

Three Essays on Social Networks in Labor Markets

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(Abstract)

This dissertation consists of three essays examining the important role of job connections, references, and word of mouth information in labor markets. The first essay examines the importance of job connections for internal migrants. In this chapter, I develop a theoretical model where labor market networks provide labor market information with less noise than information obtained in the formal market. This model predicts lower initial wages and greater wage growth after migration for migrants without contacts. I then use data from the National Longitudinal Study of Youth (NLSY) to examine whether migrants who used social connections when finding their first job assimilate faster in the new region. Consistent with the theoretical model, I find that migrants who did not use social connections take longer to assimilate in the new region.

The second essay models how screening workers through social networks impacts labor mobility in markets with adverse selection. When there is asymmetric information in labor markets, worker mobility is constrained by adverse selection in the market for experienced workers. However, if workers can acquire references through their social networks then they can move more easily between jobs. In this chapter I develop a simple labor market model in which workers can learn the productivity of other workers through social interaction. I show that networks increase wages and mobility of high-productivity experienced workers; however, networks discourage workers from accepting jobs outside their job-contact network, because of adverse selection.

The third essay in this dissertation examines the importance of social networks in labor markets when work is produced jointly. Most employers cite ‘poor attitude’ and ‘poor fit with firm culture’ as their greatest problems in recruiting employees, rating these factors more important than skill. This is easily explained when the output of the firm requires that workers engage in work together. In this essay, I explain why it might be rational for firms to hire through social networks even when worker skill is observed perfectly, if these workers are better able to do joint work with the firm’s existing employees.

DEDICATION

This work of toil and joy is dedicated to my mother.
Who, ambitious for her offspring, whispered, “Get a Ph.D.,”
Into my ear as a youngster. Long suffering,
She has lived to regret those words to me,
“If I’d known then you’d be in school until almost 2003,
I would have counseled a career as a plumber.”

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CONTENTS

LIST OF TABLES	vii
LIST OF FIGURES	viii
1 SOCIAL NETWORKS IN LABOR MARKETS: THEORY AND EVIDENCE	1
1.1 Introduction	1
1.2 Theories on the Importance of Social Networks	3
1.3 Social Networks and Labor Market Outcomes	5
1.4 Social Networks and Migration	6
2 JOB CONNECTIONS AND ASSIMILATION OF INTERNAL MIGRANTS	10
2.1 Introduction	10
2.2 Theoretical Model	13
2.3 Empirical Model	16
2.4 Data	18
2.5 Effect of Job Connections on Migrant Assimilation	23
2.5.1 OLS estimates	23
2.5.2 Wage Growth Estimates	29
2.5.3 Effect of Job Connections on Repeat Migration	31
2.6 Summary and Conclusions	34
3 SOCIAL NETWORKS AND LABOR MOBILITY	36
3.1 Introduction	36
3.2 Networking in a Two Period Model	38
3.2.1 Assumptions	38
3.3 Results	40
3.4 Conclusions	48

4	HIRING THROUGH NETWORKS AS A MEANS OF SCREENING FOR WORKER ATTITUDES	50
4.1	Introduction	50
4.2	Methodology	53
4.3	Results	56
4.3.1	Is hiring through an old boy network advantageous for the firm?	56
4.3.2	The relative importance of skill and the returns to different formal/informal search mix	57
4.3.3	Discrimination in networks and the return to skill	60
4.4	Conclusions	61
5	APPENDIX A: SIMULATION PROGRAM CODE	63

LIST OF TABLES

2.1	Means from the Sample	19
2.2	Types of Contacts Used By Migrants	22
2.3	Hourly Wage Regressions	24
2.4	Hourly Wage Regressions Cont.	25
2.5	Hourly Wage Regressions by Whether or Not Migrant Had Contact	28
2.6	Wage Growth Equations	30
2.7	Probability a Migrant Experiences a Repeat Migration	33
4.1	Means	57
4.2	Returns to Different Informal/Formal Search Mix	58
4.3	Effects of Discrimination	61

LIST OF FIGURES

3.1	Timing of the Model	40
4.1	A Completely Networked Firm	54

CHAPTER 1

SOCIAL NETWORKS IN LABOR MARKETS: THEORY AND EVIDENCE

1.1 Introduction

An expression voiced by many discouraged job seekers is, “It’s not what you know, but who you know.” Applications sent in response to advertisements for openings seldom result in interviews, much less job offers. Many employers bypass formal employee search methods altogether, preferring to use information from their own social networks to screen applicants. Even in markets such as that for new Ph.D.s, where most jobs are advertised formally, it is recognized that most job offers result from the professional connections of the student’s advisor.

Conventional wisdom regarding the importance of social connections is supported by much research in economics and sociology. Generalizing from this research, approximately 50% of all jobs are found through social connections (Shepard and Beliitsky, 1966; Rees and Shultz, 1970; U.S. Department of Labor, 1975; Staiger, 1990; Granovetter, 1995). Data on employers’ recruitment methods also attest to the importance of connections in the job search: one study found that in 52 Indiana businesses, approximately 51 percent of openings were filled through a referral (Campbell and Marsden, 1990).

Although personal connections are important in all occupations, the use of social connections to find work varies widely across professions. Generally, the use of social connections in the labor market declines with education and increases with the amount of professional networking inherent in the worker’s occupation. Albert Rees and George Shultz, in a 1970 study of the Chicago labor market, found that

between 50 and 65 percent of blue-collar workers found their current job through a friend or relative, compared to 23% of accountants and 37% of typists.¹ Typists and accountants were also almost three times more likely to have found a job through an employment agency compared to blue-collar workers. Mark Granovetter's (1995) study of professional workers in Newton, Massachusetts found that although use of personal connections to find work was the dominant job search strategy used by professional workers, technical workers were twice as likely as either managerial or other professional workers to have found their current job through an employment agency or a job advertisement.² Granovetter argues that perhaps managers and academics interact with more people in their work, increasing their number of professional social contacts. Similarly, Parnes et al. (1970) find that the proportion of workers who find their jobs informally is smallest for professional workers and greatest among unskilled workers.

The role of personal connections in the job search may also change as workers grow older. Studies of blue-collar workers uniformly find that the use of personal contacts to find work decreases with age; the greatest use of personal contacts is in the finding of the worker's first job (Reynolds, 1951; Myers and Shultz, 1951). Granovetter, however, finds the reverse trend among professional workers: a significant increase in the use of personal contacts as the worker ages; here the first job is the job most likely found through the formal market. Granovetter argues that this finding is likely due to the greater specialization inherent in white-collar occupations. Young professional workers have not yet made the important professional contacts that will help them find work. Less specialized blue-collar workers, on the other hand, are more likely to have a friend or relative help them find work. While this argument is a convincing explanation of the differences in

¹Blue-collar professions examined in their study were: material handler, janitor, fork-lift operator, punch-press operator, truck driver, maintenance electrician, and tool and die maker.

²Although, as Granovetter admits, this figure for professional workers is somewhat misleading, given the unusually high number of academics in his sample. Academics have the highest incidence of social connections to find work; just over 77% of the academics in his sample found their jobs this way, compared to 54% of high-school teachers and 32% of other professionals.

job search methods among young workers, it fails to explain why the use of social connections declines for less skilled workers as they age. How the importance of job connections changes with age is a question in much need of further research.

Jobs found through the worker's social network appear to be more desirable jobs than those found in the formal market in several respects. In his study of the job search methods of unemployed youths in the National Longitudinal Study of Youth (NLSY), Harry Holzer (1988) found that job offers through friends and relatives had much higher acceptance rates – 81%—compared to 40% for newspaper advertisements and 65% for direct employer contact; this finding suggests that informal job offers are better than formal job offers in terms of wages or nonpecuniary aspects. Among white-collar workers, Granovetter (1974) finds evidence that professional workers who received their job offer through a social connection receive higher wages. Curtis Simon and John Warner (1992) find evidence in the 1972 Survey of Natural and Social Scientists and Engineers that workers who found their job through a social connection had higher starting wages. Staiger (1990) finds similar evidence for young workers in the NLSY.

1.2 Theories on the Importance of Social Networks

To explain the importance of social connections in the hiring process, it is important to examine why both job seekers and employers would prefer this method. Although the prevalence of using social connections to find work may simply result from lower search costs associated with this method, most economists and sociologists believe that social networks serve as a screening mechanism in labor markets. In this view, information cannot be viewed separately from the social infrastructure by which the information is conveyed. Indeed, evidence suggests that employers tend to distrust sources of information from outside their own social networks. Based on their interviews with 51 employers of high school graduates in the Chicago area, Miller and Rosenbaum (1997) found that employers considered

grades and recommendations from teachers and former employers suspect and preferred to rely on either their own impressions in interviews or recommendations from known sources when hiring workers. In particular, they found that employers' favorite source of information about applicants is their current employees. Employers believe that employees have self-interested reasons for recommending good future employees; one employer stated, "Nobody wants to send someone in who's going to make them look bad." Employers also rely on employees to provide an accurate portrayal of the work to the applicant.

James Montgomery (1991) has suggested that one reason employers may prefer hiring through social networks is that they can obtain economic profits by doing so. In his model, young workers make social connections with older workers who tend to be similar to themselves. Recognizing this 'bias' in the way social ties are assigned, employers who employ high-ability workers can make positive profits by making wage offers to the friends of their high-ability workers. Montgomery finds that workers who obtain referral offers will be, on average, higher ability workers than those who do not obtain references. This results in greater wage offers to workers with references and lower offers for workers in the formal market.

Other authors have focused instead on the role of social connections in promoting good job matches. Using Jovanovic's (1979) job-matching framework, these authors have argued that if worker productivity depends on the specific job-worker match, referral networks may result in higher wage offers to referred workers, who are more likely to be better matched to the job. To test whether informal markets promote job matches or simply represent favoritism, Datcher (1983) examines the influence of the power of the connection on labor market outcomes. She finds no effect for the 'influence' of the connection involved. She also finds evidence of lower quit rates for workers who find their job through a social connection. She concludes that this evidence is consistent with the use of social connections to improve job-matches, not to promote favoritism. Staiger (1990)

provides a theoretical model and some empirical evidence that social connections result in better job matches for workers. In his model, wage offers from social networks contain better information about the quality of the job match than offers in the formal market. He finds some evidence that informal markets improve job matching among young workers in the NLSY: workers who found their job through a social connection had longer tenure than workers who found their job in the formal market; however, he finds no evidence that workers who found their jobs through connections have lower quit rates. Simon and Warner (1992) also find longer tenures for professional workers who found their job informally.

1.3 Social Networks and Labor Market Outcomes

Given the importance of social connections in the job search and the advantages to be gained from these social connections, individuals' social networks are likely to have an impact on labor market outcomes. Different social networks do not provide the same access to ideas, influence, and information. The increasing awareness of the role of the social infrastructure in determining labor market outcomes is reflected in the recent movement in the urban poverty literature away from spatial mismatch model, toward theories incorporating how social networks affect urban poverty (Patterson, 1998). Other research has focused on the role social networks have played in securing jobs in certain industries for particular ethnic groups, such as in New York's garment and hotel districts (Waldinger, 1996).

Perhaps some of the lower wages observed among black workers can be explained by the use of 'old-boy networks' to screen potential applicants. Using a simulated labor market with social networks containing minority social groups, Tazier (2000) finds evidence that referral hiring promotes racial segregation and reduces the returns to education for minority workers, by limiting access to certain jobs to certain ethnic groups. Similarly, Holzer (1987) has found evidence that the

labor market outcomes of urban black workers can be explained in part by lower returns to informal job search for black workers. He suggests white employers may have less trust in the recommendations of their black employees. Minority social networks may also be ‘tighter’ than those of other groups. Reingold (1999) finds some evidence that urban blacks and Hispanics have more constricted social networks, implying that these groups have more limited access to word-of-mouth information than whites

Granovetter (1973) has defined the strength of a tie as a “combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie.” Granovetter (1995) found that more job seekers used weak ties and that those who used weak ties were more satisfied with their jobs. He suggests that this is because weak ties serve as channels by which distant information and influences reach the worker, increasing the opportunity for social mobility. Similarly, Montgomery (1992) argues that weak ties are drawn from a better distribution than strong ties. Lin, Ensel, and Vaughn (1981) find evidence that the use of weak ties allows job seekers to better reach contacts of higher social status and that the social status of the contact has a direct effect on the status of the attained job. Montgomery (1994) uses a theoretical model with weak and strong ties to show that an increase in weak ties reduces the inequality of outcomes in the job market.

1.4 Social Networks and Migration

The study of inter-regional migration has a long history in economics. The attention given to migration in the economics literature reflects its importance to neo-classical theory, for migration flows are the means of equalizing wages across regions. Standard neo-classical models of migration predict that in the presence of inter-regional wage disparities, there will be an outflow of workers from low wage regions to high wage regions, until wages are uniform across labor markets. Yet,

despite a highly mobile workforce, considerable wage and unemployment disparities persist across regions of the United States (Sjaastad, 1962). Although there is a considerable body of literature examining internal migration in economics, this persistence has yet to be fully explained.

Although factors such as moving costs, family ties and location-specific capital are often cited to explain the persistence of wage and unemployment disparities across regions, the discussion of the role of social networks in the hiring process above suggests an alternative explanation. Economists typically conceptualize the market for labor as a market where employers demand and hire specific skills, yet these models poorly represent the process by which workers are hired in real labor markets. Perhaps no example illustrates the quixotic nature of the hiring process than this example from Granovetter (1995:16):

“One postdoctoral student in biology received a letter from an institution to which he had applied for a job, saying that there were “no openings for an individual with your qualifications.” But when his thesis adviser took a position there, the younger man went along as a research associate; he subsequently received an effusive letter expressing the college’s delight at his appointment.”

The opportunities presented to individuals in the labor market are not easily separated from the individual’s position in the social infrastructure. The worker’s social network will determine what job opportunities he hears about as well as his likelihood of obtaining a particular job. Not surprisingly, several studies have found that social connections in a given region increase the propensity of workers to migrate to that region (see Greenwood, 1975, for a review of this literature). Pre-existing social connections in the new region also seem to indicate a greater likelihood of better migration outcomes. Both Hertzog and Schlottmann (1982) and DaVanzo (1983) found that having social connections in the new region re-

duced the probability of a return migration for the migrant. While the finding that social connections in the new region are associated with better migration outcomes may be due to better non-labor market information and financial support for these migrants, it is also consistent with better labor market opportunities for migrants with pre-existing social connections.

Young workers in particular use kinship networks to access opportunities in the labor market. As young workers have had little opportunity to develop cross-generational contacts outside their own family, the use of relatives in finding work is especially prevalent among youths. However, the use of family connections to find work would be associated with low residential mobility. Granovetter (1995) found the use of family contacts to find work was highest among natives of Massachusetts. Similarly, the migration of members of a family network used by younger members of that network to find work should result in increased migration to the new location. Carrington et al. (1996) cites evidence that black migrants in the early part of the last century often wrote home with job offers for relatives still in the south, propelling the migration of blacks northward through family networks. Consistent with evidence that the use of family connections to find work is most prevalent in less-skilled jobs, Granovetter (1995) does not find evidence that ‘migrant chains’ characterize the migration decisions of white-collar migrants; few white-collar migrants in his sample used family connections to obtain their current job.

It should not be surprising then, to find that groups of workers that rely less on family networks to find work would have greater geographic mobility. Studies of migration propensities have repeatedly found that the likelihood of migrating increases with education, but declines with age (Greenwood, 1975, Schwartz, 1976). Interestingly, the use of social connections to find work is lowest among young college educated workers. Young college educated workers have not yet established the professional connections that will enhance their mobility later in

life, and are less likely to have family members in their respective field to help them find work. Thus young college educated workers must resort to less desirable formal channels – job advertisements, college placement services, internships – to find work. As formal channels are more likely to produce distant job offers, the observed relationship between age, education and migration may be an outcome of the lack of professional connections among young educated workers.

CHAPTER 2

JOB CONNECTIONS AND ASSIMILATION OF INTERNAL MIGRANTS

2.1 Introduction

It has often been argued that social connections provide migrants with valuable job connections that ease their transition into a new labor market. However, currently little is known about the impact of job connections for internal migrants. Although some researchers have speculated about the importance of informal labor market connections in internal migration,¹ to the best of my knowledge, no studies have examined the importance of social networks – particularly labor market connections – for migrants within the United States.

In this chapter I investigate the effect of labor market connections on migrant assimilation among young migrants within the United States. Using job search and mobility data from the National Longitudinal Study of Youth, I investigate the impact of job connections on the initial migrant wage disadvantage, wage growth after migration, and repeat migration among young internal migrants in the United States. I find that migrants experience higher wage growth relative to natives, evidence that assimilation does occur among internal migrants. Unlike other studies, which have found higher starting wages among workers who found their job using job connections, I find no evidence that migrants using job connections have higher starting wages than demographically comparable migrants without job connections. Overall, this study suggests that job connections do help migrants assimilate into the new region, but that the returns to migration

¹For example, Carrington et al. (1996) argue that migration chains within the United States can explain the pattern of migration flows during the Great Black Migration of the 1920s.

are lower for these migrants.

Assimilation, the process by which migrants acquire location specific human capital and labor market information, has proven to be a key factor affecting the earnings of international migrants. Several studies have found that international migrants have an initial wage disadvantage that disappears with tenure in the new country (Chiswick, 1978; Carliner, 1980; Borjas, 1982). Borjas, Bronars, and Trejo (1992) find that a similar learning and adjustment process influences the post-migration profiles of internal migrants. They suggest that this adjustment process results from the acquisition of information and job connections in the new labor market. However, while research in economics and sociology suggests that labor market connections influence both workers' wages and job tenure, little is known about the importance of job connections for internal migrants.

Better understanding of the role of labor market connections in internal migration is important for several reasons. First, a lack of job connections may help explain the observed immobility of certain classes of less skilled workers. This is especially true in view of the importance of job connections in job search for less skilled workers (Granovetter, 1995; Rees and Shultz, 1970). Understanding the role of job connections in internal migration may also help us understand the migration patterns of certain types of workers. 'Migration chains' – the tendency for one migrant in a new location to be followed by other migrants from the migrant's social network – may occur more frequently in labor markets where social networks are frequently used as references for work. Since this type of reference occurs most frequently in less-skilled markets, it may be that migration chains occur most often in networks of less-skilled workers.

The importance of job connections in the labor market has been demonstrated in several studies. Both Simon and Warner (1992) and Staiger (1990) have found that individuals who find their jobs through social contacts have longer job tenure and higher wages than workers who find their jobs in the formal market. Gra-

novetter (1995) found similar results among professional and technical workers. Informal search methods also result in more job offers for unemployed workers, and those offers have much higher acceptance rates (Holzer, 1988). This evidence suggests that better information about the job opportunities and specific job-worker matches is conveyed through job-contact networks.

Although the role of informal job information has not been directly addressed in the internal migration literature, several findings suggest that job connections play an important role for migrants. Greenwood (1975) has noted that migrants have a greater propensity to migrate to regions with existing social networks. Both Hertzog and Schlottmann (1982) and DaVanzo (1983) found that migrants who move to an area where family members reside have lower probabilities of migrating again. While these findings may simply result from the desire to be located near friends and family, it may also be that family and friends provide useful information about labor markets and job opportunities that make these regions more attractive for migrants.

The next section describes a theoretical model of migrant job search that generates the following hypotheses: (1) migrants without connections will experience greater wage growth after migration, since these migrants have poorer labor market information before migrating, (2) migrants with connections will have greater initial wages upon migrating, and (3) job connections will reduce the probability of return migration, since the better quality information available to these migrants reduces their probability of making mistakes. The third section of this chapter develops the empirical model generated by the theoretical model. The fourth section discusses the data used in this study. The chapter concludes with a discussion of the empirical results.

2.2 Theoretical Model

Much of the work on the role of labor market networks has built on the job-mobility model developed by Jovanovic (1979). In Jovanovic's model, both workers and employers are uncertain about the productivity of a given job-worker match. This uncertainty drives down initial wages for workers. Since both workers and employers learn over time about the quality of the job worker match, wages grow with tenure on the job. Matches that are discovered to be unsatisfactory result in worker quitting to search for better matches.

Both Staiger (1990) and Simon and Warner (1992) have incorporated job connections into models similar to Jovanovic's to examine the impact of job connections on labor market outcomes. In both models, job connections are used by employers and workers to reduce the uncertainty of job-worker matches. Both models can be easily adapted to a spatial model to examine the role of job connections in migration; however, for the sake of brevity only Simon and Warner's (1992) model is described here. Consider a worker entering the labor market. The productivity the worker is equal to a job-specific match variable, θ , which is distributed $N(\mu, \sigma_\theta^2)$. Draws on θ are independent; the quality of one match conveys no information regarding the quality of another match. Neither workers nor employers can directly observe the quality of a job-worker match, instead, both observe $x = \theta + \varepsilon$ where ε is $N(0, \sigma_\varepsilon^2)$. The actual value of θ is observed after one period of work.

Jovanovic (1979) demonstrates that under these conditions one equilibrium offer strategy for firms is to make an initial wage offer equal to the worker's expected productivity *conditional* on the employer's error ridden prediction of it, and agree to offer the worker his or her actual productivity in following periods. The probability distribution of θ conditional on x has mean m and variance σ_m^2 , where:

$$m = E(\theta|\theta + \varepsilon)$$

$$= \mu + \sigma_m^2(\hat{\theta} - \mu)$$

and $\sigma_m^2 = (\frac{1}{\sigma_\theta^2} + \frac{1}{\sigma_\varepsilon^2})^{-1}$. Note that m itself is normally distributed, with mean μ and variance $\frac{\sigma_\theta^4}{\sigma_\theta^2 + \sigma_\varepsilon^2}$:

$$m \sim N(\mu, \frac{\sigma_\theta^4}{\sigma_\theta^2 + \sigma_\varepsilon^2})$$

Workers receive job offers both through their own job connections and through the formal market. Offers are received through job connections with an exogenous probability p . Job connections are used by employers and workers to reduce uncertainty about the applicant's true productivity. Specifically, job connections reduce the variance of the error term, σ_ε^2 . Therefore, when comparing two job offers, one received through the workers job connections and the other through the formal market, $\sigma^2(\varepsilon_R) < \sigma^2(\varepsilon_F)$, where ε_R is the error term associated with offers received through job connections and ε_F the error term associated with offers received in the formal market.

To set this framework in a spatial model and examine the implications for migration, I use Phelps' (1970) notion of an island economy. Phelps conceptualized the spatial economy as a group of islands, between which information flows are costly. To sample a wage offer on an island a worker must pay a search cost $c(h)$ where h is the distance between that worker and that island. Search costs increase with distance from the worker's location ($\frac{dc}{dh} > 0$) and $c(o) = 0$, where o is the worker's origin.

The worker now faces a dynamic programming problem in which he seeks to maximize his expected stream of income. Sargent (1987) points out that is helpful to think of the worker's problem as having three stages. In the first stage, a previously unemployed worker has yet to draw a match. Let Q denote the expected present value of wages, before drawing an offer, for a worker who behaves optimally (for simplicity it is assumed only workers who are unemployed can sample new job offers). In the second stage, the worker has drawn a match

parameter θ and has received a noisy observation of it, $(\theta + \varepsilon)$. In this stage, the worker must decide whether to accept this offer or remain unemployed to search in the next period. The third stage occurs in the period following the acceptance of an offer, when the worker has observed the true match parameter θ and must decide whether to reject this match and quit to search for a better match.

Working backward, a worker in the third stage receives an offer θ from his current employer and must decide whether to stay or quit his job. Let $J(\theta)$ denote the expected value of remaining in the current match, with $J(\theta)$ defined recursively as:

$$J(\theta) = \begin{cases} \theta + \beta J(\theta) = \frac{\theta}{1-\beta} & \text{for } \theta \geq \bar{\theta} \\ \beta Q & \text{for } \theta \leq \bar{\theta} \end{cases}$$

where $\bar{\theta}$ is the reservation wage for remaining on the job, which satisfies $\frac{\bar{\theta}}{1-\beta} = \beta Q$, and Q , the expected value of rejecting to search for another job offer, is:

$$Q = p \int V(m_R) dG[m_R|\mu, \sigma^2(m_R)] + (1-p) \int V(m_F) dG[m_F|\mu, \sigma^2(m_F)] - c(h)$$

where $V(m_R)$ and $V(m_F)$ are the value of job offers received through job connections and the formal market respectively and $dG[m_R|\mu, \sigma^2(m_R)]$ and $dG[m_F|\mu, \sigma^2(m_F)]$ are the probability densities of offers received through job connections and the formal market, respectively. Note that, given the assumption of a fixed p across islands, workers who quit to search will begin their search in the lowest cost search area, the origin, and search systematically over areas of increasing search cost. If p varies across islands, the decision of where to begin searching will depend on the different probabilities of obtaining offers through job connections across islands as well as search costs.

Now consider a worker in the second stage who is currently unemployed and has an offer m in hand. The value of an initial offer, m is equal to:

$$V(m) = \begin{cases} m + \beta \int J(\theta') dF(\theta'|m, \sigma_m^2) & \text{for } m \geq \bar{m}_h \\ \beta Q & \text{for } m \leq \bar{m}_h \end{cases}$$

where the value of the reservation wage \bar{m}_h is:

$$V(\bar{m}_h) = \bar{m}_h + \beta \int J(\theta') dF(\theta' | \bar{m}_h, \sigma_m^2) = \beta Q$$

solving for \bar{m}_h I obtain:

$$\begin{aligned} \bar{m}_h = & \beta \left\{ p \int V(m_R) dG[m_R | \mu, \sigma^2(m_R)] + (1-p) \int V(m_F) dG[m_F | \mu, \sigma^2(m_F)] - c(h) \right\} \\ & - \beta \int J(\theta') dF(\theta' | \bar{m}_h, \sigma_m^2) \end{aligned}$$

Note that as the search radius increases, $c(h)$ increases and \bar{m}_h decreases. Therefore, the reservation wage for accepting a job offer declines as the search radius expands. Therefore, migrants should have lower initial wages compared to natives. Note also that the last term on the right-hand side of the equation is an increasing function of σ_m^2 , which is, in turn, an increasing function of σ_ε^2 . Because $\sigma^2(\varepsilon_R) < \sigma^2(\varepsilon_N)$, the reservation wage for accepting a job a distance h from the origin is greater for offers received through job connections, or $\bar{m}_h(R) > \bar{m}_h(N)$. Therefore the model predicts higher initial wages for migrants who found their first job in the new location through a job connection. Note also that migrants with job connections have better information about the job match before beginning work, compared to migrants who found their jobs without connections. Because there is greater initial certainty about match quality for migrants who found their job through a connection, these migrants should also have slower wage growth on the job compared to migrants who found their jobs in the formal market.

2.3 Empirical Model

The theoretical model above provides the basis for the empirical model discussed in this section. Following Chiswick (1978), economists have used the human capital framework to analyze the labor market assimilation of international migrants. Earnings of natives and migrants are typically modeled by the following regression equation:

$$\ln w = X\beta + \gamma_1 E + \gamma_2 E^2 + \delta_0 M + \delta_1 MT + \delta_2 MT^2 + \varepsilon$$

where w represents the hourly wage, X is a vector of worker characteristics, E is experience, M is a dummy variable identifying international migrants, T measures years since migration and ε is a random error term.

The underlying idea of the above equation is that labor market experience in the foreign country is not a perfect substitute for labor market experience in the United States. The coefficient δ_0 represents the migrant-native earnings differential upon arrival in the United States; it is expected to be negative, since migrants often lack location-specific human capital that is important for success in the new job market. The coefficients δ_1 and δ_2 represent migrant assimilation over time in the new country. It is expected that migrant earnings will grow with time in the new country at a rate that decreases with migrant tenure.

Several studies confirm that migrant tenure is an important factor in immigrant earnings (Chiswick, 1978; Borjas, 1982; Carliner, 1980). Generally, these studies find that international migrants have a wage disadvantage that decreases with tenure in the new country. Borjas, Bronars and Trejo (1992) find a similar pattern affecting the earning profiles of internal migrants. They find that internal migrants to a state initially earn about ten percent less than demographically comparable natives, but because migrant wage growth is greater than that of natives, this gap disappears after a few years. Not surprisingly, they find that the earnings assimilation occurs more quickly for internal migrants than international migrants.

Borjas, Bronars and Trejo speculate that the period of assimilation necessary for internal migrants to catch up with natives is due to the need to acquire location-specific labor market information. It seems likely then that the existence of labor market connections prior to migrating would impact the pattern of assimilation for internal migrants. If this is true, then migrants with no job connections prior to

the move should experience a greater wage disadvantage and greater wage growth relative to natives than migrants with job connections.

2.4 Data

The National Longitudinal Study of Youth (NLSY79) is an ongoing longitudinal study of approximately 12,000 youths aged fourteen to twenty-one as of January 1, 1979. This survey collected data on job search methods used to find the respondent's current job during the years 1982, 1994, and 1996. The 1982 survey year in particular has detailed information on personal connections used to find the respondent's current job. I chose to use data from the 1982 survey year to examine the impact of labor market contacts prior to the move on assimilation, wage growth, and the probability of return migration for young workers.

The 1982 year of the NLSY has several unique qualities that make it desirable for this study. In particular, the 1982 survey asks respondents, "Did you have to move to take this job?" This question allows me to pinpoint the worker's first job in a new region.² This is important, as it allows me to separate migrants who had a job contact before they accepted a job in a new region from those who might have acquired job contacts after they arrived. Although this is the primary reason for choosing the 1982 survey year, there are two other advantages of using the 1982 data. First, the level of detail regarding the use of job contacts in the 1982 survey is unusually rich, allowing me to examine the types of connections that are used by internal migrants when relocating. Second, the workers in the sample in 1982 are quite young, in their early twenties. Young workers are typically more mobile and have a greater tendency to use social connections to find work, factors that should allow for a larger sample of migrants using job connections.

A 'migrant' in this study is a worker who changed counties to take his or her 1982 job. Specifically, a worker is defined as a migrant if he or she answers yes

²This question is not asked in any other year of the NLSY.

Table 2.1: Means from the Sample

Variable	All	Natives	Movers	Migrants		
				All	contacts	no contacts
Miles moved	–	–		460.43 (619.27)	494.52 (713.19)	430.17 (523.96)
Years in county	–	–		1.09 (1.01)	1.04 (1.02)	1.14 (1.01)
Ave. hourly wage	4.51 (3.17)	4.37 (3.07)	6.12 (3.92)	6.25 (3.81)	5.74 (3.19)	6.69 (4.25)
Age	21.12 (2.03)	21.03 (2.02)	21.96 (1.98)	22.20 (1.84)	21.99 (1.86)	22.39 (1.81)
Education	11.72 (1.83)	11.60 (1.59)	12.77 (2.40)	13.10 (2.43)	12.71 (2.29)	13.44 (2.52)
Experience	3.40 (2.20)	3.42 (2.21)	3.18 (2.20)	3.10 (2.00)	3.27 (2.14)	2.95 (2.25)
Married	.25 (.43)	.25 (.43)	.29 (.45)	.32 (.47)	.32 (.48)	.32 (.47)
Female	.49 (.50)	.50 (.50)	.36 (.48)	.37 (.48)	.35 (.48)	.39 (.49)
Black	.26 (.44)	.28 (.45)	.16 (.37)	.12 (.29)	.13 (.33)	.11 (.31)
Hispanic	.17 (.38)	.17 (.38)	.14 (.35)	.13 (.34)	.15 (.36)	.12 (.33)
Lives in SMSA	.72 (.45)	.72 (.45)	.65 (.48)	.64 (.48)	.65 (.48)	.63 (.48)
Sample Size	3860	3567	359	293	136	157

to the question, “Did you move to take (1982 job)?” and the worker’s county of residence changed within a year of starting the 1982 job and 1982. As location data is not available in the NLSY between age 14 and 1979, workers who moved to take a job they started before or during 1979 are classified as migrants if their county of residence changed between age 14 and the year they started this job. A migrant is regarded as having found their first job in the region with the use of a job contact if he or she answers “Yes” to the question “Did someone help you find this job?” Of all workers in the NLSY, 547 report that they moved to take their 1982 job. Of these, 358 changed counties to take their 1982 job.³

A ‘native’ is a worker whose county residence in the years 1979-1982 is the same as their county of residence at the age of 14. Separated from both the native and migrant samples are return migrants, those migrants who changed counties between age 14 and 1982, but subsequently returned to a county they resided in between age 14 and 1982. Because return migrants typically have different returns to migration than migrants moving to a new location, they need to be analyzed separately.

Because I wish to abstract from the schooling decision, workers must be out of school and in the labor force for at least one year to be included in the sample.⁴ Workers must also not be in the active armed forces, not be enrolled in school, and have positive working hours in 1982. These restrictions reduce the sample considerably; the final sample contains 359 movers, 293 migrants, and 3567 natives who were between the ages of 17 and 25 in 1982. Of the migrants, 136 (46%) report that someone helped them obtain their first job in the new location. Twenty-five are return migrants (14 of these migrants used job connections, 11 did not).

³Ninety workers are dropped from the migrant sample because of missing county data in the relevant years. Ninety-three workers in the mover sample did not change counties at the time of the move.

⁴In other words, to be included in the final sample a worker must be: (1) not enrolled in school from 1979 and in the labor force in 1979, (2) not enrolled in school in 1980 and in the labor force in 1980 (3) not enrolled in school 1981 and in the labor force in 1981 (4) not enrolled in school in 1982 and in the labor force in 1982.

There are a number of pitfalls with the final sample. First, the sample is very young, which may limit the generalizability of the results. More importantly, to separate migrants who did and did not have a job connection before migrating, I am forced to exclude migrants for whom I have no information on their first job after migrating, that is, migrants who migrated before taking their 1982 job. To see if this sample of migrants is atypical, I compare wage equations using this sample of migrants to those using larger samples from the NLSY. The wage equations for these migrants are very similar to those estimated by Borjas, Bronars and Trejo (1982) using a much larger sample of migrants, suggesting that this group of migrants is not atypical.

The characteristics of the final sample are described in Table 2.1 (standard deviations are in parentheses). At first glance, the pattern of earnings for migrants and natives seems the reverse of that predicted by the model: migrants, on average, earn more than natives, with migrants who moved without job connections having the highest mean wage. However, closer examination reveals that migrants are more educated than natives, are more likely to be married, and less likely to be either female or black, all of which are associated with higher earnings. Also, migrants without job connections tend to be more educated than migrants who used job contacts, not surprising as the greatest use of contacts to find work is typically found among blue-collar workers. These differences in education may account for the higher average wage among migrants who did not use contacts. Once these differences are controlled for, the apparent advantage of migrants without connections may disappear.

The dependent variable used is the natural logarithm of 1982 wage. Labor market experience is calculated as age minus education minus six. Because job connections prior to the move may improve migrant assimilation by allowing migrants access to better jobs, I do not control for characteristics of the individuals job such as industry, occupation, union status, or government employment. In

Table 2.2: Types of Contacts Used By Migrants

Type of Contact	Percent Used	
Relative	53.94%	
Non-Relative	46.06%	
– Knew from school	(14.52%)	
– Knew from work	(22.58%)	
– Teacher	(8.06%)	
– Other non-relative	(54.84%)	
Sex of Contact	Sex of Migrant	
	Male	Female
Male	88%	58%
Female	13%	42%

the vector of control variables I include only personal and family background variables such as education, gender, race, marital status and health. To control for cost-of-living differences, I include dummy variables for residence in an SMSA.

Table 2.2 examines the types of contacts used by internal migrants. It appears that internal migrants use job contacts from a variety of social relationships. Slightly more than half the contacts used by migrants are relatives, with 54% of the migrant sample using a relative as their job contact. Of non-relative contacts, only half are individuals known to the migrant through either school or work, the other half are contacts made in other venues. It is also interesting to note that almost half of all female migrants used a female job contact, compared to only 13% of male migrants.

2.5 Effect of Job Connections on Migrant Assimilation

2.5.1 OLS estimates

This section presents a cross-sectional analysis of internal migrant assimilation using data from the 1982 year of the NLSY. Borjas (1985) has pointed out that cross-sectional analysis can provide biased estimates of international migrant assimilation if there are changes in migrant cohorts over time. To get better estimates of assimilation, he recommends using data from several cohort years and examining assimilation within cohorts. The limited availability of data on contacts before migrating precludes using several cohort years here. However, there are two reasons not to be particularly concerned about this. First, the focus of this study is assimilation among internal migrants, not international migrants. Borjas, Bronars, and Trejo (1992) have shown that internal migrant assimilation tends to occur rather quickly, within three years, so the time period of interest to this study is much shorter than that of international migrant assimilation. Second, there is less reason to think that the quality of internal migrants has varied over time.

Assimilation will be overstated in the cross-sectional results if the group of migrants moving in 1982 is of lower quality than that moving in 1979. This may occur if the timing of the 1981-1982 migrations, which occur in the middle of a recession, affect the quality of internal migrants. If mid-recession movers are less able workers than early recession movers, the starting wage disadvantage for migrants will be underestimated and the rate of assimilation will look faster than it truly occurs. However, the faster rate at which assimilation occurs among internal migrants makes changing cohorts less problematic than in the study of international migrant assimilation.

Tables 2.3 and 2.4 report the results of ordinary least squares estimates of hourly earnings regressions, using the NLSY79 constructed 1982 hourly wage as the dependent variable. The coefficients on the control variables are not surprising

Table 2.3: Hourly Wage Regressions

Variable	All Movers and Natives	All Migrants and Natives	Onward Migrants and Natives
(denote standard errors)	(1)	(2)	(3)
Mover, <1 year in local	-.02231 (.03123)		
Mover, 1-2 years in local	.11354 (.04566)		
Mover, 3+ years in local	.34060* (.09665)		
Migrant, <1 year in local	—	-.03221 (.03792)	-.01985 (.03988)
Migrant, 1-2 years in local	—	.13295 (.04953)	.13020 (.05076)
Migrant, 3+ years in local	—	.35879 (.11717)	.35805 (.11723)
Sample Size	N=3420	N=3369	N=3346

Table 2.4: Hourly Wage Regressions Cont.

Variable	(1)	(2)	(3)
Is female	.03521 (.14574)	.08805 (.14579)	.10030 (.14673)
Experience	.06447 (.01204)	.06405 (.01211)	.06515 (.01214)
Experience ²	-.00112 (.00133)	-.00115 (.00135)	-.00127 (.00135)
Female*Experience	-.02553 (.00876)	-.02605 (.00876)	-.02606 (.00878)
Education	.09351 (.00769)	.09685 (.00774)	.09736 (.00779)
Female*Education	-.01145 (.01102)	-.01575 (.01103)	-.01733 (.01112)
Is Married (spouse present)	.15520 (.02870)	.16081 (.02885)	.16670 (.02902)
Female*Married	-.17653 (.03891)	-.17869 (.03899)	-.18683 (.03916)
Black	-.09281 (.01996)	-.09330 (.01997)	-.09359 (.02002)
Hispanic	-.0070 (.02259)	-.00561 (.02256)	-.00524 (.02262)
Lives in SMSA	.12429* (.01825)	.13069* (.01827)	.12972* (.01837)
Constant	4.7236* (.10056)	4.6839 (.10089)	4.6764 (.10137)

and similar in both sign and magnitude to those found by Borjas, Bronars & Trejo (1992). There are positive returns to both experience and education. Being married has a positive effect on wages for men, and a negative effect for women. Individuals living in rural areas make less than their urban counterparts and blacks earn less than comparable whites.⁵

Turning to the migration variables that are the interest of this study, Tables 2.3 and 2.4 report estimates of the effect of migrant status on wages. To retain the largest sample size possible, column (1) examines the wages of all movers, column (2) all migrants, and column (3) excludes return migrants. Results for the three groups are almost identical: like Borjas, Bronars and Trejo (1992), I find that migrants initially experience a small wage disadvantage relative to natives and that there is a positive return to tenure in the new region. The initial wage disadvantage experienced by migrants is very small, only 2-3%. For all three groups, the slight initial wage disadvantage disappears very quickly; within two years after migrating, migrant wages exceed those of demographically comparable natives. Migrants living in the location for more than one year but less than three have 11-13% higher wages than natives, suggesting a strong return to tenure in the first few years in the new location. The dummy variable for more than three years in the location suggests the returns to tenure may continue after the third year, but the smallness of the migrant sample with more than 3 years of tenure precludes making much of this result.

The estimate of a 2-3% wage disadvantage for migrants is smaller than the 7% wage disadvantage found by Borjas, Bronars, and Trejo (1992). This is not surprising, as this study examines county-to-county migrants instead of state-to-state migrants. It would be understandable if migrants who migrate greater distances experience greater initial wage disadvantages. However, estimating the

⁵This model specification restricts the effects of the control variables to be the same for migrants and natives. To test this restriction, I used an joint F test to test if any of the coefficients were different between the two samples. The joint F test does not come close to rejecting the restriction that the effects of the control variables are the same for the two groups.

wage equations using Borjas, Bronars and Trejo's dependent variable of annual wage income divided by yearly hours of work provides an estimate of a 8% initial wage disadvantage for migrants in the first year, much closer to that found by Borjas, Bronars, and Trejo. This suggests that it is the different dependent variable, not the migrant sample, that is driving the difference between the two estimates.

Table 2.5 divides the migrant groups by whether or not they used a job contact for their first job in the new region.⁶ Because there are only eighteen migrants with 3 years or more of tenure, these migrants are dropped from this analysis, and only migrants with less than three years tenure are examined. Column (1) of Table 2.5 estimates wage equations for all movers, column (2) estimates wage equations for all migrants, and column (3) excludes return migrants. Again, the wage equations for all three groups are very similar.

Overall, the results in Table 2.5 provide mixed evidence for the model described earlier in this chapter. Consistent with the model, the return to migrant tenure is much stronger for migrants who moved without job connections. Almost all of the increase in wages for migrants with one to two years of tenure observed in Tables 2.3 and 2.4 are attributable to migrants without connections, and only migrants without connections have statistically significant greater wages than demographically comparable natives. This higher wage growth for migrants without connections is consistent with the theory that there is greater uncertainty about the match quality of jobs found through the formal market, and that migrants who found their first job through the formal market will have a greater return to tenure in the new location.

However, there is no evidence here that migrants who found their first job through a job connections have higher initial wages than those migrants who

⁶Control variables for these regressions are education, marital status, experience, experience squared, location in SMSA, race, sex, and interactions between sex, education, and marital status.

Table 2.5: Hourly Wage Regressions by Whether or Not Migrant Had Contact

Variable	All Movers and Natives (1)	All Migrants and Natives (2)	Onward Migrants and Natives (3)
Mover, <1 year in local * contact	-.03037 (.04244)		
Mover, <1 year in local * no contact	-.01508 (.04384)		
Mover, 1-2 years in local * contact	.10316 (.07038)		
Mover, 1-2 years in local * no contact	.12078* (.05823)		
Migrant, <1 year in local * contact		-.06089 (.05257)	-.05157 (.05624)
Migrant, <1 year in local * no contact		-.00245 (.05245)	.01100 (.05461)
Migrant, 1-2 years in local* contact		.06266 (.07770)	.06273 (.07979)
Migrant, 1-2 years in local * no contact		.17907* (.06275)	.17439* (.06433)
Sample Size	3370	3317	3294

found their first job through the formal market. Indeed, the point estimates suggest a slightly larger wage disadvantage for migrants with contacts, 5%-6%, compared to a wage disadvantage of 1% for migrants without contacts. This wage disadvantage disappears after the first year in the new location, and the wage growth experienced by these migrants is smaller than that experienced by migrants who did not use contacts. This is consistent with the notion that job contacts provide greater certainty about the match quality of jobs found through contacts, but suggests that the overall returns to migration may be lower for migrants who used job contacts for their first job in the new location.

A simple modification of the theoretical model can explain these results. The model described in the previous section assumes that individuals choose locations solely on the basis of the present value of expected wages. Workers search for jobs, having higher reservation wages for jobs found through social connections, and lower returns to tenure in the new location. However, if instead workers choose locations based on a basket of location-specific goods that includes the value of having existing social connections in the region, the model predictions would be much closer to the evidence provided here. Migrants would require an expectation of higher future wages to compensate them for accepting a job in a region where they have no social connections, so I would expect to see higher wages among migrants who found job in the formal market. However, greater uncertainty about the job match for jobs without connections would result in higher wage growth for these migrants.

2.5.2 Wage Growth Estimates

Next I exploit the panel aspect of the NLSY to compare wage growth between 1982 and 1983 for natives and migrants who migrated between 1979 and 1982. Looking at wage growth directly is important for two reasons. First, as the model predicts that wage growth after migration will be greater for migrants who found

Table 2.6: Wage Growth Equations

Dependent Variable:	Movers &	Movers &	Migrants &	Migrants &
ln83wage-ln82wage	Natives	Natives	Natives	Natives
Variable	(1)	(2)	(3)	(4)
Intercept	.05949 (.00920)	.05949 (.00920)	.05861 (.00910)	.05861 (.00909)
Mover	.03233 (.02668)	-.01373 (.03800)		
Mover*no contact		.08574 (.05023)		
Migrant			.00347 (.03299)	-.05602 (.04909)
Migrant*no contact				.10476 (.06401)
Sample Size	2807	2807	2710	2710

jobs in the formal market, it is better to look at wage growth directly rather than infer wage growth from the migrant tenure dummies. Second, if individual heterogeneity is important – if migrants who do not use connections are more able workers than those who use job connections, for instance – the results in the cross-sectional analysis will be biased. Looking at wage growth will tend to difference out these individual effects, providing a better test of whether it is the use of connections that is driving the differences between the returns to tenure in the two groups.

Overall, the results reported in Table 2.6 are consistent with evidence from the wage equations from Table 2.5, although they show somewhat stronger evi-

dence of higher returns to tenure for migrants without contacts.⁷ Columns (1) and (3) of Table 2.6 report wage growth estimates for all movers and migrants (excluding return migrants), respectively. Note that the constant in these equations refers to wage growth for natives. These estimates suggest a 0-3% higher wage growth for migrants compared to natives, although this difference is not statistically significant.

Columns (2) and (4) of Table 2.6 introduce an interaction term for lack of contacts for migrants. Now the 0-3% higher wage growth experienced by migrants is broken up into a 1-5% lower wage growth for movers and migrants with job contacts and 8-10% higher wage growth for migrants who did not use job connections and the difference in wage growth between migrants with job contacts and without contacts is statistically significant at the 10% level. The low level of statistical significance may be resulting from the smallness of the sample size (only 250 migrants migrated between 1979 and 1982) which results in higher standard errors. However, these results do suggest that migrants without connections have greater returns to tenure in the new location, findings consistent with the notion that assimilation is a more important process for migrants who use the formal market to locate their first job in the new region.

2.5.3 Effect of Job Connections on Repeat Migration

Labor market networks may also impact patterns of return and onward migration. As pointed out by DaVanzo (1983), “most moves are not people’s first moves, but rather are repeat moves – either onward to new locations or back to places where they lived before.” Although many moves are intentionally short-lived, other repeat moves occur because the initial move was not a success, or because the benefits of the initial move were overestimated by the migrant.

⁷The estimates provided in this table are unchanged when I add variables controlling for changes in health, marital status, and experience squared. Natives who migrated between 1982 and 1983 are excluded from the analysis.

As labor market connections should increase the quality of labor market information available to the migrant before the move, it may be expected that migrants with labor market connections will be less likely to overestimate the benefits of the initial migration and will experience less repeat migration (either onward migration or return migration). To test this, I examine the impact of having found the first job in the initial migration through a job connection on the probability of a return or onward migration between 1983 and 1987. As the impact of job connections is expected to negatively affect the probability of both onward and return migration, I examine the impact of using job connections on the likelihood of experiencing a repeat migration within one year after relocating and within five years.

Table 2.7 reports the results of logit equations estimating the impact of several variables, including the job connection variable, on the probability of repeat migration. Column (1) of Table 2.7 reports the results of logit equations estimating the determinates of experiencing a remigration between 1982 and 1983 for migrants who migrated between 1980 and 1982. Consistent with other studies on remigration, very young migrants are more likely to experience a repeat migration very shortly after the initial move. None of the other control variables have a significant effect on experiencing a repeat migration in 1983, including the job contact variable, which is negative, as predicted, but insignificant due to the high error term. Column (2), repeats the analysis for the interval 1983-1987. Here again, the sign for the use of job contacts is negative, but insignificant.

Columns (3) and (4) of Table 2.7 repeat the analysis of columns (1) and (2), this time separating contacts by whether or not the contact was a relative. Now it is apparent that the negative effect for the use of job contacts on remigration is almost entirely due to the negative effect experienced by migrants who used a relative as their job contact. Using a relative as a job contact decreases the

Table 2.7: Probability a Migrant Experiences a Repeat Migration

	1983	1983-1987	1983	1983-1987
Variable	(1)	(2)	(3)	(4)
Migrant had job connection	-.28028 (.31676)	-.16538 (.29402)		
Contact was relative			-.33818 (.43973)	-.71562 (.40995)
Contact was not a relative			-.09442 (.35337)	.20856 (.34621)
Age	-.15366 (.09174)	-.05707 (.05707)	-.17700* (.08943)	-.07656 (.08520)
Education	.01512 (.07233)	-.03156 (.06571)	.01745 (.06906)	-.05968 (.06453)
Constant	2.1981 (1.7142)	2.1963 (1.6614)	2.9853 (1.7203)	3.3467 (1.6819)
Sample Size	206	214	206	214

probability of migrating again in both 1983 and the interval 1983-1987, although the effect is significant (at the 10% level) only in the interval 1983-1987. Thus it seems the negative effect of job contacts on remigration within five years is almost entirely due to the negative effect of using family members as job contacts, a finding consistent with previous findings that the presence of relatives in the area deters future migrations. There is no evidence here that using non-relative job contacts is a significant deterrent to migrating again within five years.

2.6 Summary and Conclusions

This chapter examines whether the use of job contacts impacts the rate at which migrants assimilate in their new labor markets. This chapter finds support for the theory that assimilation is a much more important process for migrants who did not use job contacts to find their first job in the new location. In particular, evidence from the wage growth regressions suggests that all of the higher wage growth experienced by migrants is attributable to migrants who did not use job contacts and that migrants without connections have greater wage growth after migration than those with connections. Overall, the evidence here suggests that job connections do help migrants assimilate into the new labor market.

That wages for young migrants who found their first job in the new location through formal means soon exceed those of migrants who used job connections suggests that migrants may be willing to accept lower wage prospects to locate in areas where they have existing social connections. The preference for locations where family members live is also evidenced by the lower probabilities of repeat migration for migrants who used a family member as a job contact. Another plausible reason migrants may be willing to accept lower wage prospects in areas with existing social connections is if the presence of social connections lower relocation costs for the migrant.

There are a number of interesting extensions to this study that could be

conducted with a larger sample of migrants in which the use of connections can be identified. Are job connections more important for some migrant groups? Does education diminish the importance of job contacts for migrants? Does higher job growth in the destination region affect the importance of job contacts for migrants? Are job connections more or less important for older migrants, minorities, or women? All of these pose interesting questions for future research on the role of social networks in internal migration.

CHAPTER 3

SOCIAL NETWORKS AND LABOR MOBILITY

3.1 Introduction

About one-half of all workers find their jobs through a friend or relative (Rees & Shultz, 1970; Granovetter, 1995). Despite this fact, there has been little investigation of the impact of personal contacts on worker mobility. In this chapter I argue that social networks increase worker mobility within the network by increasing the quality of information about workers within the network. I also show that networks reduce worker mobility outside the network, due to adverse selection.

In his classic paper on adverse selection in labor markets, Greenwald (1986) shows that information asymmetries in labor markets lead to wage penalties for job-changing workers. This adverse selection results from the monopoly employers have on information regarding the productivity of their employees. In this chapter I argue that networking – the ability of workers to network with other workers – decreases the wage penalty for changing jobs by allowing other employers to obtain information about workers' abilities. Yet networking lowers wages for workers in the formal market for job-changing workers. The resulting wage penalty may discourage workers from changing jobs in the formal market.

Several reasons may account for the pervasive use of social connections to find work. First, workers may rely on personal connections to obtain information about the characteristics about a job that are difficult to obtain in an interview. Such information would include the managerial style of supervisors, possibilities for promotion, and the attitude of co-workers toward women and minorities. Such information is difficult to obtain except by working in the specific job and can be used to reduce the probability of obtaining a bad job-worker match.

Second, employers also rely on personal connections to obtain information about potential applicants. In their survey of employers in the Chicago area, Miller and Rosenbaum (1997) found that employers distrust references from those the employer does not know. Employers generally discredit references provided by teachers and former employers, believing that teachers and employers do not have good incentives to provide reliable information. What employers do trust is information about applicants provided by those the employer knows, particularly their own employees, who generally desire good fellow employees and are well-informed about the personnel needs of the firm.

Much of the previous research on personal connections in labor markets has focused on the effect of connections on job-match quality. Generally, these studies have found evidence that personal connections improve job-worker matches. In his comprehensive study of job-changing workers in Newton, Massachusetts, Granovetter (1995) found that workers with jobs found through personal connections reported higher starting wages and greater job satisfaction. Both Staiger (1990) and Simon and Warner (1992) find that workers who found their job using social connections had higher starting wages and slower wage growth, suggesting that workers are better matched to these jobs. That personal connections may connect workers to more desirable jobs is also suggested by the finding that young unemployed workers are more likely to accept such job offers (Holzer, 1988).

To the best of my knowledge, the use of personal contacts to convey information about worker abilities is investigated only by Montgomery (1991). Montgomery develops a theoretical model with social matching to examine why employers may prefer hiring through old-boys networks. He finds that when good workers are more likely to be matched to other good workers, hiring through social connections results in higher wages for workers hired through personal connections and positive profits for the employer.

my interest here is the effect of information conveyed through personal connec-

tions (or networking) on adverse selection in labor markets. The model developed in this chapter is similar to the classic two-period adverse selection model developed by Greenwald (1986) except that workers are allowed to meet (or network) and learn one another's ability. In this model, workers of unknown productivity are hired by employers when young. During the first period of work: (1) employers discover the productivity of their workers and (2) workers have the opportunity to network with the workers at other firms. If the networking is successful, workers will have recommendations from employees at other firms. At the end of the first period of work, workers may seek other wage offers with different employers for the second period of work. Workers then either change jobs or remain with their current employer. They then work through the second period and retire at the end of the period. I find that networking increases the information about applicant productivity in the economy, decreasing the wage penalty for changing jobs. However, networking lowers the formal market wage for job-changing workers, discouraging workers from searching for work in the formal market.

3.2 Networking in a Two Period Model

3.2.1 Assumptions

To examine the effect of networking on worker mobility I adapt Greenwald's two period labor market model to include worker networking. The following assumptions are made about workers and firms:

Workers:

Workers are described by an ability measure, θ^i , where i denotes an index of workers $1, 2, \dots, N$ and θ is distributed on $[0,1]$. Workers are high-ability (H) with probability ρ and low-ability (L) with probability $1 - \rho$. Workers are observationally equivalent before hiring; employers observe productivity during the first period of work. Each worker works two periods, retiring at the end of the second

period of work.

At the end of the first period, workers may quit their jobs to accept another wage offer. The probability that a worker quits his or her job is described by q^i :

$$q^i = \begin{cases} \gamma & \text{if } z \leq y \\ 1 & \text{if } z > y \end{cases}$$

where z is the wage the worker will get if he or she quits and y is the wage the worker will get if he or she remains with the employer. This function indicates that any worker will quit if he or she will receive a higher wage by doing so. Otherwise, a worker may leave his or her employer with probability γ . As jobs are heterogeneous, some workers will be willing to quit even if they receive a lower wage by doing so.

Firms:

Each firm's profit is equal to $\sum_{i=1}^{n^f} \theta^i - w^i$, where n^f is the number of workers employed by firm f and w^i is the wage paid to worker i . There is free entry of firms.

At the end of period one, firms may make wage offers to other firms' employees. Employers can counter-offer wage offers from other firms. These counter-offers cannot be observed by other firms.

Networking:

During the first period, each worker networks with D employees of different firms.¹ During each of these networking opportunities, there is a probability $\tau \in [0, 1]$ that the worker's productivity is learned and a reference for work is created. For the sake of simplicity, I assume that referers observe the productivity of the referee perfectly. I assume that employees only refer workers if they have learned that the worker is high ability.

¹It is important to note here that we are assuming that *each* of these D networking contacts work for *different* firms. This assumption simplifies the probabilistic structure of the model significantly.

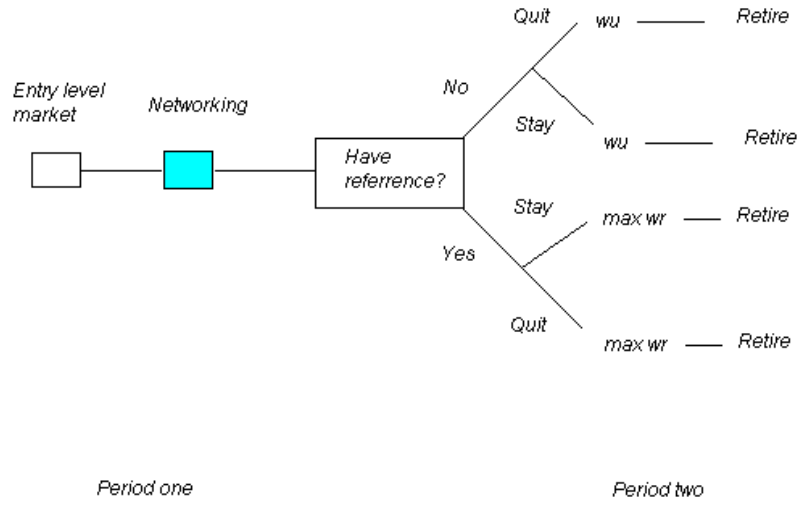


Figure 3.1: Timing of the Model

Timing:

The timing of the model is illustrated in Figure 1. At the beginning of period one, young workers are hired in a competitive market. During period one, young workers work for their employers and engage in networking with other workers. During this period, young workers also convey any information they learn about other workers while networking to their employers. At the end of period one, young workers seek wage offers from other employers. Other firms make wage offers to workers based on the information available to them. Employers then make counter-offers. Workers then either quit or stay with their employers according to the quit probability q^i . Workers then work throughout the second period and retire at the end of the period.

3.3 Results

Given the assumptions outlined above, the Nash equilibrium for wages in the second period is described by Proposition 1.

Proposition 1 *In equilibrium, second period wage offers for workers will be described by the following functions:*

Let g denote the firm that employs worker i . For firms $f \neq g$:

$$w^{if} = \begin{cases} w_r & \text{if } i \in R^f \\ w_U & \text{if } i \notin R^f \end{cases}$$

And the counter-offers of g are described by:

$$w^{ig} = \begin{cases} \max w^{if} & \text{if } i = H \\ 0 & \text{if } i = L \end{cases}$$

where w_r is a referral wage distributed on $[w_U, w_R]$, R^f is the set of workers who have been referred to firm f , w_U is the competitive wage for unreferred workers equal to $\frac{\alpha}{\alpha+1-\rho}$ and w_R is the maximum referred wage, equal to $1 - \frac{\alpha}{\rho}(1 - \frac{\alpha}{\alpha+1-\rho})$ where $\alpha = \rho\gamma(1 - \tau)^D$.

Proof:

The competitive wage for unreferred workers in period two will be a wage such that the expected profit from hiring an unreferred worker is zero. The expected profit from hiring an unreferred worker is

$$\begin{aligned} E(\pi_{w_U}) &= \gamma(1 - w_U) * \Pr(H \mid \text{unreferred}) \\ &\quad + \Pr(L \mid \text{unreferred}) * (0 - w_U) \end{aligned}$$

where the probability that an unreferred worker is high ability is:

$$\begin{aligned} \Pr(H \mid \text{unreferred}) &= N\rho(1 - \tau)^D / (N(1 - \rho) + N\rho(1 - \tau)^D) \\ &= \rho(1 - \tau)^D / (1 - \rho + \rho(1 - \tau)^D) \end{aligned}$$

and the probability that an unreferred worker is low ability is:

$$\begin{aligned}\Pr(L \mid \text{unreferred}) &= N(1 - \rho)/(N(1 - \rho) + N\rho(1 - \tau)^D) \\ &= (1 - \rho)/(1 - \rho + \rho(1 - \tau)^D)\end{aligned}$$

So:

$$E(\pi_{w_U}) = \frac{\alpha}{1 - \rho + \frac{\alpha}{\gamma}}(1 - w_U) - \frac{1 - \rho}{1 - \rho + \frac{\alpha}{\gamma}}w_U$$

where $\alpha = \rho\gamma(1 - \tau)^D$. Solving for w_U , I obtain,

$$w_U = \frac{\alpha}{\alpha + 1 - \rho}$$

Montgomery (1991) has shown that when the probability of a worker having more than one reference is less than one, wage offers to referred workers will be distributed on the interval $[w_U, w_R]$, such that the expected profit for each referred wage offer in the range is constant in equilibrium.

To find the maximum wage w_R offered to referred workers, I need to find the wage, w_R , such that $1 - c = w_R$, where $c = E(\pi_{w_r})$ in equilibrium.

$$\begin{aligned}E(\pi_{w_r}) &= \Pr \text{ worker accepts } w_r * (1 - w_r) \\ &= \Pr i \text{ receives no offer } w_g > w_r * \Pr i \text{ quits} * (1 - w_r)\end{aligned}$$

where

$$\begin{aligned}\Pr i \text{ receives no offer } w_g > w_r &= 1 - \Pi(\Pr i \text{ receives } w_g > w_r) \\ &= 1 - \Pi(\Pr i \text{ receives } w_g * \Pr w_g > w_r) \\ &= [1 - \tau[1 - F(w_r)]]^{D-1}\end{aligned}$$

and in equilibrium

$$E(\pi_{w_r}) = \gamma[1 - \tau[1 - F(w_r)]]^{D-1} * (1 - w_r) = c$$

To solve for c , substitute w_U for w_r .

$$c = \gamma[1 - \tau]^{D-1} * \left(1 - \frac{\alpha}{\alpha + 1 - \rho}\right)$$

and solving for w_R

$$\begin{aligned} w_R &= 1 - c \\ &= 1 - \frac{\alpha}{\rho} \left(1 - \frac{\alpha}{\alpha + 1 - \rho}\right) \end{aligned}$$

Finally, it needs to be shown that firm g will not deviate from the equilibrium strategy described above. To begin, I need to check whether firm g should deviate from the described strategy of counter-offers to the high-ability workers it employs. If g offers its high-ability workers $w^{ig} < \max w^{if}$, then it will lose its high-ability workers with probability one, giving it an expected profit of zero. If the employer firm offers its high-ability workers instead $w^{ig} > \max w^{if}$, then it still keeps its high-ability workers with probability γ , but its profit

$$\Pi(w^{ig} > \max w^{if}) = \gamma(1 - w^{ig})$$

is less than if the employer simply matches $\max w^{if}$. So firm g has no incentive to deviate from the stated equilibrium counter-offers to the firm's high-ability workers.

As for counter-offers to low-ability workers, if firm g deviates from the equilibrium strategy by offering a positive wage offer to a low-ability worker, the expected profit from such an offer is negative if the low-ability worker accepts the offer, and zero otherwise. So firm g cannot improve profits by deviating from this strategy. This completes the proof. ■

Because it is assumed that only high-ability workers can obtain references, older workers without references will generally be lower-ability workers. This adverse selection problem results in low wages for all workers without references, some of whom will be high-ability workers. Any increase in either the number of

social interactions, D , or the rate of learning, τ , increases the expected second period wage of referred workers and decreases the expected wage of unreferred workers.

The unreferred wage for experienced workers, w_U , can be thought of as the competitive market wage for unreferred workers. It is equal to the expected average ability of workers in the formal market. The average ability of job-changing workers in the formal market is an increasing function of the fraction of high-ability workers, ρ , and the turnover rate, γ . It is a decreasing function of both the amount of networking, D , and the rate of learning, τ .

Compared to classic adverse selection models, networking reduces the monopoly the employer has on information about the job changing worker. Other employers obtain information about the productivity of other firm's employees through their own employees, resulting in higher wage offers to those workers. The ability of workers to network, however, reduces the quality of job-changing workers in the formal market. Workers with references will be discouraged from accepting jobs in the formal market, due to the resulting loss of wages.

Proposition 2 *The first period competitive wage for workers will be:*

$$w_y^* = \rho + D\tau\rho c + \rho(1 - \gamma) [1 - E(\max w^{if})]$$

Proof: The zero profit condition means that $w_y^* =$ Expected productivity in period one + Expected profit from referrals the employee will provide in period one + Expected profit from retaining the worker in period two. Expected productivity of a worker in period one is ρ . The expected profit from referrals is equal to $D\tau\rho c$, where c is the equilibrium profit from making a referral offer, D is the number of contacts the worker will make and $\tau\rho$ is the probability that a reference is created.

The expected profit from retaining a worker in period two is equal to $\rho(1 - \gamma) [1 - E(\max w^{if})]$, where $E(\max w^{if})$ is the expected maximum wage offer that

an employer will have to match to retain an employee. That expected match offer is:

$$E(\max w^{if}) = \sum_{d=0}^D [p_d(D, \tau) * \int_{w_U}^{w_R} \frac{dF^d(w_r)}{dw_r} dw_r]$$

where $p_d(D, \tau)$ is the probability of obtaining exactly d references, $F(w_r)$ is the cumulative distribution of referral wages, and $\int_{w_U}^{w_R} \frac{dF^d(w_r)}{dw_r} dw_r$ is the expected maximum of d referral offers on $F(w_r)$. This concludes the proof. ■

Thus allowing workers to form references for work in later periods has both a downward and upward pull on wages for first period workers. Wages for first period workers will increase because of the expected profit that employers can obtain from references provided by the young worker at the end of period one. However, the possibility of that young worker also obtaining references for work lowers first period wages, by increasing the likelihood that the employer will have to make a higher match offer to retain a good worker in period two. The net effect on first period wages will be determined by the parameters of the model. However, it is to be expected that as the probability of obtaining multiple references increases, there will be downward pressure on first period wages, as shown in Proposition 3.

Proposition 3 *If $D \geq 2$, and $\tau \rightarrow 1$, then $w_y^* \rightarrow \rho$, $w_U \rightarrow 0$, and $F(w_r) \rightarrow 0 \forall w_r < 1$.*

Proof: First I need to show that the expected maximum offer for high-ability workers approaches 1 as $\tau \rightarrow 1$, or that,

$$(1) \lim_{\tau \rightarrow 1} E(\max w^{if}) = 1$$

It is easy to see that the probability that an high-ability worker receives no offers, $[1 - \tau]^D$, approaches zero as $\tau \rightarrow 1$. Similarly, it is also easy to see that the probability of obtaining exactly one offer, $\tau[1 - \tau]^{D-1}$, approaches zero as $\tau \rightarrow 1$.

Generalizing, as the rate of learning increases, the probability of obtaining exactly d references, $p_d(D, \tau)$ approaches zero, or:

$$(2) \lim_{\tau \rightarrow 1} p_d(D, \tau) = 0 \quad \forall d < D$$

We know that by definition:

$$(3) \sum_{d=0}^D p_d(D, \tau) = 1$$

(2) and (3) together imply (4):

$$(4) \lim_{\tau \rightarrow 1} p_D(D, \tau) = 1$$

(2) and (4) imply that

$$\lim_{\tau \rightarrow 1} E(\max w^{if}) = \lim_{\tau \rightarrow 1} \int_{w_U}^{w_R} w r \frac{dF^D(w_r)}{dw_r} dw_r$$

The next step is to show that

$$\lim_{\tau \rightarrow 1} \int_{w_U}^{w_R} w r \frac{dF^D(w_r)}{dw_r} dw_r = 1$$

We know that the cumulative density function $F(w_r)$ defined on the closed interval $[w_U, w_R]$ has the property that $F(w_r) < 1$ for all $w_r < w_R$ when $f(w_R) > 0$. Since $f(w_R) > 0$ by definition in the equilibrium, we know that as $\tau \rightarrow 1$, the corresponding function $F^D(w_r) \rightarrow 0$ for all $w_r < w_R$ and $F^D(w_R) \rightarrow 1$. Therefore:

$$\lim_{\tau \rightarrow 1} \frac{dF^D(w_r)}{dw_r} = \begin{cases} 0 & \text{for } w_r < w_R \\ \infty & \text{for } w_r = w_R \end{cases}$$

as the density of $\frac{dF^D(w_r)}{dw_r}$ becomes concentrated at w_R , and as $\tau \rightarrow 1$, $w_R \rightarrow 1$, these together imply that

$$\lim_{\tau \rightarrow \infty} \int_{w_U}^{w_R} w r \frac{dF^D(w_r)}{dw_r} dw_r = 1.$$

Now, to show that $w_y^* \rightarrow \rho$ as $\tau \rightarrow 1$, we only need to show that the expected profit from making a referral hire, c , approaches zero as D approaches infinity. The profit from making a referral hire, c is equal to:

$$c = \gamma[1 - \tau[1 - F(w_r)]]^{D-1}(1 - w_r)$$

As $\tau \rightarrow 1$, $F(w_r) \rightarrow 0 \forall w_r < 1$, eliminating the positive profit from referrals. Given this result and the result that the expected maximum offer for high-ability workers in period two approaches 1, we can conclude that $w_y^* \rightarrow \rho$ as $\tau \rightarrow 1$. This concludes the proof. ■

The intuition of the result is straightforward. As the rate of learning in the economy increases, the referral market for workers approaches a Bertrand outcome. Similarly, as $\tau \rightarrow 1$ wages for young workers fall to ρ , due to the decrease in expected profit from making a referral offer, c , and as $E(\max w^{if}) \rightarrow 1$ when $\tau \rightarrow 1$.

Thus, compared to Greenwald's result, networking lowers the competitive wage offered to young workers, by reducing the the expected profit from retaining a high-ability worker in period two. As more high-ability workers acquire references, the expected profit from retaining a high-ability worker approaches zero.

Proposition 4 *Compared to a labor market without networking, networking increases second-period wage offers for most workers with references and decreases the wage in the formal market.*

Proof: When no social network exists, period two wage offers for all workers in the no-networking market are

$$\begin{aligned} w_n^{if} &= \Pr(\theta^i = 1 | w_n^{if}, q^i) \\ &= \rho\gamma/\sigma \end{aligned}$$

where σ is the expected number of job-changing workers in the formal market and $\sigma = (1 - \rho) + \rho\gamma[1 - \tau]^D$. Since $\rho\gamma/\sigma > w_U = \rho\gamma[1 - \tau]^D/\sigma$, $w_n^{if} > w_U$.

To show that networking reduces the penalty for changing jobs for most high-ability workers, I need to examine the probability that any referred wage offer is greater than the second-hand wage no-networking market, which is equal to:

$$[1 - F(w_n^{if})] = -\frac{1}{\tau} \left[\left(\frac{1 - w_R}{1 - w_n^{if}} \right)^{\frac{1}{D-1}} - 1 \right]$$

where

$$\lim_{\tau \rightarrow 1} [1 - F(w_n^{if})] = 1 \quad \blacksquare$$

Allowing workers to network in an adverse selection model reduces the wage penalty for changing jobs for those workers who obtain references. However, networking reduces the average quality of job-changing workers in the formal market, reducing the formal market wage. Because networking reduces the formal market wage, some workers will receive $w_r < w_{nn}^{if}$. However the probability of receiving $w_r < w_{nn}^{if}$ falls to zero as $\tau \rightarrow 1$. Intuitively, this is because as the probability of high-ability workers acquiring references increases, $F(w_r) \rightarrow 0 \forall w_r < 1$.

3.4 Conclusions

This chapter examines how the widespread practice of networking affects worker mobility in a market with adverse selection. These results suggest that information transmitted by networking increases wage offers to high-ability job-changing workers. Thus references act to decrease the monopoly on information about work productivity in a market with adverse selection. This decreases the penalty for changing jobs, increasing job mobility. But networking also increases the adverse selection problem in formal markets, due to the number of high-ability workers captured in the informal market.

This adverse selection problem results in lower wages for workers changing jobs in the formal market, which would likely encourage workers to change jobs

using connections from their social networks. This result may explain why Granovetter (1995) found that as workers aged, their use of personal contacts to find work increased. Although it is likely that the number of professional contacts a worker makes increases throughout his or her lifetime, it may also be that these networks are used to avoid lower wage offers in the formal market due to the adverse selection problem in the market for job changing workers.

CHAPTER 4

HIRING THROUGH NETWORKS AS A MEANS OF SCREENING FOR WORKER ATTITUDES

4.1 Introduction

Approximately 50% of jobs are found through an applicant's social connections (Sheppard and Beliitsky, 1966; Rees and Shultz, 1970; U.S. Department of Labor, 1975; Staiger, 1990; Granovetter, 1995). Employers rely on social connections to obtain better information about the applicant than is available in the formal job market. They also have more confidence in information that comes from a known source. "When (an employee) recommend(s) somebody, they understand that they're putting their name and character on the line," stated one employer interviewed in a study on employer attitudes by Miller and Rosenbaum (1997).

Is hiring on the basis of 'who you know' rather than 'what you know' truly beneficial for employers? Given all the varied and readily available information about applicants in the formal market – education, skill certifications, work history, etc. – why do employers continue to rely so heavily on information from people they know? And given that most firms (as well as workers) use a mix of formal and informal methods in the job search – what determines which mix of methods is used?

Much of the previous work on social networks in labor markets has focused on how information from social networks can reduce uncertainty about employee productivity. In particular, models have focused on using networks to hire people of higher ability (Montgomery, 1991) or those better matched to the job (Simon & Warner, 1992; Staiger, 1991). In both cases, information about worker produc-

tivity is missing or incomplete, with employers using networks to acquire better information about applicants. This chapter is in a similar vein, but expands these existing theories by examining more specifically what worker characteristics are screened through social networks.

Specifically, I will argue that networks are used to screen for desirable worker traits *that are poorly signaled* in the formal job market. In particular, while the formal market is quite good at signalling worker skills – education, worker training programs, and skill certifications – the formal job market is a very poor provider of other information desired by employers, such as worker reliability, willingness to follow direction, attitude, and trustworthiness. In the formal market, employers must acquire a taste for these characteristics in an interview, a notoriously difficult task.¹ Yet a discussion with a person who knows the applicant personally can reveal much about an applicant’s character and attitude on the job.

That networks are used to acquire information about these softer worker characteristics is suggested by one of the more surprising facts in the personnel literature, that social networks are more pervasively used by unskilled and semi-skilled workers to find work. Although we typically think of networking as a white collar phenomenon, the truth is that unskilled workers are much more likely to find jobs through a personal connection. Rees and Shultz (1970), for example, found that 85% of manufacturing workers are hired through someone they know, compared to 30% of accountants. Staiger (1990) also found that more educated workers were less likely to have found their last job through a social connection. Even among professional workers, managers, whose jobs involve overseeing workers or heading project teams, rely more on personal connections in the job search than do technical workers such as computer programmers (Granovetter, 1995). It appears that the more dependent job performance is on softer skills that are difficult

¹An employer in Miller and Rosenbaum’s study stated the thoughts of many on this topic, “If a person has any skill at all, in being deceptive or a good actor, you can learn next to nothing in an interview.”

to assess in the formal market, the more likely it is that workers found their job through someone they know.

Why would information about attitude and character be so important to employers? A likely reason is that the workplace itself functions as a social unit. Few jobs do not involve cooperation with management, other workers, and staff. Joint work requires that workers share tasks, follow direction from management, communicate with one another, and shoulder their share of the work. Hiring through employee social networks may minimize the risk of hiring a ‘bad apple’ who will disrupt a well-functioning firm. Thus hiring through social networks may increase profits for the firm by helping the firm to maximize joint output.

This paper examines whether the need of the firm to work together can explain why firms hire through social networks, using a simulation approach. In this model, workers are assumed to have two attributes that relate to productivity: ‘skill’, which is observable, and ‘character’ which is not. Workers with poor character do not work well with others, do not follow orders well, and produce little in the way of joint output. While character cannot be directly observed, some information about an applicant’s character can be obtained if the applicant is connected to the employer’s social network

The results of these simulations suggest that employers use a mix of formal and informal search strategies that maximize the returns to search. Jobs where output is largely dependent on worker skill profit best from a mix of strategies which combines network hiring with skill requirements. Jobs where output is largely dependent on softer traits do best under a hiring system that hires members of the network without regard to ability. This mirrors observed patterns in choice of formal/informal search mix across different industries. Examination of the returns to skill under different hiring strategies suggest that differences in returns to skill between whites and minority workers may be less in industries that depend more heavily on formal methods in their recruitment.

4.2 Methodology

I will analyze the effect of hiring through social networks on firm output using a labor market simulation with a team-style firm architecture. Each firm consists of a six-employee team, where each worker working independently produces a output equal the individual's ability level. Individual firm members can also choose to form coalitions with other members, increasing their joint productivity. Individual employees form these coalitions according to the costs and benefits of each coalition. Some workers are difficult to work with, discouraging collaborative work. While worker's skill is assumed to be observed perfectly in the marketplace, whether a worker works well with others (i.e. is a low or high cost connector) is unobserved. However, employers can obtain some information about whether applicants work well with others through social networks.

Workers

There are N workers in the economy. At the start of the simulation, each worker is assigned an ability score $a_i \in [0, 1]$ and a social connection cost c_i , where the connection cost is either low or high.² This connection cost can be thought of as an 'attitude' measure, capturing how well the worker gives/follows direction and works with others. Workers with high connection costs are difficult to work with, do not take direction well and workers with low connection costs work with others and follow direction rather well. I assume that a_i is observable, and that c_i is not. However, c_i is observed by the firm after the first period of work.

Firms

There are $N/6$ firms. The architecture of each firm is shown in Figure 4.1. Each firm has six positions and six employees.

The output of each firm y^f is equal to:

$$y^f = \sum_{i \in f} a_i + \sum_{i, j \in f} l^{ij}$$

²In the simulations in this paper, connection costs are set at 0.1 for low and 0.4 for high.

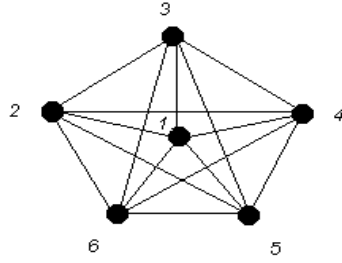


Figure 4.1: A Completely Networked Firm

where l^{ij} is the productivity of joint work resulting from a link between workers i and j at firm f , equal to:

$$l^{ij} = a_i * a_j$$

Profits are shared among the workers at firm f according to a profit sharing rule where each worker obtains his or her contribution to the firm output at the end of each period. The surplus from the formation of each link is shared according to a rule where each worker receives a percentage of the joint output equal to their share in its production. Thus at the end of each period each worker i at firm f receives:

$$a_i + \sum_{j \in T^i} \frac{a_i}{a_i + a_j} l^{ij}$$

where T^i is the set of individuals linked to i at work.³

Networks within the Firm

Once hired, workers can form links with any other workers at the firm. I assume that a link is formed between two workers only if both mutually agree to

³For the sake of simplicity, I am assuming that the joint output depends only on the productivity resulting from direct links between workers. A more complicated model could have joint output resulting from indirect links as well.

form the link, or, if the net benefit to both parties forming the link is positive. Therefore a link is formed between adjacent workers i and j if:

$$\frac{a_i}{a_i + a_j} l^{ij} - c^j \geq 0$$

and

$$\frac{a_j}{a_i + a_j} l^{ij} - c^i \geq 0$$

If either condition is not met, the link is not formed.

Vacancies and Job Search

Workers are assigned a random job at the start of the simulation. At the beginning of each period, x workers die, creating x vacancies, and x workers are born who are unemployed. Newly born workers are assigned up to y social ties to workers in the existing workforce.

These ties are assigned such that, given that the tie exists, the probability of two workers being connected to each other is μ if both workers are of the same connection type, and $(1 - \mu)$ if they are of different connection types, where $\mu > 1/2$. Thus, social ties are assigned such that workers with good attitudes who work well with others are more likely to know other workers with good attitudes who work well with others.

Firms then rank workers according to a_i and whether or not the worker is referred by a low connection cost worker. Referred workers are hired first. Unemployed workers rank potential employers according to the only information available to them, the observed $\sum l^{ij}$ of the firm in the last period. Unemployed workers are then assigned to vacancies and work throughout the period.

4.3 Results

4.3.1 Is hiring through an old boy network advantageous for the firm?

Following the intuition that workers are more likely to recommend applicants who will work well with the existing firm staff, I examine whether the need for collaboration in production might explain employer's preference to hire through social connections with the following experiment. In this experiment, firm output is compared under three types of hiring structures. In the first, the No Network Hiring simulation, workers are ranked only by their observable qualifications for the job. In the second set of simulations, the Pure Old Boy Network simulations, members of the network are given first priority in hiring, *regardless* of ability. The third set of simulations, Old Boy Network With Skill Requirements, is similar to the strict network simulation, except that there is a skill requirement. In this simulation, applicants referred through the old boy's network must have an ability at least as high as the average applicant in the pool to get preference in hiring.

Table 4.1 reports the results of 500 simulations, excluding the first 100 results, with the model parameters set at: $N = 90$, $x = 5$, $y = 10$, and $\mu = .8$. Low connection cost is set at 0.1 and high connection cost is set at 0.4. These parameters mean that most low cost workers will form connections with one another, but few workers will be willing to work with high cost workers. The results of these simulations suggest that when firm output is produced cooperatively, hiring through personal connections is advantageous to the firm *even in the case where the applicants referred through the network are less skilled*. Comparing the maximum firm output in the simulations with no network hiring and with pure network hiring reported in columns 1 and 2 of Table 4.1, the maximum firm output almost twice as great in the pure network hiring simulation, in spite of the fact that the average skill of a network hire is lower. Not surprisingly, network hiring is associated with

Table 4.1: Means

Means (over 500 simulations)	No Network Hiring	Old Boy Network	Network w/Skill Restrictions
Max firm output	5.73	10.00	12.28
Min firm output	2.16	1.43	1.18
Average ability			
– of network hire	n/a	.46	.72
– of formal hire	.50	.52	.47
Average connection cost			
– of network hire	n/a	.17	.16
– of formal hire	.25	.29	.26
Ave. % network hires	0	45%	13%

even greater output when firm use network hiring with skill restrictions, with the highest average firm output more than twice as large as in the simulation with no network hiring.

4.3.2 The relative importance of skill and the returns to different formal/informal search mix

If finding workers who's personalities and attitudes work well with the existing staff is a primary objective when seeking applicants through social networks, it seems likely that the returns to informal search would be sensitive to the portion of the job description that involves working with others. In some industries, productivity on the job is highly sensitive to the ability to work well with others. In others, such as computer programing, output is more sensitive to a specific set of skills and training. If formal and informal channels convey different types of information about applicants, the best mix of job search strategies is likely to be

Table 4.2: Returns to Different Informal/Formal Search Mix

Returns to Hiring Strategies	No Network Hiring	Old Boy Network	Network w/Skill Restrictions
Mean output of top 5 firms			
– 8% total output is joint	4.95	5.21	5.72
– 45% total output is joint	4.36	5.05	6.11
– 95% total output is joint	2.81	5.52	5.31
Ave. % hired through networks			
at top 5 producing firms	0%	45%	18%

sensitive to the type of position that needs to be filled. To see how sensitive the returns of hiring through social networks are on the relative importance of skill on the job, I next experiment with changing the weights on the importance of individual skill and joint output in the firm production function.

Table 4.2 reports the returns to different hiring strategies under different assumptions of the importance of joint work in the firm’s production function. In these simulations, weights are attached to worker skill and joint output and altered such that firms with different reliance on ‘character’ in the firm production function are compared. In the first set of simulations, a weight of 0.5 is placed on joint output and 1.5 on skill, resulting in an average of 8% of total firm output resulting from joint collaboration. This is analogous to a firm where most of the output consists of individual members working independently from one another, a workplace where output is highly dependent on worker skill and less dependent on collaborative effort or highly managed tasks. Examples of such jobs would be computer programming, accounting, typing, scientific work, and engineering.

In the second set of simulations, weights of 1 and 1 are placed on skill and joint work, resulting in a production function where 45% of total output on average results from collaborative, or joint work. The last set of simulations, with a weight

of 2 on character and 0.1 on skill, results in an average of 95% of total output resulting from collaborative work. This corresponds to semi-skilled or unskilled work, professions and firms that depend heavily on character in their production function, either because the management style of the firm requires a cooperative staff that follows orders extremely well or because the firm requires other skills that are not easily signalled in the formal job market for workers.

In all scenarios, both hiring mixes involving network hiring outperform hiring on the basis of credentials only, even in the case where less than 10% of output is produced jointly. This may help explain the prevalence of hiring through social connections even among skilled jobs. In most cases, a system of using a mix of network recommendations and skill requirements outperforms hiring through a pure old boy's network, even though fewer network hires are made under this hiring strategy. The only case where the pure old boy's network dominates is when only the smallest fraction of firm output depends on worker skill, and even in this case, the advantage is slight.

The results of these simulations suggest that the return to hiring through social networks is highest in professions and firms that depend heavily on character in their production function, either because the management style of the firm requires a cooperative staff that follows orders extremely well or because the firm requires other skills that are not easily signalled in the formal job market for workers. This may help to explain why semi-skilled manufacturing workers (whose output is largely dependent on the ability to follow the direction of supervisors and be reliable) are the most likely to be hired through social networks, while technical workers (whose output is much more sensitive to a specific set of skills that can be signalled through education and training) are much less likely to be hired through social networks. Thus firms may choose a mix of informal and formal hiring strategies that maximizes the return to search for a given job description.

4.3.3 Discrimination in networks and the return to skill

Although hiring through social networks may have high returns for employers, one drawback from the perspective of applicants is that hiring through social networks tends to benefit the well connected at the expense of the less connected. This is of particular concern to those workers who are unlikely to be recommended by employees at the firm not because they have a reputation for poor work, but because they are of a different race or gender than those who are making recommendations. Lack of access to these networks can effectively bar many jobs to workers not in the network.

To see how the returns to skill to different groups may differ when there is discrimination in the network, I perform the following experiment. Two groups are introduced into the simulation described in the previous section, Group A and Group B. For the first 100 simulations, there are only Group A workers in the labor force. Thus Group A workers are given a monopoly on the highest paying jobs in the market. After 100 simulations, 15% of new workers introduced into the labor market are Group B workers. Worker recommendations are established much the same as before, however, workers of different groups are much less likely to ‘meet’ one another, drastically lowering the probability of connections forming between members of different groups.

Table 4.3 compares the results for Group A and Group B during the first 50 simulations after Group B is introduced. The average return to skill is the average wage for a low-cost connector in that group, divided by that worker’s skill. As can be seen in Table 4.3, hiring through a pure old boy network effectively bars many positions at the highest paying firms from Group B. Overall, a low connection cost worker from Group B has on average a 41% lower return to skill than a low connection cost worker in Group A. The difference in return to skill is much less, however, when firms use a mix of formal and informal strategies when hiring workers. The results for simulations where referred workers are hired first

Table 4.3: Effects of Discrimination

Ave. over 10 runs of 150 simulations	Group A	Group B
Pure Old Boy Network		
– % hired through personal connections	45%	5%
– average return to skill	5.358	3.776
– % difference in returns to skill		-40%
Network Hiring w/Skill Restrictions		
– % hired through personal connections	21%	3%
– average return to skill	4.129	3.753
– % difference in returns to skill		-10%

only if they are at least as able as the average applicant show a marked decrease in the difference in the return to skill between groups. In these simulations, Group B has a return to skill only 10% less than that of Group A. These results suggest that the wage difference between minority workers and whites should be less in professions that rely more on skill screening than network hiring.

4.4 Conclusions

Although several studies have examined why employers might use social networks as a mechanism for screening workers, no studies have tackled the question of why the use of social connections in hiring varies across professions and occupations. In this study, I have explored the idea that social networks are used largely to screen for character, worker reliability, and ability to follow orders – traits which the formal market for workers provides little information. These traits desired by employers because of the need for workers to work together on output, to follow orders and take direction. The results of these simulations suggest that employers use a mix of formal and informal search strategies that maximize the returns to search. Firms where output is largely dependent are

worker skill profit best from a mix of strategies that combines network hiring with skill requirements. Jobs where output is largely dependent on softer traits do best under a hiring system that hires members of the network without regard to skill. These results may explain why personal connections are more important in the job search of less-skilled workers, whose productivity is largely determined by traits that are difficult to observe in the formal market.

When networks are biased in such a way that members of minority groups are excluded from the social network of employees at the highest-paying firms, the returns to skill for minority workers are substantially lower. However, differences in returns to skill between whites and minority workers may be less in industries that depend more heavily on formal methods in their recruitment. These results suggest that discrimination in education among minority students may be doing them a double harm. By providing minority students with a lower quality education it not only decreases their human capital but may also deny them access to skilled industries where the lack powerful social networks may not be as great an impediment to their job searches. Future research in this area should examine whether the wage gap between whites and minorities is less in industries that use a lower mix of network hiring in their search.

CHAPTER 5

APPENDIX A: SIMULATION PROGRAM CODE

The following pages describe the Matlab code used to obtain the simulation results described in Chapter 4 of this dissertation. The particular example provided here produces the results of the Networks with Restrictions hiring simulations. Other programs are similar and are available from the author.

```

%*****Simulation Networks with Limitations*****
clear
%*****(1) initial parameters *****
T=500; %T is the number of simulations
N=90; %N is the number of workers. Must be multiple of 6
I=[1:N]; %I is the matrix of workers
ex=5; %determines the number of vacancies created each period.
why=10; %determines the number of possible kinship links.
low=.1; %low = low connection cost; high = high connections cost
high=.8;
rho=.5; %rho is the fraction of low cost people in the population
alpha=.8; %alpha is network bias (the probability that like costs are kin)
sigma=.1; %weight on skill in firm output
psi=2; %weight on teamwork in firm output (sigma and psi must sum to 2)
ability=rand(1,N); %assigns uniformly distributed abilities.
cost=rand(1,N); %assigns uniformly distributed random numbers.
E=N/6; %E is the number of firms/employers
%***ccost: (1xN) matrix of connection costs
n=0;
for i=1:N
n=n+1;
if cost(:,n)<=rho;
ccost(:,n)=low;
else
ccost(:,n)=high;
end;
end;
%***Job_i, Job_a, Job_c: Job matrices *****
k=0;
m=1;
n=6;
for i=1:E
k=k+1;
Job_i(k,:)=I(m:n); %creates a Ex6 matrix of which workers hold what jobs
Job_a(k,:)=ability(m:n); %creates a Ex6 matrix of abilities held in each job
Job_c(k,:)=ccost(m:n); %creates a Ex6 matrix of ccosts held in each job
m=m+6;
n=n+6;
end
%***** Begin simulations *****
t=0;
for i=1:T
t=t+1;
%***links are formed and initial output is produced *****
%connect_out: matrix of cooperative output *****
k=0;

```

```

for i=1:E
k=k+1;
%connection 1 between individuals in job 1 and job 2
if psi*Job_a(k,1)* Job_a(k,2)*(Job_a(k,1)/(Job_a(k,1)+ Job_a(k,2)))-
Job_c(k,2)>=0&psi*Job_a(k,1)* Job_a(k,2)*(Job_a(k,2)/(Job_a(k,1)+
Job_a(k,2)))-Job_c(k,1)>=0
connect_out(1,k)=psi*Job_a(k,1)* Job_a(k,2);
else
connect_out(1,k)=0;
end
%connection 2 between individuals in job 1 and job 3
if psi*Job_a(k,1)* Job_a(k,3)*(Job_a(k,1)/(Job_a(k,1)+ Job_a(k,3)))-
Job_c(k,3)>=0&psi*Job_a(k,1)* Job_a(k,3)*(Job_a(k,3)/(Job_a(k,1)+
Job_a(k,3)))-Job_c(k,1)>=0
connect_out(2,k)=psi*Job_a(k,1)* Job_a(k,3);
else
connect_out(2,k)=0;
end
%connection 3 between individuals in job 1 and job 4
if psi*Job_a(k,1)* Job_a(k,4)*(Job_a(k,1)/(Job_a(k,1)+ Job_a(k,4)))-
Job_c(k,4)>=0&psi*Job_a(k,1)* Job_a(k,4)*(Job_a(k,4)/(Job_a(k,1)+
Job_a(k,4)))-Job_c(k,1)>=0
connect_out(3,k)=psi*Job_a(k,1)* Job_a(k,4);
else
connect_out(3,k)=0;
end
%connection 4 between individuals in job 1 and job 5
if psi*Job_a(k,1)* Job_a(k,5)*(Job_a(k,1)/(Job_a(k,1)+ Job_a(k,5)))-
Job_c(k,5)>=0&psi*Job_a(k,1)* Job_a(k,5)*(Job_a(k,5)/(Job_a(k,1)+
Job_a(k,5)))-Job_c(k,1)>=0
connect_out(4,k)=psi*Job_a(k,1)* Job_a(k,5);
else
connect_out(4,k)=0;
end
%connection 5 between individuals in job 1 and job 6
if psi*Job_a(k,1)* Job_a(k,6)*(Job_a(k,1)/(Job_a(k,1)+ Job_a(k,6)))-
Job_c(k,6)>=0&psi*Job_a(k,1)*Job_a(k,6)*(Job_a(k,6)/(Job_a(k,1)+
Job_a(k,6)))-Job_c(k,1)>=0
connect_out(5,k)=psi*Job_a(k,1)* Job_a(k,6);
else
connect_out(5,k)=0;
end
%connection 6 between individuals in job 2 and job 3
if psi*Job_a(k,2)* Job_a(k,3)*(Job_a(k,2)/(Job_a(k,2)+ Job_a(k,3)))-
Job_c(k,3)>=0&psi*Job_a(k,2)* Job_a(k,3)*(Job_a(k,3)/(Job_a(k,2)+
Job_a(k,3)))-Job_c(k,2)>=0

```

```

connect_out(6,k)=psi*Job_a(k,2)* Job_a(k,3);
else
connect_out(6,k)=0;
end
%connection 7 between individuals in job 3 and job 4
if psi*Job_a(k,4)* Job_a(k,3)*(Job_a(k,4)/(Job_a(k,4)+ Job_a(k,3)))-
Job_c(k,3)>=0&psi*Job_a(k,4)* Job_a(k,3)*(Job_a(k,3)/(Job_a(k,4)+
Job_a(k,3)))-Job_c(k,4)>=0
connect_out(7,k)=psi*Job_a(k,4)* Job_a(k,3);
else
connect_out(7,k)=0;
end
%connection 8 between individuals in job 4 and job 5
if psi*Job_a(k,4)* Job_a(k,5)*(Job_a(k,4)/(Job_a(k,4)+ Job_a(k,5)))-
Job_c(k,5)>=0&psi*Job_a(k,4)* Job_a(k,5)*(Job_a(k,5)/(Job_a(k,4)+
Job_a(k,5)))-Job_c(k,4)>=0
connect_out(8,k)=psi*Job_a(k,4)* Job_a(k,5);
else
connect_out(8,k)=0;
end
%connection 9 between individuals in job 5 and job 6
if psi*Job_a(k,6)* Job_a(k,5)*(Job_a(k,6)/(Job_a(k,6)+ Job_a(k,5)))-
Job_c(k,5)>=0&psi*Job_a(k,6)* Job_a(k,5)*(Job_a(k,5)/(Job_a(k,6)+
Job_a(k,5)))-Job_c(k,6)>=0
connect_out(9,k)=psi*Job_a(k,6)* Job_a(k,5);
else
connect_out(9,k)=0;
end
%connection 10 between individuals in job 2 and job 6
if psi*Job_a(k,6)* Job_a(k,2)*(Job_a(k,6)/(Job_a(k,6)+ Job_a(k,2)))-
Job_c(k,2)>=0&psi*Job_a(k,6)* Job_a(k,2)*(Job_a(k,2)/(Job_a(k,6)+
Job_a(k,2)))-Job_c(k,6)>=0
connect_out(10,k)=psi*Job_a(k,6)* Job_a(k,2);
else
connect_out(10,k)=0;
end
%connection 11 between individuals in job 2 and job 4
if psi*Job_a(k,4)* Job_a(k,2)*(Job_a(k,4)/(Job_a(k,4)+ Job_a(k,2)))-
Job_c(k,2)>=0&psi*Job_a(k,4)* Job_a(k,2)*(Job_a(k,2)/(Job_a(k,4)+
Job_a(k,2)))-Job_c(k,4)>=0
connect_out(11,k)=psi*Job_a(k,4)* Job_a(k,2);
else
connect_out(11,k)=0;
end
%connection 12 between individuals in job 5 and job 3
if psi*Job_a(k,3)* Job_a(k,5)*(Job_a(k,3)/(Job_a(k,3)+ Job_a(k,5)))-

```

```

Job_c(k,5)>=0&psi*Job_a(k,3)* Job_a(k,5)*(Job_a(k,5)/(Job_a(k,3)+
Job_a(k,5)))-Job_c(k,3)>=0
connect_out(12,k)=psi*Job_a(k,3)* Job_a(k,5);
else
connect_out(12,k)=0;
end
%connection 13 between individuals in job 4 and job 6
if psi*Job_a(k,6)* Job_a(k,4)*(Job_a(k,6)/(Job_a(k,6)+ Job_a(k,4)))-
Job_c(k,4)>=0&psi*Job_a(k,6)* Job_a(k,4)*(Job_a(k,4)/(Job_a(k,6)+
Job_a(k,4)))-Job_c(k,6)>=0
connect_out(13,k)=psi*Job_a(k,6)* Job_a(k,4);
else
connect_out(13,k)=0;
end
%connection 14 between individuals in job 5 and job 2
if psi*Job_a(k,2)* Job_a(k,5)*(Job_a(k,2)/(Job_a(k,2)+ Job_a(k,5)))-
Job_c(k,5)>=0&psi*Job_a(k,2)* Job_a(k,5)*(Job_a(k,5)/(Job_a(k,2)+
Job_a(k,5)))-Job_c(k,2)>=0
connect_out(14,k)=psi*Job_a(k,2)* Job_a(k,5);
else
connect_out(14,k)=0;
end
%connection 15 between individuals in job 3 and job 6
if psi*Job_a(k,6)* Job_a(k,3)*(Job_a(k,6)/(Job_a(k,6)+ Job_a(k,3)))-
Job_c(k,3)>=0&psi*Job_a(k,6)* Job_a(k,3)*(Job_a(k,3)/(Job_a(k,6)+
Job_a(k,3)))-Job_c(k,6)>=0
connect_out(15,k)=psi*Job_a(k,6)* Job_a(k,3);
else
connect_out(15,k)=0;
end
end
sum_I_out=sigma*sum(Job_a');
total_team_output=sum(connect_out);
total_output=total_team_output+sum_I_out;
%****Create vacancies ****
death_lotto=randperm(N);
die=death_lotto(:,1:ex); %chooses the first x workers to die
borna=rand(1,ex); %assigns random ability and cost
n=0;
for i=1:ex
n=n+1;
if rand<=rho %this loop assigns connection cost to
bornc(:,n)=low; %those just born.
else
bornc(:,n)=high;
end
end

```

```

end
n=0;
for i=1:ex %for loop assigns newborn's ability and
n=n+1; %costs into the ability and ccost matrices
ability(:,die(:,n))=borna(:,n);
ccost(:,die(:,n))=bornc(:,n);
end
n=0; %empvac: Xx1 column vector of emps with vacs
for i=1:ex %posvac: Xx1 column vector of positions vac
n=n+1;
[empvac(n,:),posvac(n,:)]=find(Job_i==die(:,n));
end
n=0; %this code creates 'allhires' (TxE)
for i=1:E %which counts how many hires firm e
n=n+1; %makes in each simulation
mark=find(empvac==n);
if isempty(mark)==1
allhires(t,n)=0;
else
allhires(t,n)=length(mark);
end
end
end
% ****Create kinship networks ****
% ****poskin: possible kin; empkin: employers of kin****
% **** empgreet: column vector of employers of possible kin**
I_spared=setdiff(I,die); %I_spared: set of workers still alive
poskin=zeros(ex,why);
empkin=zeros(ex,why);
%kin ties are established such that no new worker is tied to another
%new worker and that no new worker has more than one tie with each
%employer (the later to keep the probabilistic structure simple).
n=0;
for i=1:ex
n=n+1; %n is the new worker index (rows)
m=1; %m is the index moving through greetorder
k=1; %k is the kin index
greetorder=randperm(N);
while k<=why
[empgreet,posgreet]=find(Job_i==greetorder(:,m));
if ismember(greetorder(:,m),I_spared)==1 &
ismember(empgreet,empkin(n,:))==0
poskin(n,k)=greetorder(:,m);
empkin(n,k)=empgreet;
k=k+1;
m=m+1;
else

```

```

m=m+1;
end
end
end
%****kin: a (XxY) matrix of kinship ties between old and new workers****
%the following loop assigns actual kin such that if a tie exists, the probability of a new
%worker being the same connection cost as their reference is equal to alpha.
n=0;
for i=1:ex
n=n+1; %n new worker index
m=0; %m poskin index
for i=1:why
m=m+1;
k=rand(1);
if k<=alpha & bornc(:,n)==ccost(:,poskin(n,m));
kin(n,m)=poskin(n,m);
elseif k>alpha & bornc(:,n)~=ccost(:,poskin(n,m));
kin(n,m)=poskin(n,m);
else
kin(n,m)=0;
end
end
end
%****Firms estimate connection cost of applicants*****
%**ref: [vac1ref1,vac1ref2...vac1refx;vac2ref1,vac2ref2....etc]*****
%a (XxX) matrix of which workers are referred for each vacancies.***
sum_borna=sum(borna);
borna_ave=sum_borna/ex;
n=0;
for i=1:ex
n=n+1;
m=0; %n=vacancy index (rows)
for i=1:ex
m=m+1; %m=worker index (columns)
y=intersect(kin(m,:),Job_i(empvac(n,:),:));
if isempty(y)==0 & ccost(:,y)==low & borna(:,m)>=borna_ave
ref(n,m)=die(:,m);
else
ref(n,m)=0;
end
end
end
%***Firms rank workers *****
rank_i=zeros(ex,ex);
n=0;
for i=1:ex

```

```

n=n+1; %n is vacancy index
r=nnz(ref(n,:)); %r is the # of referred workers to vac n
if r>0 %if there are any referred workers for vac n
l=0;
clear referred
clear refn
referred=find(ref(n,:));
for i=1:r
l=l+1;
refn=ref(n,referred(:,l)); %refn: workers referred to vac n
end
else
refn=[0];
end
noref=setdiff(die,refn); %noref is the set of i in die not ref. to vac n
m=0;
for i=1:ex
m=m+1; %m is worker index
noref_remain=setdiff(noref, rank_i(n,:)); % "norefremain"=set of unranked unref i
ref_remain=setdiff(refn, rank_i(n,:)); % "ref_remain"=set of unranked ref i
if isempty(ref_remain)==0
k=0;
clear ref_remain_a
for i=1:length(ref_remain);
k=k+1;
ref_remain_a(:,k)=ability(:,ref_remain(:,k));
%creates a 1x_ vector listing abilities of those referred
%who are not yet ranked
end
j=max(ref_remain_a);
p=find(ref_remain_a==j);
rank_i(n,m)=ref_remain(:,p);
else
k=0;
clear noref_remain_a;
for i=1:length(noref_remain)
k=k+1;
noref_remain_a(:,k)=ability(:,noref_remain(:,k));
end
j=max(noref_remain_a);
p=find(noref_remain_a==j);
rank_i(n,m)=noref_remain(:,p);
end
end
end
%*****Workers are assigned to jobs *****

```

```

unique_empvac=unique(empvac);
num_empvac=length(unique_empvac); %number of employers hiring this round
firm_order=zeros(1,num_empvac);
%***this loop creates 'firm_order':the order firms will make offers****
clear remaining_vac
n=0;
for i=1:num_empvac
n=n+1;
m=0;
clear re_out
clear y
clear z
remaining_vac=setdiff(unique_empvac,firm_order);
%the set of employers not yet ranked
for i=1:length(remaining_vac)
m=m+1;
re_out(:,m)=total_team_output(:,remaining_vac(:,m));
end
y=max(re_out);
z=find(re_out==y);
if y>0
firm_order(:,n)=remaining_vac(:,z(:,1));
else
lotto2=rand(1,length(z));
%this randomizes the order workers are
%assigned to firms that had no joint output last period
y2=max(lotto2);
z2=find(lotto2==y2);
firm_order(:,n)=remaining_vac(:,z(:,z2));
end
end
%***Place new workers in their new jobs *****
newemp=zeros(1,ex);
n=0;
m=1;
l=1; %l is newemp index
for i=1:num_empvac
n=n+1; %n is employer index
clear g
clear firmpos
g=find(empvac==firm_order(:,n));
%gives column vector of indices where firm n has vac
clear firmpos
k=0;
for i=1:length(g)
k=k+1;

```

```

firmpos(:,k)=posvac(g(k,:),:);
%lists the position openings at firm n
end
yy=sort(firmpos);
m=1;
k=1;
while m<=length(g)
isstill=intersect(rank_i(g(1,:),k),newemp);
if isempty(isstill)==1 %if kth ranked person is still unemp
Job_i(firm_order(:,n),yy(:,m))=rank_i(g(1,:),k);
newemp(:,l)=rank_i(g(1,:),k);
m=m+1;
k=k+1;
l=l+1;
else
k=k+1;
end
end
end
%**** New worker abilities and ccost are assigned to jobs **
l=0; %l is employer index
k=0; %m is position index; k is worker index
for i=1:E
l=l+1;
m=0;
for i=1:6
m=m+1;
k=k+1;
Job_a(l,m)=ability(:,Job_i(l,m));
Job_c(l,m)=ccost(:,Job_i(l,m));
end
end
%***** Collect information on network and non-network hires *****
n=0;
for i=1:E
n=n+1;
mark2=find(empvac==n);
if isempty(mark2)==1; %if firm n had no vacancies this period
networkhires(t,n)=0;
else
refhires=intersect(Job_i(n,:),ref(mark2(1,1),:));
if isempty(refhires)==1
networkhires(t,n)=0;
else
networkhires(t,n)=length(refhires);
end
end
end

```

```

end
end
if t>100
n=0; %n is worker index
for i=1:ex
n=n+1;
m=1; %m is unique_empvac index
l=0; %l is a trigger denoting when the while loop should break
while l==0
g=find(empvac==unique_empvac(m,:));
%g gives the row indexes that correspond
%to which rows in 'ref' list that employers
%referred workers
if ismember(die(:,n),Job_i(unique_empvac(m,:),:))==1 &
ismember(die(:,n),ref(g(1,1),:))==1
%if new worker is now employed by employer m and is a
% member of the set of referred workers of m
a_net_hire(t-100,n)=borna(:,n);
a_nonet_hire(t-100,n)=0;
c_net_hire(t-100,n)=bornc(:,n);
c_nonet_hire(t-100,n)=0;
l=1;
elseif ismember(die(:,n),Job_i(unique_empvac(m,:),:))==1 &
ismember(die(:,n),ref(g(1,1),:))==0
%if new worker is now employed by employer m and is *not*
%a member of the set of referred workers of m
a_net_hire(t-100,n)=0;
a_nonet_hire(t-100,n)=borna(:,n);
c_net_hire(t-100,n)=0;
c_nonet_hire(t-100,n)=bornc(:,n);
l=1;
else
m=m+1; %else go to next employer in 'unique_empvac' list
end
end
end
end
%**** Collect data on firm output *****
%*****Collect average firm output: ave_total *****
output(t,:)=total_output;
teamout(t,:)=total_team_output;
tot_sim_out(t,:)=sum(total_output); %returns the sum of all firm output
if t>100
fraction_joint(t-100,:)=teamout(t,:)/output(t,:);
ave_firm_out(t-100,:)=tot_sim_out(t,:)/E;
max_out(t-100,:)=max(total_output);

```

```

min_out(t-100,:)=min(total_output);
end
if t==T
sum_fract_joint=sum(fraction_joint);
ave_fract_joint=sum_fract_joint/(T-100)
sum_ave=sum(ave_firm_out);
sum_max=sum(max_out);
sum_min=sum(min_out);
ave_total=sum_ave/(T-100);
ave_max=sum_max/(T-100);
ave_min=sum_min/(T-100);
sum_a_net_hire=sum(a_net_hire'); %sums abilities and ccosts over hires
sum_a_nonet_hire=sum(a_nonet_hire'); %in all simulations, returning a 1xT
sum_c_net_hire=sum(c_net_hire'); %vector summing a and c over that t.
sum_c_nonet_hire=sum(c_nonet_hire');
end
% *** Get % network hired *****
if t==T
n=0;
for i=1:T-100
n=n+1;
output_T_100(n,:)=output(100+n,:);
allhires_T_100(n,:)=allhires(100+n,:);
networkhires_T_100(n,:)=networkhires(100+n,:);
end
total_firm_output=sum(output_T_100); %returns the sum of each firm's output over
totalhires=sum(allhires_T_100); %all simulations except the first 100
totalnethires=sum(networkhires_T_100);
percent_net=totalnethires/totalhires;
n=0;
for i=1:E
n=n+1;
firm_per_nethires(:,n)=totalnethires(:,n)/totalhires(:,n);
ave_firm_output(:,n)=total_firm_output(:,n)/(T-100);
end
end
% *** Get average a and c of network and non-network hires *****
if t==T
total_sim_hires=sum(totalhires);
total_sim_nethires=sum(totalnethires);
total_sim_nonethires=total_sim_hires-total_sim_nethires;
ave_sim_a_nethires=sum(sum_a_net_hire)/total_sim_nethires;
ave_sim_c_nethires=sum(sum_c_net_hire)/total_sim_nethires;
ave_sim_a_nonethires=sum(sum_a_nonet_hire)/total_sim_nonethires;
ave_sim_c_nonethires=sum(sum_c_nonet_hire)/total_sim_nonethires;
end

```

```

%****End simulations*****
end %end for loop running simulations
%***** Display results *****
disp(' ')
disp(' ')
disp('Number of Simulations')
disp(T)
disp(' ')
disp('Number of Workers (N)')
disp(N)
disp(' ')
disp('Number of Vacancies Each Period (x)')
disp(ex)
disp(' ')
disp('Number of Potential Contacts for Young Workers (y)')
disp(why)
disp(' ')
disp('Low connection cost is:')
disp(low)
disp(' ')
disp('High connection cost is:')
disp(high)
disp(' ')
disp('Fraction of low cost people in population')
disp(rho)
disp(' ')
disp('Network bias')
disp(alpha)
disp(' ')
disp(' ')
disp('Average firm output over all simulations except the first 100')
disp(ave_total)
disp(' ')
disp('Average maximum firm output over all simulations except for the first 100')
disp(ave_max)
disp(' ')
disp('Average minimum firm output over all simulations except for the first 100')
disp(ave_min)
disp(' ')
disp('Average percentage of workers hired through connections (all simulations)')
disp(percent_net)
disp(' ')
disp('Average ability of those hired through network hires')
disp(ave_sim_a_nethires)
disp(' ')
disp('Average connection cost of those hired through network hires')

```

```

disp(ave_sim_c_nethires)
disp(' ')
disp('Average ability of those hired through the formal market')
disp(ave_sim_a_nonethires)
disp(' ')
disp('Average connection cost of those hired through the formal market')
disp(ave_sim_c_nonethires)
disp(' ')
disp('Average per firm output over all simulations except the first 100')
disp(ave_firm_output)
disp(' ')
disp('Per firm percentage of workers hired through networks over all simulations
except the first 100')
disp(firm_per_nethires)
%***Make plots *****
plot(firm_per_nethires,ave_firm_output,'d')
h=legend('Old Boy Network w/ Restrictions:', 'Skill weight = 1, Collaboration weight =
1',2)
j=xlabel('Percentage of employees hired through personal connections')
k=ylabel('Average firm output over 500 simulations')

```

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