Social Network Structure, Segregation, and Equality in a Labor Market with Referral Hiring*

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Abstract

We construct a model of referral hiring to examine the effects of social network structure on group level inequality. Our study departs from many studies of social networks and labor market outcomes in that we focus on groups and not on individuals. We find that more random social networks yield higher employment rates than less random social networks if the population is integrated or information flows about job vacancies are random. However if the population is highly segregated and information flows about job vacancies are non-random then less random social networks have higher employment rates than more random social networks. This second finding holds because non-random social networks allow a group to better contain job information inside the group when a population is segregated. We also study the robustness of this finding with respect to the size of minority and majority groups and the amount of social segregation.

JEL Classification: J15, J18, J78
Keywords: Social Networks, Referral Hiring, Inequality, Labor Markets

1 Introduction

When comparing the labor market outcomes of ethnic groups in the United States one notices substantial differences across groups. For instance, the difference between black and white wages is approximately 25–40% (Smith and Welch 1989). The differences extend to many other ethnic groups as well (Farley 1990; Darity Jr., Guilkey, and Winfrey 1996) and some minority groups in the US (such as Hungarian, Japanese, and Russian) have above average earnings (Farley 1990). Some, but not all, of these differences can be explained by varying levels of education and other job market skills across groups (Farley 1990; Card and Krueger 1992; Darity Jr., Guilkey, and Winfrey 1996). One clear candidate for the remaining differences is discrimination. Another is more subtle: since approximately 50 percent of workers find their jobs through friends, relatives, and other social contacts (Granovetter 1995) differences in social networks may cause un-equal information flows about jobs for some groups. (Hereafter, hiring through the use of social or familial contacts is referred to as *referral hiring*.) Indeed, some have used the prevalence of referral hiring as evidence for the old adage "it's not what you know but who you know" (Montgomery 1991). From this belief a line of research has developed that argues that referral hiring may be one of the many potential causes of the persistence of inequality for labor force minorities.[1] Since an individual's social network tends to consist of members of the same ethnic group, race, or social class (Marsden 1988) and large amounts of job information travel through social networks, a member of an under-represented group in the labor market may find out about fewer job opportunities relative to a member of a more widely represented group. Thus a potentially self-perpetuating poverty trap (Durlauf 2003) can be created where members of a group cannot get good jobs because their friends do not have good jobs, and so on. In other words referral hiring may leave some groups out of portions of the labor market.

[1] See the appendix to Granovetter (1995) for a review of the referral hiring literature through 1995. More recent work includes Arrow and Borzekowski (2000), Calvo-Armengol (2004), Calvo-Armengol and Jackson (2002), and Mouw (1999).

The effect of the structure of social networks on job information flows can be even more subtle than this. Social networks tend to contain *cliques* where friends of a given individual are more likely to be friends with each other than they are with other randomly chosen members of the population. As an example it is very likely that an individual's two best friends know each other. However, each individual also tends to have some number of random friends who do not know the individual's other friends. For instance your freshman year roommate with whom you keep in touch but have nothing in common with may know none of your current friends. These random friends are generally not as close (in social terms) as an individual's best friends. Thus these random friends are sometimes referred to as *weak ties* (Granovetter 1973). Taken together these descriptions suggest that social networks tend to contain some amount of randomness and some amount of non-randomness. Non-randomness originates from the overlap of close friends being friends with each other. Randomness originates from individuals having friends who do not know each other.

The amount of randomness versus non-randomness affects the properties of a social network. Non-random networks have longer path lengths on average than random networks. As a simple example of a non-random network imagine a population of agents arranged in a circle where each agent is connected to her nearest neighbor in each direction. In this case the shortest path to the agent on the opposite side of the circle would require one to pass through one-half of the agents in the population. The average distance between two randomly drawn members of the population would be the population size divided by four. In this example average distance scales linearly with population size. On the other hand random graphs tend to have shortcuts which greatly decrease average distance between population members on average.[2] It can be shown that the average distance between nodes in uniform random graphs scales as a logarithmic function of graph size, and that uniform random graphs approximate the shortest average path length between all pairs of nodes for

[2]See Watts (1999) for several nice examples.

a given number of edges and nodes (Bollobas 2001).

Here we explore how the structure of social networks may affect information flows about jobs. Suppose each agent in a population potentially has information about job openings. If social networks are organized randomly an agent in the social network is closer to more job information than if the social network is organized in a non-random fashion. This proximity to information may appear to be an advantage for any given agent since an individual with more random social connections is always closer to more job information on average. But there may also be a disadvantage to being close to other individuals: Since any job information held by a given agent in a random graph is closer to all other members of the population, keeping the information inside a group of agents becomes increasingly difficult. In one respect an individual agent prefers more random networks in order to be proximate to information she does not hold but a group potentially would like to distance itself from other groups in order to protect information it does hold. Thus it is not immediately clear which social network structure is preferred for the purpose of acquiring job information at the group level.

Despite the concern over group level inequality discussed above most studies of referral hiring concentrate on individual earnings or individual employment outcomes. These studies document three items: First, theoretical studies document that individuals with more weak ties or random connections in their social networks should earn higher wages or have higher rates of employment (Montgomery 1992; Montgomery 1994; Calvo-Armengol 2004; Calvo-Armengol and Jackson 2002). Second, for the individuals who find jobs through social connections, many of these connections are weak ties or random connections (Bridges and Villemez 1986; Wegener 1991; Lin, Ensel, and Vaughn 1981; Marx and Leicht 1992; O'Reagan and Quigley 1993; Granovetter 1995). Third, there is empirical evidence that increased breadth of social networks due to less overlap of friendships increases individual earnings (Tassier 2005a). But note that all of these studies reveal relationships between social network structure and *individual* — not *group* — outcomes. And even though previous research indicates that individuals experience better labor market outcomes with random networks we know that individual outcomes do not always translate to groups. As we know from examples such as the *tragedy of the commons* individually optimal behaviors do not always imply optimal behavior for the group. Thus the relationship between social network structure and group level outcomes is far from clear.

In this paper we systematically study how employment rates between social groups vary as a function of the social network of the group. Understanding the effect that the structure of social networks has on employment outcomes at the group level is especially important since many minority groups tend to have less random social networks than majority groups. For instance, using data from the General Social Survey, Patterson (1998) finds blacks to have more overlap in their social connections than whites. Portes and Sensenbrenner (1993) cite numerous reasons related to social capital theory and provide examples that suggest recent immigrants are likely to live in tightly knit non-random social networks. Additionally, the breadth of social networks is believed to be positively correlated with social status (Homans 1950; Patterson 1998). Given these differences in social networks across groups we aim to investigate how a group's network structure affects the group's employment outcomes when referral hiring occurs in a labor market.

We uncover three main findings in regard to the structure of social networks: First, we find that a group with a more random social network will have higher employment rates than a group with a less random social network if the worker population is integrated and connections between jobs are random. Thus the results of our study of groups agrees with previous research on individuals under these conditions. However if the worker population is highly segregated and there is a large amount of overlap in connections between jobs then a group with a non-random social network has higher employment rates than a group with a random social network on average. Under these assumptions the effect of protecting information dominates the effect of being close to the information of others. A group with a non-random social network is able to contain job information inside the group. Most of the research on referral hiring is concerned with the persistent inequality of some minority groups. Thus our second main result considers how minority groups fair in the labor market as segregation changes. We find that the employment rate of a minority group with a non-random social network *increases* as segregation increases. Essentially our result suggests that a minority group whose members have large amounts of overlap in their social networks wants to isolate itself from the rest of the population. Our third main result considers the effect of population size. In an integrated society, the employment rate of a group with non-random social networks decreases as population size decreases. Thus small minority groups in an integrated society with non-random networks do poorly in the labor market. Taking the second and third of these results together suggests that minority groups may have incentives to isolate themselves in the labor market. As a clear example an exclusive country club attempts to create a small isolated group by limiting their membership. Similarly the result speaks to the potential benefits of minority organizations that provide networks for job finding. We will discuss these implications further in the final section of the paper.

2 Model Specification

As mentioned above social networks tend to contain non-random components where friends of a given individual are more likely to be friends with each other than they are with other randomly chosen members of the population. Such a non-random property of social networks can be modelled by creating *regular* graphs (Watts and Strogatz 1998; Watts 1999; Tassier and Menczer 2001). And, again as mentioned above, each individual also tends to have some number of random friends. In this paper we model the structure of a group's social network by varying the amount of social connections that are regular vs. random.[3]

Previous research suggests that random social networks perform better for the purposes of acquiring jobs at the individual level. As mentioned earlier this paper differs from this line of research in that we focus on group level outcomes. Thus one main aim of this paper is to investigate whether individual incentives to create more random social networks for the purpose of job finding improve group level employment rates. In other words are random networks always preferred at the group level as they are at the individual level.

Additionally we generalize two main assumptions from previous research on referral hiring: First, previous models assume there is one underlying population that is well mixed. Second, previous models assume that job information arrives to individuals in the society randomly from an anonymous firm (usually with uniform probability to each individual). In this paper we relax each of these assumptions. First, we allow for the possibility that the population may not be well-mixed; there may be segregation between populations groups. Second, we assume that job information arrives to individuals as a result of their position in the labor market. One finds job information as a function of their location in a job network. As an example if an agent is employed we assume she knows about job openings at her firm.

More specifically, in this paper we allow for the possibility that the population is composed of distinct exogenous groups such as women and men or black and white. Further, we allow for the possibility that the composition of the social network of an individual from a given group is biased toward one's own group. As an example a typical African American likely knows more African Americans than a typical Hispanic person; A typical woman likely will have more women in her social network than the typical man. In other words we assume that segregation can exist in the population.

We also assume that job information originates from employed workers who observe

[3]As we will describe below, random networks do not imply that groups are integrated; the social networks of a given group can be completely random within the group and still maintain complete segregation from other groups.

vacancies at jobs similar to their own. As an informal example, an engineer is more likely to know of engineering vacancies than teaching vacancies; or all else equal, a worker in Chicago is more likely to know of a vacancy in Chicago than a vacancy in New York. Thus we model a job structure where there can be correlations in job information between jobs that are similar in terms of either job type or geographic proximity. To model this job structure we again use random and regular graphs. If the job structure is random no correlations between jobs exist; engineers are equally likely to know about any job vacancy. If job structure is regular (non-random), employees are more likely to learn about jobs similar to their own; chemical engineers are more likely to know about chemistry and engineering vacancies.

We proceed by specifying a computational model of the referral hiring process. The main advantage of using a computational framework in this context is the ability to easily model networks of various topologies. Previous models that study the effects of referral hiring have been limited by analytical tractability to studying random matching processes (Mailath, Samuelson, and Shaked 2000), random networks (Tassier 2005b), or simplified networks such as dyads (Montgomery 1991; Montgomery 1994). Our model of the agents' social network is flexible both in terms of size and structure. Thus we are able to define a series of experiments to test how labor market outcomes are influenced by social networks over a wide set of structures.

2.1 Agents, Jobs, and Networks

As alluded to above, our model consists of two networks, one for jobs and one for social connections, and a hiring process related to the networks. Number the jobs $1, 2, \ldots, M$. Each job is in one of two states: occupied or vacant. A job j is occupied, if an agent is currently employed at job j; Job j is vacant if no agent is currently employed at job j. Let each job be a node on a graph. Label the directed edges of the job graph $J(j, k)$ if job j is connected to job k.[4] If the edge $J(j,k)$ exists this indicates that an agent employed at job j knows the state of job k.

Number the agents $1, 2, \ldots, N$. An agent can be in one of $M+1$ states. She can be employed at one of M jobs or she can be unemployed. Similar to above let each agent be a node on a social graph. Label a directed edge of the social graph $S(h,i)$ if agent h is connected to agent i. If edge $S(h,i)$ exists this indicates that agent h can receive job information from agent i.

Our modelling of the structure of networks is inspired by Watts (1999). To begin we arrange the jobs into a network such that it forms a one dimensional toroidal lattice (a circle) where consecutively labelled jobs are neighbors on the lattice. Each job has k_J (for simplicity, an even number) connections in the network. Each job is connected to $k_J/2$ jobs in each direction. Thus is if $k_J = 4$ job 8 is connected to jobs 6, 7, 9, and 10.

The reader may think of this as being a specification of how the jobs are related. A job is located spatially close in the job network to similar jobs. Thus occupants of a given job are able to both learn of available open jobs similar to theirs and provide referrals for these jobs. Most of the labor search or matching literature does not place a structure such as this on jobs. Instead they assume that jobs and workers are randomly matched as a function of worker or firm search intensity. We can approximate the uniform randomness of their models in our model by "re-wiring" (Watts 1999) the connections described above. Let each connection from job j to job k be broken with probability δ_J. When a connection is broken we choose a new job k' with uniform probability over all the jobs in the economy and replace the connection $J(j,k)$ with connection $J(j,k')$. As δ_J increases the job network loses structure (becomes more random) and approximates a uniform random graph in the limit as $\delta_J \to 1$.

[4] We create a directed as opposed to an undirected graph because of potential asymmetries in job knowledge and access. For instance a bank president probably can recommend a bank teller for a position but a bank teller probably cannot recommend a bank president.

The networks of agents are slightly more complicated. As described above there are N agents. We divide the agents into two groups with γN belonging to *Group A* and $(1-\gamma)N$ belonging to *Group B*, $\gamma \in (0,1)$. Thus there is a minority and a majority group for any $\gamma \neq 1/2$. Both γ and the group to which an agent belongs are exogenously chosen in the model.

Agent networks are initialized by forming two one-dimensional lattices. One lattice consists exclusively of members of Group A and the other consists exclusively of members of Group B. Each member of the population has k_S connections. Note that each group in the model has the same number of information sources since all members have the same number of connections. So, differences in group performance will occur only from the network structure of the group.[5] Again, the number of connections is assumed to be an even number and each agent is connected to $k_S/2$ neighbors in each direction. Thus we initially form two non-random and segregated networks, one for group A and one for group B. As mentioned above the edges of the network are directed. We can create uniform random networks using the same process as we used for the job network. Let δ_{sa} be the rewiring probability for the social network of Group A and define δ_{sb} similarly for group B. When we re-wire a connection in the agent network we introduce one additional constraint. When a social network connection, $S(h,i)$, is re-wired we require that the new connection be from the same group as agent h with probability ψ. Thus with probability ψ we require that agent h and agent i' are from the same group for the new connection $S(h,i')$. With probability $1-\psi$ we create the connection $S(h,i')$ without regard to group affiliation. We use ψ to change the amount of segregation in the model. Thus by changing parameters δ_{sa}, δ_{sb}, and ψ we can create social networks that are segregated and structured, segregated and internally random, non-segregated and random, or any interior combination of segregation and randomness.

[5]This simplification will decrease the the magnitude of the overall effect social networks on labor market outcomes. If agents also varied in number of connections there would be larger social network effects but it would be difficult to differentiate between the effect of the network structure and the effect of the network size.

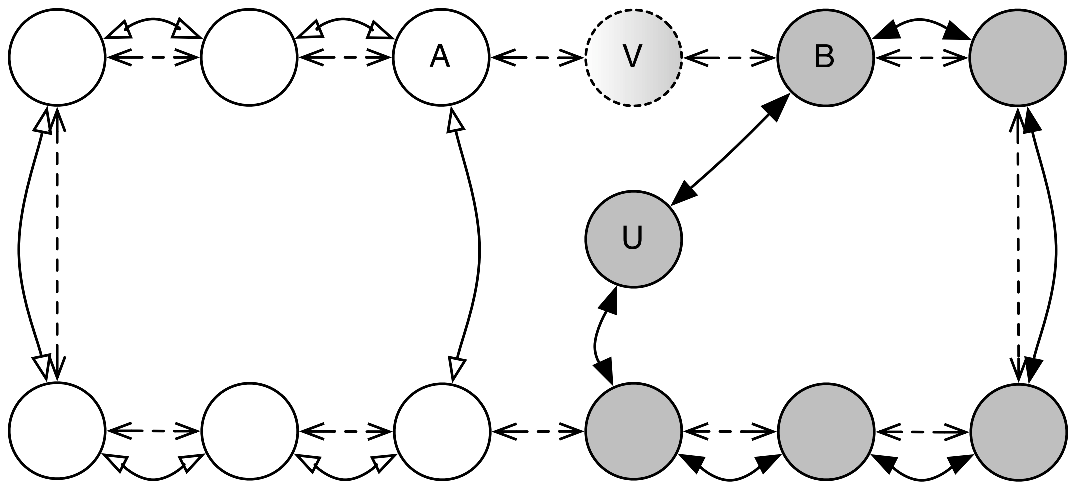

Figure 1: An example social network with $N = 12$ agents and $\gamma = 1/2$. The agents of Group A are shown as white nodes and the agents of Group B as gray nodes. The social network connections ($K_S = 2$) are shown by white and black arrows for Group A and B, respectively. Dashed arrows represent the job network connections ($M = 12$, $K_J = 2$). The dashed circle (V) represents a vacant job, while the circle labelled U represents an unemployed agent.

The job network and the social network are linked through the employment of agents at jobs. An agent h employed at job j knows the states of jobs that are connected to job j in the job network. Thus she can tell the agents to whom she is connected in the social network about openings at any of these jobs. This is the way in which we create referrals in the model labor market.

As an illustration of the two networks consider Figure 1. In the example all agents except U are employed, and all jobs except V are occupied. There are six members of each group and 12 jobs. The social network of Group A is shown by the nodes on the left side of the graph. The social network of Group B is shown on the the right side of the graph. Consider the node labelled A in the picture. This node represents an agent of group A who is employed at a job. This job is connected to the jobs immediately to the right and to the left. Therefore A knows about the vacancy of job V. Agent B also knows of vacancy V, and unemployed agent U can learn about vacancy V from her social connection with B. The example in Figure 1

```
Initialize M jobs arranged on a lattice
Initialize N agents
Assign agents to groups A and B
Initialize a regular social graph for each group
Permutate social graph edges according to ψ, δ_sa, and δ_sb
Assign initial jobs to agents according to experiment structure
for each period
   for each agent i
      Fire i with probability ρ
      Update open job list
   endfor
   for each open job j
      for each agent i
         Notify i of available jobs based on search intensity, s_a or s_b
         Notify i of available jobs based on social connections
      endfor
      Agents apply for job j
      Randomly choose an applicant to fill job j
   endfor
   Measure statistics
endfor
```

Figure 2: Psuedocode of the dynamics used to simulate our job market.

shows a job network that is completely regular ($\delta_J = 0$) and social networks that are also regular ($\delta_{sa} = \delta_{sb} = 0$) and segregated ($\psi = 1$). In most instances the mapping between social and job networks will be much more complicated than in this example.

Agents have positive utility if they are employed and a reservation utility of 0 if unemployed. Thus agents always prefer employment to unemployment. We assume all workers are equally qualified for all jobs. Thus we are considering a labor market with a specified skill level and the set of workers who meet the qualification.

2.2 Job Search and Dynamics

We now discuss the dynamic process by which agents find and lose jobs and how they interact in the labor market. A summary of the algorithm is provided in Figure 2. Agents may be either employed or unemployed. Employed agents are subject to separation from their jobs with probability ρ each period. This creates open jobs in the economy. A list of open jobs is maintained throughout the simulation. In each period all open jobs are chosen from the list in a random order and given the opportunity to be filled. When a job is chosen to be filled each worker is notified of the job opening with probability s_A or s_B, $s_i \in [0,1]$, as determined by the group affiliation of the agent. This models the search intensity in the labor economics literature. In addition, each member of the population may receive information about job openings from any of its k_S neighbors in the social network. Each agent who has a social network connection who knows of the opening is notified about the opening with probability 1. Recall, an agent knows of an open job j if she is employed at job k and job k is connected to job j in the job network, i.e., $J(k,j)$ exists. After notification all workers learning of the opening who are unemployed apply for the job. A firm makes a hiring decision by choosing randomly from the applicants (since the workers are all equally qualified the firm is indifferent as to the specific worker hired). It may be that no one applies for a given open job. In this case the job remains open until the following period, at which time another attempt will be made to fill it.

2.3 Parameters

In all of the experiments below we initialize the model with $N = M = 1,000$ agents and jobs. Each of the jobs is connected to two jobs in each direction, $k_J = 4$. Each agent has four social connections, $k_S = 4$. Specific parameters of the networks (ψ, δ_{sa}, and δ_{sb}) vary across experiments. We specify these parameters in the introduction to each experiment. In order to emphasize the effect of referral hiring and network structure in our model we choose a low level of search intensity, $s_A = s_B = 0.0001$. It should be clear that as we increase s_A and s_B referrals become less important for job acquisition and thus the relative effect of social network structure becomes less important. (If $s_A = s_B = 1$ every agent knows of every vacancy regardless of social network structure and referrals.)

3 Experiments and Results

Recall that the primary purpose of this paper is to compare the performance of groups with different social network structures in a labor market. We are particularly interested in the performance of random networks (those with many weak ties) relative to non-random or "regular" lattice based networks (those with few weak ties). For the experiments in this paper we set $\delta_{sa} = 1$ and $\delta_{sb} = 0$. Thus we will compare the performance of a group of agents with a random social network structure (Group A) to a group of agents with a non-random social network structure (Group B). Having set these two parameters we have three more to vary across experiments: the relative population size, γ, the amount of randomness in the job network, δ_J, and the amount of segregation in the social networks, ψ. For each experiment in the paper we run the model for 1,000 periods. We then calculate the employment rate at period 1,000 for each group. We complete 50 replications of each experiment and report average employment rates over the 50 replications for each experiment.

3.1 Equal Sized Populations

We begin with a benchmark set of experiments where Group A and Group B are equal in size, $\gamma = 0.5$. Thus the only difference between Group A and Group B is that Group A has a purely random network structure and Group B has a purely non-random network structure. We compare four benchmark cases: a random job network with no social segregation, $\delta_J = 1$, $\psi = 0$; a random job network with segregated social networks, $\delta_J = 1$, $\psi = 1$; a non-random job network with no social segregation, $\delta_J = 0$, $\psi = 0$; and a non-random job network with social segregation, $\delta_J = 0$, $\psi = 1$. The first of the listed parameter settings (random job network and no social segregation) is the closest to previous work on the effect of social network structure on employment outcomes. This previous research suggested that more random social networks should perform better than less random social networks for

Table 1: Employment Rates for Equal Sized Populations, $\gamma = 0.5$. In this and the following tables the difference shown is between the employment rates of Group A and Group B, so that a positive difference indicates that Group A (random social network) has higher employment and a negative difference indicates Group B (regular social network) fares better.

δ_J	ψ	Group A	Group B	Difference
1	0	96.4%	94.9%	+1.5%*
1	1	96.3%	95.9%	+0.4%**
0	0	96.0%	95.6%	+0.4%**
0	1	95.5%	97.4%	−1.9%*

(*) significantly different from 0.0 at the 99% level.
(**) significantly different from 0.0 at the 95% level.

individuals (Calvo-Armengol and Jackson 2002). Thus we first ask whether random social networks also perform better at the group level under these assumptions. The results of our computational experiments suggest that random networks are better at the group level when $\delta_J = 1$ and $\psi = 0$. The population with a random network (Group A) has an average employment rate of 96.4% across the 50 replications and the group with a non-random social network (Group B) has an average employment rate of 94.9%. (See Table 1 for a summary of the results for this subsection.)

Similarly, we find that random social networks yield higher employment rates than non-random networks if job networks are random and there is social segregation, $\delta_J = 1$ and $\psi = 1$, and when job networks are non-random and there is no social segregation, $\delta_J = 0$ and $\psi = 0$. However the difference between employment rates for the group with random social networks and the group with non-random social networks has decreased from approximately 1.5% to approximately 0.4%. Again groups are better off with random networks under these parameters. Thus group and individual incentives are aligned.

Finally if we have a non-random job network and social segregation, $\delta_J = 0$ and $\psi = 1$, we find that the group with non-random social networks (Group B) has a higher employment rate than the group with random social networks (Group A). Here the employment rate for Group B is 97.4% and the employment rate for Group A is 95.5%. That there is a parameter configuration where non-random networks have higher employment rates than random networks suggests that the previous findings that random social networks are superior to non-random networks for individuals does not generalize to the group level under some conditions. In addition it is possible that the results at the individual level may depend upon assumptions about the arrival of job vacancy information and the amount of mixing that occurs in the population. Overall if one assumes that job information arrives randomly (information arrives from a random job network) or there is no segregation in the population, then random social networks perform well at both the individual and the group level. These assumptions imply that job information is spread fairly evenly across the population. Thus an agent wants to be as close as possible to all other agents in the population on average. A random social network performs best under these conditions because a uniform random graph yields the minimum average distance between all nodes in a graph (Bollobas 2001). However, when there is a non-random job network, jobs can become segregated in the sense that it becomes more likely that friends work in neighboring jobs. Thus it may become possible for a subset of agents (in a given "clique") to control all the job information in a subset of the job network. Further if social networks are also segregated then it becomes less likely that once a subset of agents controls a subset of jobs, another group can invade. In sum the non-random group is able to hoard job information if there are a sufficiently small number of random links between jobs and a sufficiently small amount of integration.

3.2 Network Structure and Minority Groups

The first set of experiments demonstrates that non-random networks can outperform random networks under some circumstances. We now examine how those results vary as a function of relative population size, γ. For each experiment above we perform an additional 100 replications, 50 with $\gamma = 0.25$ (Group A is a *minority* group) and 50 with $\gamma = 0.75$ (Group

Table 2: Difference in Employment Rates (Group A - Group B) as a Function of Population Size

γ	$\delta_j = 1$, $\psi = 0$	$\delta_j = 0$, $\psi = 0$	$\delta_j = 0$, $\psi = 1$	$\delta_j = 1$, $\psi = 1$
0.25 (Group A is a Minority)	$+0.7\%^{*}$	$-0.8\%^{*}$	$-2.1\%^{*}$	$+0.3$
0.50 (Equal Size)	$+1.5\%^{*}$	$+0.4\%^{*}$	$-1.9\%^{*}$	$+0.4\%^{**}$
0.75 (Group A is a Majority)	$+1.8\%^{*}$	$+1.9\%^{*}$	$-1.7\%^{*}$	$+0.1$

(*) significantly different from 0.0 at the 99% level.
(**) significantly different from 0.0 at the 95% level.

A is a *majority* group.) In three of the four cases described above we find that as we reduce the relative population size of a group their employment rate falls relative to the other group as can be seen in Table 2. This table shows the difference in employment rates between Group A and Group B. As the population size of Group A increase their employment rate relative to Group B increases.

Note that Group A (the random network) outperforms Group B (the non-random network) for all population sizes tested when the job network is random and social networks are integrated, $\delta_J = 1$ and $\psi = 0$. The opposite is true if we have non-random job networks and segregated social networks, $\delta_J = 0$ and $\psi = 1$; the non-random network outperforms the random network. This is not the case if we let the job network structure be non-random but we retain integration, $\delta_J = 0$ and $\psi = 0$. Under these parameter settings Group A (with a random social network) has a higher employment rate than Group B (with a non-random social network) when population sizes are equal as described in the previous subsection. But when Group B is a majority roup, $\gamma = 0.25$, they have a higher employment rate than Group A. When Group B is a minority group they do worse. Overall the results of this section agree with common wisdom that minority groups are hurt most by referral hiring.

3.3 Comparing Levels of Segregation

The results of the previous subsections suggest that non-random social networks perform best when segregation exists in the population and job networks also are non-random. So far we have only considered purely segregated or non-segregated networks, $\psi = 0$ or $\psi = 1$. We now test the robustness of the performance of non-random social networks across varying levels of social segregation. We set the job network to be non-random and vary ψ between 0 and 1. Here we are most interested in the case for a minority population with non-random networks compared to a random network majority population. Thus we set $\gamma = 0.75$.(Recall the studies in the introduction suggesting that minority groups tend to have less random social networks than majority groups. Thus this experiment is most closely tied to our knowledge of existing social networks.) Recall that when $\psi = 1$ non-random networks have a higher employment rate (97.4%) than random networks (95.7%); and when $\psi = 0$ random networks have a higher employment rate (96.0%) than non-random networks (94.1%).

Our results show that for non-random networks to outperform random networks a fairly large amount of segregation must exist. For $\psi = 1$ and $\psi = 0.875$ the minority group with non-random networks has a higher employment rate than the majority group with random networks. For $\psi = 0.75$ and $\psi = 0.625$ there is no statistically significant difference between the groups. At $\psi = 0.50$ the employment rate of the group with a non-random network has decreased to a level such that the group with a random network has a higher employment rate as they do at the endpoint of $\psi = 0$. These results are summarized in Table 3 and Figure 3. Note that the employment rate of the group with random networks does not significantly change as we vary segregation. The difference between the employment rates of the two groups occurs because the employment rate of the minority group with non-random networks increases as social segregation increases.

Table 3: Effect of Varying Segregation on Minority (B) Employment Rates, $\delta_J = 0$, $\gamma = 0.75$.

ψ	Group A	Group B	Difference
1.000	95.7%	97.4%	$-1.7\%^*$
0.875	96.0%	96.6%	$-0.6\%^*$
0.75	96.1%	96.2%	-0.1%
0.625	96.2%	95.9%	$+0.3\%$
0.500	96.1%	95.5%	$+0.6\%^*$
0.000	96.0%	94.1%	$+1.9\%^*$

(*) significantly different from 0.0 at the 99% level.

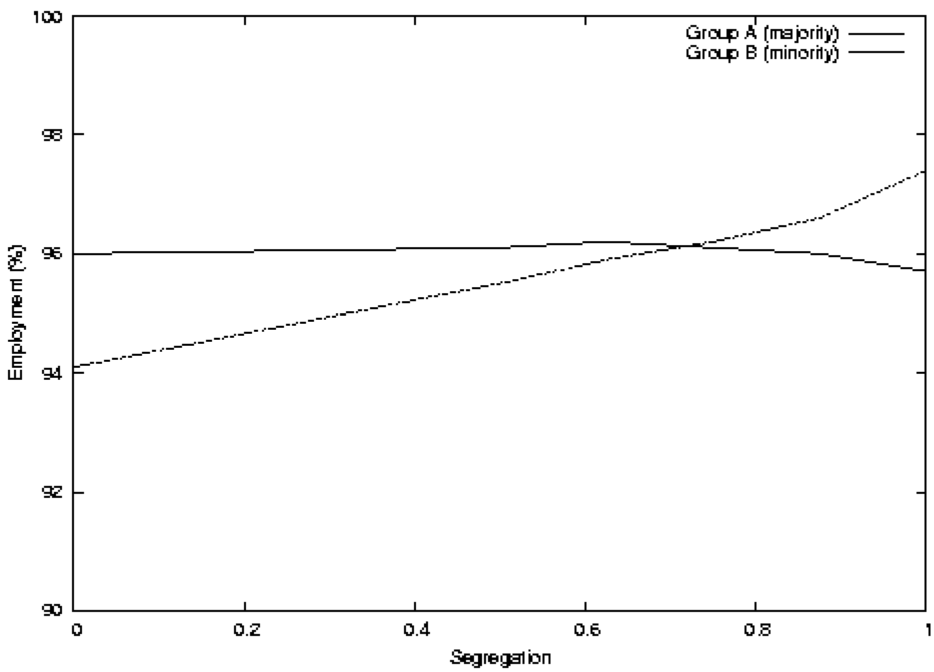

Figure 3: The employment rate of a minority group with non-random social networks increases as segregation increases.

3.4 Magnitude of the Results

The primary purpose of this paper is theoretical in nature. Specifically we examine how changes in group level network structure impact information flows and employment outcomes as measured by employment rates. The results above highlight three items: First, a non-random network structure for a group may perform better for the purpose of finding a job if job information is non-random and groups are sufficiently segregated. Second, it appears that minority groups may be disadvantaged by a large prevalence of referral hiring. Third, minority groups with a non-random social network may do better if they are segregated from a random majority group. The results of experiments in this paper show changes in employment rates of one to two percent that may be attributable to changes in network structure.

By itself a variable that changes employment rates by even one percent would be considered large by most economists. But we want to be careful in interpreting these results. The experiments in this paper looked at a simplified labor market that was designed to emphasize the effect of network changes on employment rates. Thus one may question whether results of this magnitude may be observable in empirical labor market data in a world that is not as simple as the one in our model. Whether the group level network effects we describe in this paper are empirically observable is an open question that would require a sufficiently large data collection project to test. However, such tests have been done at the individual level. For instance Tassier (2005a) has found social network effects of up to three percent of individual earnings in data from the General Social Survey. The effects found in that study are due to both the structure of an individual's social network and the size of an individual's social network.[6] We want to emphasize that this is an example of a study of the effect of

[6]Note that we have only considered social network structure in the present paper. The effects of a group having more contacts is clear; more contacts equates to more information and higher employment rates. Thus we chose not to complicate the analysis by introducing this additional level of heterogeneity in this paper. Had we done so we would likely have found larger social network effects than by considering network structure alone.

network structure on individual labor market outcomes. To our knowledge there has not been an empirical study on the effects of network structure on group level outcomes.

4 Discussion

In this paper we have compared the rate of employment for groups with different social network structures as a function of job network structure and social segregation. Our model is consistent with the previous findings on referral hiring and social networks in that a group with a more random social network does better than a group with a non-random social network if job information in the population is spread uniformly due to random connections between jobs and a non-segregated population. However, we find that this result depends on assumptions about social integration and the origin of information about jobs. If social networks are highly segregated and information about jobs arrives in a non-random fashion then a group with a non-random social network can do better than a group with a random social network. The non-random social network can help the group protect the job information they hold and restrict the access of outsiders to their job information.

Overall these results suggest that groups with more overlap in social networks should do well if the job network is non-random and do worse if the job network is random. If we consider the network structure of various types of jobs it is possible that the job networks for high skill jobs may be less random than those for low skill jobs. To refer a high skill worker for a job, say an engineer, one needs to know about the skills required to perform as an engineer. Thus it is likely that many high skill employees are referred by someone in their profession; engineers are referred by other engineers. If one considers the referral process for low wage and/or low skill jobs, this is probably less true. For instance someone referring a person for a job as a cashier at a department store probably only needs to know that the person they refer is trustworthy, friendly, and dependable; it is possible to observe these characteristics even if one is not a cashier oneself. Thus job networks for low skill referrals may be more random than those for high skill referrals. Since minority groups tend to have more overlap and structure in their social networks, our model predicts that individuals in a minority group should do well if they qualify for high skill jobs; however their network may be a poor fit for a low skill labor market. These results help to explain why minority groups with high levels of education have done well in the labor market.

Additionally our results suggest that minority groups are most likely to be adversely affected by referral hiring practices as common wisdom suggests. But somewhat contrary to intuition minority groups may want to segregate themselves from the majority group if information about jobs is non-random. One interpretation of this result concerns exclusive groups such as country clubs or fraternities and sororities on college campuses. Groups such as these may want to be purposely exclusive in order to contain information within their group. In addition by providing an interaction setting between members they also create a dense social network. In other words, there may be very few random social connections within the group. Thus an exclusive club is very likely creating a minority group with a segregated and non-random social network that will fair well in a non-random and high skilled labor market. Of course the minority group in this case is not disadvantaged and further, it is likely to increase the level of inequality in society at large. Another interpretation suggests that movements toward minority owned and staffed firms may have positive effects for the minority group in terms of job information flows in ways similar to organizations that provide job leads to women and other labor force minorities. Minority staffed firms and minority organizations and clubs both create more overlap in the social networks of members. Thus they help to create a network structure that will benefit members in a non-random (high skill) labor market.

While we have shown that non-random social networks may outperform random social networks in the labor market under certain conditions at the group level, we have not discussed individual incentives in this paper. Any member of a tightly woven social group may be able to increase their individual knowledge about jobs by adding a new random connection. In other words there may be collective action problems in that a given member of a group with a non-random network may want to defect to having individual random connections. Individual incentives may not align with group level incentives. This may appear to be a limitation of the model presented here. There are however two main motivations behind our choice to model social networks exogenously. First, note that real world social networks are chosen for reasons that are not exclusively job search related. We choose to form social connections for many reasons: similar interests, hobbies, social activities, geographic proximity, social affinity, and so on. Thus it is not realistic to assume that people may defect on existing social connections just to marginally increase their chances of acquiring a job. These other reasons for choosing social connections temper the incentive for a group member with numerous overlapping connections to replace existing connections with new random connections. A second motivation for our exogenous model of social networks is that we know that differences exist in properties of social networks for minority and majority groups, as reviewed in Section 1. Therefore it is a useful exercise to study the effect of various network topologies in a labor market. In the future we plan to extend the work contained here by merging the referral hiring model with a prior model allowing for the study of endogenously evolved social network connections in labor markets (Tassier and Menczer 2001).

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