm the predictions of the information transmission model. Table (3) 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. A one standard deviation increase in $t-1$ network size decreases the probability of employment by 4.8%. Given that the mean level of employment in the sample is 64%, this constitutes a decline of over 7%. 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%.[16] Therefore this negative network effect is an economically significant factor in determining refugee labor market unemployment. As shown in Table (2), this component is lost if I only estimated the effect from the stock of the network instead of looking for the dynamic component of social network behavior. This is an important step in understanding how networks function beyond estimating a composite reduced form effect.

As is consistent with the model, however, a larger number of refugees with two to four years of experience living in the U.S. at the time of arrival of a new refugee 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%. In this specification, the number of refugees who arrived in the prior 3 and 4 years were combined, and the estimates of γ_3 and γ_4 are jointly significant at the 5% level. 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.[17] 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 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. Age displays a concave relationship with the employment rate, increasing at a decreasing rate. Household size is negative, reflecting that a larger household may also contain more potential workers, thereby diminishing the incentive to work or providing the opportunity to pursue education or full-time language training for any given individual. The coefficients on the year indicators, available upon request from the author, are consistent with the IRC's intuition that the economic opportunities of newly arrived refugees diminished dramatically after September 11th, only recently recovering in 2005 and beyond.

Table (3) includes city, and nationality group-year dummy variables. If individuals are able

[16]See Table (14)

[17]The 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 know if those individuals continue to live in their initial location.

to influence the way the INS adjudicates individual cases or the timing between when an individual is granted refugee status and when he is allowed to travel to the U.S., there could be differences in the quality of cohorts over time. If the IRC is aware of these differences and change their placement policy accordingly, the estimates of γ would be biased. For example, individuals who enter the U.S. after a large cohort may differ in an unobservable way from those who enter at the same time as the large cohort. In that case, τ_{jt} would be correlated with $N_{jk(t)}$ for all t. To address this concern, all estimates include fixed effects for nationality-year.

The specification estimated in Column 1 contains a limited number of demographic covariates. There are accordingly individual characteristics which may have been used by the IRC when choosing an individual's location, thereby being in ϵ_{ijkt} and correlated with network size. Column 2 addresses this potential concern by including a wide range of individual characteristics as well as interaction terms between household size and the resettlement city. The estimates of $N_{jk(t)}$ for all t are robust to the inclusion of these variables as can be seen in Column 2 of Table (3). The coefficients remain largely the same and continue to be significant. This set of variables span the information which is available to the IRC at the time of placement. This is important since it removes the correlation between unobserved individual characteristics and the network size variables. Any other characteristic affecting employment outcomes would not have been known by the IRC when making decisions over placements and therefore uncorrelated with $N_{jk(t)}$ for all t. The interaction terms between household size and individual regional offices control for the IRC's placement rule sending large families to cities with less expensive housing. These terms also capture any bias induced by the IRC taking into account differential welfare policies, since larger families are likely to benefit more from TANF, food stamps and public housing.

To return to the correlation matrix presented in Table (12), if any correlation exists between network size in a given period and ϵ_{ijk}, then the covariance structure between the network variables themselves could cause the observed pattern. However, the positive correlation across all periods fortunately indicates that this is not the case. Further confirmation that the correlation between the network variables is not creating a spurious pattern will be shown in section 5.3 where an alternative measure of network size which is out of the control of the IRC is used.

5.2 Probability of Employment: Robustness Analylsis

The above analysis relies on the assumption that factors other than individual characteristics influencing labor market outcomes are equal across refugees of the same nationality group who were sent to different cities. In this section, I discuss and address the most important of these factors. First, individuals in an ethnic group may perform better in particular cities if the return to that group's skill set varies across localities. Second, the number of family reunification refugees resettled in a city may both influence the labor market outcomes of non-family refugees and reflect unobservable characteristics of a city. Third, IRC's placement policies could create a correlation between network size and factors which are not controlled for in the above analysis. The last section analyzes whether the network effect estimated in the previous section is driven by the network's ability to provide translation services instead of the job information mechanism outlined in the theoretical framework.

5.2.1 City-Ethnic Group Comparative Advantage

An alternative hypothesis and a common problem in identifying network effects based on geographic variation is that there may be city-ethnic group specific matches which are both unobserved and correlated with network size. This 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. Thus if particular immigrant groups receive differentially higher wages in a particular city and the IRC uses this information while making decisions on how to distribute refugees, network size would be endogenous. There are two reasons this is unlikely to be the case. First, the IRC themselves state that they take no position on whether certain cities are preferable for particular ethnic groups. In fact, the employment outcome data which is used in this analysis has never before been analyzed by the IRC to gauge where groups perform better.[18] Not unlike the canonical pool player subconsciously calculating angles while playing, though, this alone does not definitively rule out the possibility that there are not other unobservable characteristics of a city-ethnic group pair which are being used to determine placement by the IRC. The second argument is that a comparative advantage story 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 me to include 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 results

[18] Given that the majority of the data used in the project were created from paper records, there is little possibility that any systematic review of this information was done by the IRC.

of this specification are shown in Columns 3 and 4 of Table (3). Despite the large number of additional controls this requires, Column 3 shows that the estimates are robust.[19] 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 4 includes the full set of control dummies plus a wider set of individual characteristics. In this case, $\hat{\gamma}_3$ and $\hat{\gamma}_4$ are statistically insignificant but qualitatively similar. $\hat{\gamma}_1$ and $\hat{\gamma}_2$ remain strongly significant and negative.

This specification removes the possible bias originating from time invariant unobserved city-ethnic group match quality. 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 as long as there are not year-specific shocks which vary at the city-ethnicity level that the IRC is using to determine placement.

In contrast to the analysis of the stock of network size shown in Table (2), the results are not sensitive to the inclusion of additional fixed effects. This highlights the problem in that estimation. 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 easily detected and not sensitive to the specification used.

5.2.2 Role of Family Reunification Refugees

In the above analysis, I define the relevant network as being the number of non-family reunification refugees resettled in a city from the same country of origin. This is arguably the best definition to use since refugees who already have family in the U.S. at the time of arrival do not need to depend on "weak" ties for job information. Nor do these refugees have a strong incentive to participate in such networks as insurance is provided to them by their family network. In this section, I provide sensitivity analysis to this assumption.

I include the number of refugees who arrived via family reunification and were resettled by the IRC in Table (4). Since these refugees are immediately reunited with their family already in the U.S., their placement in the U.S. is chosen by their family members. If there were specific match qualities at either the jk or jkt level, then the family members of these refugees would exploit this and self-select into preferable cities. If that is the case, a larger number of family

[19] There are 198 nationality-city, 91 city-year and 149 nationality-year pairs.

reunification refugees would be associated with higher employment rates for all refugees from that ethnic group j in city k at time t. Thus the analysis in Table (4) tests the joint hypothesis that family reunification refugees are not the relevant social network group for non-family reunification refugees and that unobserved factors at the jkt are not correlated with network size. If family reunification refugees do participate in the same social networks as the refugees in my sample, then the coefficients on those variables should be similar to those on the non-family reunification refugee variables: negative for periods t and $t-1$ and positive for period $t-2$ and $t-3/t-4$. If there is sorting among family reunification refugees, however, then we expect these coefficients to all be biased upwards.

There is no evidence that the number of family reunification refugees resettled in a city impacts the labor market outcomes of non-family reunification refugees of the same nationality. All specifications used in Table (4) show that these coefficients are statistically insignificant both independently and jointly. Moreover, the sign of the coefficients are not consistent with sorting nor social network participation. The coefficients of interest are also largely unchanged from their counterparts in Table (4). In fact, the coefficients in Column 1 of each table are not statistically different from one another.

5.2.3 Placement Rule

The earlier section on the institutional environment of refugee resettlement explained the key placement strategies used by the IRC. The series of control variables included in Columns 1-4 in Table (3) control for the principle sources of endogeneity caused by the placement policies. For example, the employment rate of previous refugees at a given site is included in the year-city dummies variables. Additionally, the existence of an ethnic or nationality-based community is reflected in the city-nationality controls. Another placement criteria used by the IRC is to attempt to send each refugee to an office where someone can speak the same language as the refugee. I therefore include 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. As can be seen in Table (5), these variables do not significantly affect the probability of employment. In fact, having a staff member in the office who speaks the same language is negatively associated with employment. However, this coefficient is estimated with a great deal of noise which is likely to be the explanation for this unintuitive result. Column 2 shows that having a volunteer who speaks the refugee's language is positively correlated with employment. The estimates of γ continue to be as predicted by the model of information transmission.

5.2.4 Heterogeneous Effects by Initial English Level

Finally, social networks play an important role in many aspects of a refugee's life. In particular, network members may be helpful in providing translation services either during the job search process or on-the-job. This effect could be influencing the coefficients on $N_{jk(p)}$, for $p < t - 1$. A larger number of network members to translate at the workplace site is likely to increase the probability of employment of recently arrived refugees. This benefit of the network would be stronger for those individuals who arrive in the U.S. with no or low English knowledge. I therefore test to see if there are heterogeneous network effects depending on refugees' initial English levels. Table (6) shows results of including $N_{jk(t)}$ for all t and $N_{jk(t)}$ 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 do not reflect the ability of social networks to provide English language services but is instead more consistent with the model of job information transmission.

5.3 Probability of Employment: Census Data Specification

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 statuses. In this case, individual network members have self-selected into their preferred location based on a number of unobserved factors. So again, while this measure of the network does not rule out the possibility of a selection bias due to comparative advantage on a *prima facie* basis, it instead supports the generality of the job information sharing effect across two independently constructed network measures. Table (7) shows 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%. This is a similar effect to that estimated when the network was defined as exclusively within the refugee community. The interaction term between the 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 referral 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.

5.4 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. Table (8) shows 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. By contrast, the proportion of individuals who receive job information indirectly, through other employed network members, will reduce. Since these wages are lower on average, the average wages of those who are employed rises. Columns 1 and 2 of Table (8) 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 3, I estimate equation (1) with the full male sample with wage offers for the unemployed imputed as zero. Claim 2 argues that an increase in network size should have heterogeneous effects on hourly wages unconditioned on employment. The estimates are exactly what the model would predict. As shown in Column 1 of Table (9), 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. 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 2 of Table (9) leads to little change in the network coefficients. Additionally, the estimates on the control variables are consistent with their effects on employment. Age is again concave: wages increase with age at a decreasing rate as is observed in numerous settings in the U.S. labor market. Household size is again negative, and IRC exemption from employment is negatively correlated with wages.

However, there remains a potential problem in estimating the wage equation with the full sample. The model predictions imply that the effect of network size should have an effect on *offer* wages. However, the data provided by the IRC only provides wages for those individuals who are employed, and as such offer wages for those who are unemployed are unknown. According to the model, individuals who are unemployed have received no job offers. Therefore, a wage of zero for these individuals is the correct offer wage. However, there may be a censuring problem if some individuals reject an offer because their reservation wage is higher than the wage offer. While this is not in the model, I address this concern in the empirical analysis. In this case, the interpretation of coefficients on the network variables is unclear when wage equations (1) and (2) are estimated by OLS. Estimates based on imputing a zero wage for those individuals who rejected positive wage offers due to their high reservation wage will be biased.

The classic solution to this problem is to estimate a structural model of wage offers and labor market participation. Without a suitable exclusion restriction, however, classic selection models are not necessarily identified.[15] One alternative solution is to impute unobserved wages as zero and estimate the wage equation using least absolute deviations (LAD). Following Johnson, Kitamura and Neal (2000), consider the following model:

$$w_i = X_i'\beta + \epsilon_i$$

where w_i is wage offer, X_i are observed characteristics and ϵ_i are unobserved traits for individual i. However, w_i is unobserved if i is unemployed. Let I_i denote individual i's employment status, where $I_i = 1$ implies that i is employed. We can therefore create another variable y_i such that $y_i = w_i$ if $I_i = 1$ and $y_i = 0$ if $I_i = 0$. The key assumption is that all unemployed individuals receive wage offers below the median offer made to employed workers with comparable skills:

$$w_i < X_i'\hat{\beta} \qquad if \quad I_i = 0$$

Under this assumption, LAD estimation is unaffected by imputing unobserved wage offers as zero. Johnson, Kitamura and Neal show that in the NLSY, the assumption is confirmed in the vast majority of cases. They use panel data to follow up on those individuals who were unemployed in 1990 and 1991 to show that this method is a fairly accurate way to get unbiased estimates in the face of selection problems.

The analysis of wages using LAD estimation shows results consistent with OLS results. As shown in Columns 3 and 4 of Table (9), a larger number of refugees who arrived in years t and $t-1$ negatively impact the average hourly wage of a new arrival. The point estimates are, however, smaller than in the OLS specification and have larger standard errors. The analysis, however, 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. This additional specification, however, provides evidence that the main results in Columns 1 and 2 are not driven by wage censuring.

Given that the model's predictions are driven by the distinction between employed and unemployed network members, ideally the size of the network would be broken down along those lines. Unfortunately, since there are no individual records prior to 2001 and the IRC only collects employment and wage data as of 90 days after arrival, this is not possible. However, restricting the sample to those refugees who arrived between 2003 and 2005 allows for an analysis which is at least suggestive of this preferable specification. By making the assumption that there is persistence in employment outcomes over time, i.e. that the probability of employment at 90 days is a good predictor of whether that individual will spend most time on average employed, I can construct the number of network members who arrived during the previous two years who are likely to be employed at time t. Indeed, Table (10) confirms that an increase in the number of individuals who were unemployed as of 90 days after their arrival in the U.S. is negatively associated with employment rates of refugees who arrive in time t, up to two years after the arrival of the network members. Conversely the number of refugees who were employed as of 90 days after arrival is positively correlated with employment outcomes. This same pattern is found for wages for the sample who are employed using OLS.

5.5 Wages: Census Data Specification

Changing the estimation approach to use the Census data as in equation (2) provides qualitatively similar results. Again, as indicated by Column 1 of Table (11), the OLS estimates show no significant effect of network size on wages of those employed. The coefficients in Columns 2 and 3 from using the full sample with LAD estimation tell a very different story. The network effect for refugees who arrived in 2002 is positive and statistically strong. An increase in the network size from the median to the 75th percentile improves wages by $0.10. 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 as well as those predictions of the theoretical model.

The results of the LAD estimation in sections 5.5 and 5.4 depend on the assumption that unemployed refugees receive offer wages which are below the median wage of those employed with similar observable characteristics. While it is difficult to provide direct evidence on the validity of this assumption for the sample of refugees used in this study without panel data, I will note that the majority of refugees in the IRC sample come to the U.S. with very low levels of education and often little to no English skills. As can be seen in Table (1), 47% of men in the sample arrived in the U.S. with no English ability. The refugees in sample generally find employment in low skilled service positions, such as housekeepers, in low-skilled industries. [20] It is therefore likely that those who are unable to gain employment in the initial 90 days after arrival are those with limited skills, beyond which is observed by the econometrician, who would otherwise have low wage offers.

The OLS results in Columns 2 and 3 of Table (8) show that tenured network members positively influence hourly wages of recently arrived refugees. Taken in conjunction with the LAD estimates, the analysis provides consistent evidence supporting the job information transmission model.

6 Conclusion

This paper presents strong evidence on the importance of ethnic networks in facilitating access to local labor markets for refugees recently resettled in the U.S. The empirical results support a model of job-related information flows within a social network. Both the size and the structure of the

[20] See Table (13).

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 important 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. The existence of significant costs to having a larger social network is lost when the dynamic relationship between employment, wages and social network structure is ignored. Using correctly specified network variables is also important for accurately showing the presence of network effects. A static analysis of the effect of total network size on labor market outcomes, for example, can show erroneously inconclusive evidence on the existence of social network effects. In the long-run, as shown by Calvo-Armengol and Jackson, a larger network size will improve labor market outcomes of network members. However, the short-run labor market outcomes are important in that they affect the level of social assistance refugees and other immigrant groups need while in the U.S.

Evidence of social networks providing labor market information suggests that there are spillovers from policy interventions. For example, a job training program which increases the employment rate of some individuals in a social network will generate a spillover to other network members. According to the model, such an intervention would create a net increase in the information available to unemployed network members who were not directly exposed by the program. This makes the returns to programs providing employment and training services to refugees even higher than otherwise measured looking at program participants alone.

The results also have implications for the literature looking at the effects of low-skilled immigration on other immigrant wages. Cortes (2005) finds no direct evidence of a downward pressure of immigration on the wages of other immigrants. This paper suggests an explanation for these results: the effects of job information transmission within social networks. A larger number of immigrants may improve immigrant wages by improving information about the labor market in the long-run but depress wages if there are a sufficient number of newly arrived immigrants in the network. This may lead to ambiguous results while attempting to identify wage depression due to the supply effect.

The results in this paper are also interesting in that they are found in an unlikely environment. Given that the refugees in this sample did not know anyone in the receiving community prior to resettlement, it is striking to find evidence that these networks function well and as predicted by a theoretical model within the first 90 days after the refugee's arrival. I would argue that this sample of refugees, therefore, teaches us about how networks function more generally, as the construction of the network is fairly analogous to "anonymous" networks which form due to geographic proximity within, say, a neighborhood.

It is relevant to note that while this paper provides evidence of the importance of social networks in providing labor market opportunities, and therefore points to one drawback of dispersal policies, these effects are estimated as of 90 days after arrival and the long run impact of social networks on integration and language acquisition remains an open question and an area of future research. Additionally, while social networks and job referrals have been shown to play an important role in influencing economic outcomes, there are numerous other location characteristics which need to be taken into account, including local labor market conditions and the political/social environment of a particular locality. Therefore the decision to place a refugee in a given location must take into account the local labor market characteristics in addition to the size of the available ethnic community, insofar as these factors are at time at odds with each other.

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7 Appendix

Table 1: Summary Statistics

	Mean	Std. Dev.	No. Obs
IRC Data:			
Age	33.98	11.05	1723
HH Size	2.76	2.04	1723
Employment rate	0.66		1723
Wage (conditional on employment)	7.48	1.36	1127
Spoke No English Upon Arrival	0.47		1455
Education Unknown	0.056		1723
Technical Training (Unspecified)	0.020		1723
Adult Education	0.001		1723
Other Technical Training	0.005		1723
No Education	0.044		1723
Primary School	0.180		1723
Secondary School	0.464		1723
Vocational School	0.027		1723
University or Above	0.182		1723
# Refugees Resettled in Year t	10.52	13.56	1723
# Refugees Resettled in Year $t-1$	29.47	34.11	1723
# Refugees Resettled Year $t-2$	25.12	43.79	1723
# Refugees Resettled Years $t-3$ and $t-4$	65.82	102.57	1723
2000 Census Data:			
Network Size which Arrived in 1999	112.70	223.86	1164

Table 2: Employment Probability on Composite Network Size

	Column 1	Column 2	Column 3	Column 4
# Refugees Resettled Years t to $t-4$	0.0003 ***	0.0003 ***	-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0005)	(0.0005)
Age	0.022 ***	0.021 ***	0.025 ***	0.024 ***
	(0.006)	(0.006)	(0.006)	(0.007)
Age Sq	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
HH Size	-0.015 **	-0.013 *	-0.020 ***	-0.018 **
	(0.007)	(0.007)	(0.007)	(0.008)
IRC Exemption from Employment	-0.540 ***	-0.543 ***	-0.552 ***	-0.552 ***
	(0.051)	(0.050)	(0.057)	(0.056)
P-value of education		0.387		0.116
P-value of Initial English Level		0.002		0.0003
P-value of Religion		0.365		0.593
No obs	1720	1720	1720	1720
Adjusted R squared	0.224	0.229	0.273	0.280

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

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

c Columns 3 and 4 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.

Table 3: Linear Probability Model of Employment Probability on Network Size

	Column 1	Column 2	Column 3	Column 4
# Refugees Resettled in Year t	-0.00236 **	-0.00245 **	-0.00340 **	-0.00345 **
	(0.0012)	(0.0012)	(0.0016)	(0.0017)
# Refugees Resettled in Year $t-1$	-0.00140 **	-0.00117 *	-0.00257 ***	-0.00232 **
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
# Refugees Resettled Year $t-2$	0.00104 ***	0.00100 ***	0.00113 **	0.00105 **
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
# Refugees Resettled Years $t-3$ & $t-4$	0.00037 **	0.00034 **	0.00056	0.00044
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Age	0.023 ***	0.022 ***	0.026 ***	0.025 ***
	(0.005)	(0.006)	(0.006)	(0.007)
Age Sq	-0.0003 ***	-0.0003 ***	-0.0004 ***	-0.0004 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HH Size	-0.015 **	-0.013 **	-0.021 ***	-0.019 ***
	(0.007)	(0.007)	(0.007)	(0.008)
IRC Exemption from Employment	-0.540 ***	-0.543 ***	-0.557 ***	-0.557 ***
	(0.051)	(0.050)	(0.056)	(0.054)
P-value of Education		0.449		0.250
P-value of Initial English Level		0.002		0.000
P-value of Religion		0.318		0.581
No obs	1720	1720	1720	1720
Adjusted R squared	0.231	0.236	0.282	0.288

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

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

c Columns 3 and 4 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.

Table 4: Employment Robustness Analysis with Family Reunification Refugees

	Column 1	Column 2	Column 3	Column 4
# Refugees Resettled in Year t	-0.0024 **	-0.0026 **	-0.0035 **	-0.0035 **
	(0.0012)	(0.0012)	(0.0016)	(0.0017)
# Refugees Resettled in Year $t-1$	-0.0016 **	-0.0014 *	-0.0030 ***	-0.0027 **
	(0.0007)	(0.0008)	(0.0011)	(0.0011)
# Refugees Resettled Year $t-2$	0.0010 **	0.0010 **	0.0006	0.0004
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
# Refugees Resettled Years $t-3$ and $t-4$	0.0005 **	0.0005 **	0.0005	0.0003
	(0.0002)	(0.0002)	(0.0005)	(0.0006)
Age	0.023 ***	0.022 ***	0.026 ***	0.025 ***
	(0.005)	(0.006)	(0.006)	(0.007)
Age Sq	-0.0003 ***	-0.0003 ***	-0.0004 ***	-0.0004 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HH Size	-0.0152 **	-0.0137 **	-0.0210 ***	-0.0193 ***
	(0.0066)	(0.0071)	(0.0071)	(0.0076)
IRC Exemption from Employment	-0.543 ***	-0.547 ***	-0.559 ***	-0.560 ***
	(0.050)	(0.049)	(0.057)	(0.054)
# Family Reunification Refugees Resettled in Year t	0.0007	0.0009	-0.0005	-0.0001
	(0.0010)	(0.0011)	(0.0016)	(0.0015)
# Family Reunification Refugees Resettled in Year $t-1$	0.00001	-0.00007	0.00131	0.00127
	(0.0006)	(0.0006)	(0.0011)	(0.0011)
# Family Reunification Refugees Resettled Year $t-2$	-0.0004	-0.0004	0.0007	0.0009
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
# Family Reunification Refugees Resettled	-0.0001	-0.0001	-0.0008	-0.0008
Years $t-3$ and $t-4$	(0.0002)	(0.0003)	(0.0006)	(0.0007)
No obs	1720	1720	1720	1720
Adjusted R squared	0.230	0.235	0.281	0.287

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

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

c Columns 3 and 4 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.

Table 5: Employment Robustness Analysis with Staff Controls

	Column 1	Column 2	Column 3	Column 4
# Refugees Resettled in Year t	-0.0021 *	-0.0022 *	-0.0033 **	-0.0033 **
	(0.0011)	(0.0012)	(0.0016)	(0.0017)
# Refugees Resettled in Year $t-1$	-0.0014 **	-0.0011	-0.0026 ***	-0.0024 **
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
# Refugees Resettled Year $t-2$	0.0010 **	0.0009 **	0.0011 **	0.0010 *
	(0.0004)	(0.0004)	(0.0006)	(0.0006)
# Refugees Resettled Years $t-3$ & $t-4$	0.0003 **	0.0003 *	0.0005	0.0004
	(0.0002)	(0.0002)	(0.0005)	(0.0004)
Staff Member Speaks Same Language	-0.014	-0.013	-0.017	-0.013
	(0.030)	(0.029)	(0.041)	(0.041)
Volunteer who Speaks Same Language	0.066	0.077 *	-0.001	0.016
	(0.043)	(0.041)	(0.084)	(0.080)
Age	0.023 ***	0.022 ***	0.026 ***	0.025 ***
	(0.006)	(0.006)	(0.006)	(0.007)
Age Sq	-0.0003 ***	-0.0003 ***	-0.0004 ***	-0.0004 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HH Size	-0.016 **	-0.015 **	-0.022 ***	-0.020 ***
	(0.007)	(0.007)	(0.008)	(0.008)
IRC Exemption from Employment	-0.538 ***	-0.543 ***	-0.551 ***	-0.553 ***
	(0.053)	(0.051)	(0.057)	(0.055)
P-value of Education		0.378		0.378
P-value of Initial English Level		0.005		0.005
P-value of Religion		0.262		0.262
No obs	1644	1644	1644	1644
Adjusted R Squared	0.227	0.232	0.282	0.288

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

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

c Columns 3 and 4 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.

Table 6: Employment Robustness Analysis with Heterogenous English Effects

	Column 1	Column 2
# Refugees Resettled in Year t	-0.0020	-0.0025
	(0.0016)	(0.0017)
# Refugees Resettled in Year $t-1$	-0.0022 **	-0.0019 **
	(0.0009)	(0.0010)
# Refugees Resettled Year $t-2$	0.0011	0.0010
	(0.0007)	(0.0008)
# Refugees Resettled Years $t-3$ and $t-4$	0.0008 **	0.0007 **
	(0.0003)	(0.0003)
# Refugees Resettled in Year t * No English	0.0000	0.0007
	(0.0024)	(0.0023)
# Refugees Resettled in Year $t-1$ * No English	0.0013	0.0011
	(0.0009)	(0.0010)
# Refugees Resettled Year $t-2$ * No English	-0.00067	-0.00059
	(0.0010)	(0.0010)
# Refugees Resettled Years $t-3$ and $t-4$ * No English	-0.00027	-0.00028
	(0.0003)	(0.0003)
No English	-0.077	
	(0.048)	
Age	0.019 ***	0.017 ***
	(0.007)	(0.008)
Age Sq	-0.0003 ***	-0.0003
	(0.0001)	(0.0001) ***
HH Size	-0.012	-0.011
	(0.008)	(0.008)
IRC Exemption from Employment	-0.531 **	-0.536 ***
	(0.058)	(0.058)
P-value of No English Interactions	0.320	0.320
No obs	1471	1471

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

b Also includes fixed effects for nationality and regional office-year.

c Column 2 includes additional individual covariates: education level, initial English level, religion.

Table 7: Employment Effects Using Census Data for Network Measure

Network size which arrived in 1999 * Refugee arrived in 2001	-0.0003 **
	(0.0001)
Network size which arrived in 1999	0.0003 **
	(0.0001)
Age	0.022 **
	(0.010)
Age Squared	-0.0004 ***
	(0.0001)
HH Size	-0.024 **
	(0.011)
2001 Year Dummy	0.080
	(0.057)
Constant	0.626 ***
	(0.188)
No obs	1156

a Standard errors are in parentheses and clustered by city-ethnicity pairs.

b Also included are fixed effects for nationality and regional office.

c The sample is restricted to refugees who arrived in 2001 and 2002.

d Network Size is number of individuals in the 2000 Census who arrived in 1999 by place of birth/MSA.

Table 8: Wages on Network Size

	Column 1	Column 2
# Refugees Resettled in Year t	0.0016	0.0023
	(0.0037)	(0.0037)
# Refugees Resettled in Year $t-1$	0.00000	0.00034
	(0.0025)	(0.0026)
# Refugees Resettled Year $t-2$	0.0058 ***	0.0054 ***
	(0.0021)	(0.0021)
# Refugees Resettled Years $t-3$ and $t-4$	0.0044 ***	0.0039 ***
	(0.0014)	(0.0013)
Age	0.083 ***	0.078 ***
	(0.021)	(0.021)
Age Sq	-0.001 ***	-0.001 ***
	(0.000)	(0.000)
Case Size	0.032	0.033
	(0.020)	(0.021)
IRC Exemption from Employment	0.708	0.708
	(0.645)	(0.578)
P-value of Education		0.000
P-value of Initial English Level		0.097
P-value of Religion		0.516
No obs	1127	1127
Adjusted R squared	0.311	0.328

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

c Columns 1 and 2 include fixed effects for nationality-year, regional office-year and nationality-city.

d Column 2 includes additional individual covariates including: education, initial English level, religion.

Table 9: Wages on Network Size: Full Sample and LAD

	Column 1	Column 2	Column 3	Column 4
# Refugees Resettled in Year t	-0.024 **	-0.023 *	-0.005	-0.006
	(0.012)	(0.013)	(0.005)	(0.006)
# Refugees Resettled in Year $t-1$	-0.021 ***	-0.018 **	-0.005 **	-0.004
	(0.008)	(0.008)	(0.002)	(0.003)
# Refugees Resettled Year $t-2$	0.011 **	0.010 **	0.005 ***	0.006 **
	(0.005)	(0.005)	(0.002)	(0.002)
# Refugees Resettled Years $t-3$ and $t-4$	0.006 *	0.005	0.001	0.001
	(0.004)	(0.003)	(0.001)	(0.001)
Age	0.245 ***	0.231 ***	0.133 ***	0.095 ***
	(0.039)	(0.046)	(0.029)	(0.038)
Age Sq	-0.004 ***	-0.003 ***	-0.002 ***	-0.001 ***
	(0.001)	(0.001)	(0.000)	(0.001)
HH Size	-0.130 ***	-0.114 **	-0.045	-0.034
	(0.053)	(0.056)	(0.028)	(0.036)
IRC Exemption from Employment	-4.11 ***	-4.09 ***	-6.15 ***	-6.04 ***
	(0.423)	(0.407)	(0.229)	(0.294)
P-value of Education		0.207		0.000
P-value of Initial English Level		0.000		0.030
P-value of Religion		0.463		0.084
No obs	1706	1706	1706	1706
Adjusted R squared / Pseudo R squared	0.300	0.309	0.183	0.190

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

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

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

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

Table 10: Network Size Using Within Sample Employment Info

	Employment	Wage
# Refugees Unemployed during 2 Prior Years	-0.038 ***	-0.028 ***
	(0.005)	(0.009)
# Refugees Employed during 2 Prior Years	0.018 ***	0.014 ***
	(0.003)	(0.004)
Age	0.025 ***	0.068 ***
	(0.006)	(0.022)
Age Sq	0.000 ***	-0.001 ***
	(0.000)	(0.000)
HH Size	-0.013 **	0.032
	(0.006)	(0.021)
Constant	0.463 ***	6.702 ***
	(0.166)	(0.504)
No obs	1487	848

a Network variables indicate employment status as of 90 days after the network member's arrival.

Therefore assuming persistence in employment outcomes over time.

b SE are in parentheses and are clustered by city-ethnicity-arrival year pairs.

c Also included are fixed effects for nationality, regional office and year of arrival.

d Sample includes only refugees resettled from 2003-2005.

Table 11: Wage Effects Using Census Data for Network Measure

	OLS Conditional on Employment	Median Regression: All Observations
Network size which arrived in 1999 * Refugee arrived in 2001	-0.0003	-0.0015 ***
	(0.0005)	(0.0004)
Network size which arrived in 1999	-0.0001	0.0013 ***
	(0.0005)	(0.0004)
Age	0.089 ***	0.240 ***
	(0.030)	(0.021)
Age Sq	-0.0011 ***	-0.0037 ***
	(0.0004)	(0.0003)
HH Size	-0.029	-0.091 ***
	(0.027)	(0.021)
2001 Year Dummy	-0.070	0.569 ***
	(0.174)	(0.112)
Constant	6.914 ***	-4.033 ***
	(0.571)	(1.059)
No obs	833	1141

a Standard errors are in parentheses and clustered by city-ethnicity pairs.

b Also included are fixed effects for nationality and regional office.

c The sample is restricted to refugees who arrived in 2001 and 2002.

d Network Size is number of individuals in the 2000 Census who arrived in 1999 by place of birth/MSA.

Table 12: 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 13: Largest Industries from 2001-2003

Construction	.03
Animal slaughtering and processing	.05
Grocery Stores	.07
Misc general merchandise stores	.40
Misc Retail Stores	.04
Employment services	.04
Services to buildings and dwellings	.02
Colleges, including junior colleges	.04
Hospitals	.06
Traveller Accommodation	.24
Restaurants and other food services	.09
Other	.28

Above reflect the major industries in which the IRC sample gained employment from 2001-2003.

Table 14: Probability of Employment Using ORR Data

Number of years in U.S. since Resettlement	0.034 ***
	(0.002)
Female	-0.098 ***
	(0.005)
Age	-0.008 ***
	(0.000)
Married	0.156 ***
	(0.006)
Years of Schooling Prior to Arrival in U.S.	0.029 ***
	(0.001)
Constant	0.695
	(0.440)
No obs.	30,906

a Standard errors are in parentheses.

b Also included are fixed effects for nationality, survey year, and initial resettlement state.

Table 15: Probability of Outmigration

	Column 1	Column 2
# Refugees Resettled in Year t	-0.00064	-0.00086
	(0.0008)	(0.0009)
# Refugees Resettled in Year $t-1$	-0.00050	-0.00059
	(0.0005)	(0.0007)
# Refugees Resettled Year $t-2$	0.00013	-0.00046
	(0.0004)	(0.0005)
# Refugees Resettled Years $t-3$ and $t-4$	-0.00001	0.00003
	(0.0001)	(0.0003)
Age	-0.002	-0.002
	(0.003)	(0.004)
Age Sq	0.0000	0.0000
	(0.0000)	(0.0000)
HH Size	-0.005 *	-0.007 **
	(0.003)	(0.003)
IRC Exemption from Employment	-0.024	-0.038
	(0.026)	(0.032)
No obs	1886	1886
R squared	0.116	0.236

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

b Columns 1 includes fixed effects for nationality-year and regional office.

c Column 2 includes fixed effects for nationality-year, regional office-year and nationality-city.

Figure 1: Graphical Example of Model with Wages