Social Networks and Persistent Inequality in the Labor Market

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I am grateful to Doug Staiger for providing the tabulations from the NLSY presented in Tables 1 and 2.

Abstract

This paper explores whether the widespread use of employee referrals, coupled with the observed inbreeding bias in social networks, might explain the persistent differences in wages and labor-force participation across demographic groups. In the model, higher participation implies more referrals and better job matching; the average wage is thus increasing in labor-force participation. This externality creates the potential for multiple equilibria, permitting steady state differences across groups. I demonstrate that these differences may persist even with cross-group social ties as long as social networks remain biased toward in-group members.

I. Introduction

The fact that over one-half of all workers found their present job through friends and relatives suggests that social structure--the pattern of social ties connecting individuals--may play an important role in determining labor-market outcomes.[1] This paper examines whether the widespread use of employee referrals might help explain the persistent wage inequality between males and females or blacks and whites.[2] Since individuals tend to refer others of their own sex and/or race, members of disadvantaged groups may be forced to rely more heavily upon formal (impersonal) hiring channels, perhaps receiving lower wages.[3] Lower wages, in turn, might discourage labor-force participation, limit future referrals and perpetuate the group's disadvantaged status.

To explore this possibility, I embed a model similar to that developed in Montgomery (1991) within an overlapping-generations framework and examine the steady-state labor-market outcomes. In the model, the correlation of productive traits across acquaintances provides firms with a more precise evaluation of referred workers than other workers seeking employment through a formal market. Since higher labor-force participation implies more referrals and better job matching, the average wage is increasing with labor-force participation. This externality, similar to that identified by

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[1] See Montgomery (1991) for a review of the literature on employee referrals and further discussion of this point; Table 1 below provides further empirical evidence from the NLSY on the widespread use of employee referrals.

[2] See Cain (1986) for a survey of the empirical evidence.

[3] As discussed in Section III.A, the existence of an "inbreeding bias" between individuals of the same race and sex (as well as other socio-demographic characteristics) is well established in the sociology literature. Table 2 provides more direct evidence from the NLSY that workers tend to receive referrals from others of the same sex.

Diamond (1982), permits multiple equilibria: the labor-market could be characterized by low labor-force participation, few referrals, and low wages or alternatively high participation, many referrals, and high wages. Rather than interpret multiple equilibria as alternative macroeconomic states, however, I show that they may represent alternative outcomes for demographic groups. Given the (observed) bias in social networks toward in-group members, I demonstrate that differences in wages and labor-force participation may persist even when cross-group social ties exist.

The paper proceeds as follows: In Section II, I develop the single-group model, noting the potential for multiple equilibria. In Section III, I first discuss the observed propensity for individuals to know others similar to themselves. I then extend the model to consider two groups (males and females) with social ties between groups, demonstrating the potential for persistent group differences in wages and labor-force participation. I show that the model is consistent with two major findings from NLSY data: males are more likely than females to be hired through referral and are also more likely to be referred by someone of their own sex. Section IV contains a brief conclusion.

II. Social Networks in an Overlapping-Generations Model

A. Assumptions

Researchers have offered a variety of explanations for the widespread use of employee referrals. Based upon interviews with employers, Rees and Shultz (1970) and Doeringer and Piore (1971) claim that workers tend to refer others like themselves. This claim is also found in personnel textbooks such as Heneman, et al. (1980). In a labor market characterized by adverse selection, employee referrals may thus provide useful information on prospective workers. Given the correlation between the characteristics of a firm's current employee and his referred acquaintance, firms may be able to more accurately match referred workers to jobs. Formalizing this explanation for the use of employee referrals, I now construct an overlapping-generations model of the labor market with the following assumptions on workers, social structure, and firms:

Workers

- Each individual lives two periods, making a $\{0,1\}$ education decision in the first period and working in the second period.
- Individuals are of either type A or type B; there is an equal measure of each type in each generation.
- All individuals have the same reservation wage r.
- Education costs may vary across individuals; these costs are distributed according to $s(c)$.
- Individuals are risk neutral.
- An individual's education choice is observable, but his type is not.

Social Structure

- Each individual knows at most one person in the next generation, possessing a social tie with probability $\tau \in [0,1]$.
- Individuals are more likely possess social ties to others of the same type. Conditional upon holding a social tie, a worker knows someone of the same type with probability $\alpha \in [1/2,1]$.
- Controlling for the above "inbreeding bias" between individuals of the same type, social ties are assigned randomly.

Given the stochastic assignment of social ties, some individuals will hold several ties to workers in the previous generation while others hold none.

Firms

- Each firm employs one worker.
- A firm's profit in each period is equal to the output produced by its employee minus the wage paid. (Product price is exogenously determined and normalized to unity.)
- Each firm possesses two technologies:

$$\text{under technology A, output} = \begin{cases} 1 & \text{if employee is educated and type A} \\ 0 & \text{otherwise} \end{cases} \;;$$

$$\text{under technology B, output} = \begin{cases} 1 & \text{if employee is educated and type B} \\ 0 & \text{otherwise} \end{cases} \;.$$

  Each firm may choose either technology in a given period, but this choice is made before the worker's type is revealed.

- Firms must set wages before the worker's type is revealed; output-contingent contracts are not permitted.[4]
- Firms are free to enter the market in any period.

Given that worker type is not observable, firms increase expected output by hiring through referral: a job applicant referred by a type-A worker is likely to also be type-A and will be placed on a job with technology A. In contrast, a worker hired through the market is equally likely to be of either type; a firm hiring through this channel randomizes over technology.[5] While the partition of the population into two different types may seem contrived, this is perhaps the simplest form of worker heterogeneity implying a role for employee referrals. The qualitative nature of the equilibrium (discussed below) depends more generally upon

[4] It is well known that adverse selection is relevant only if firms can not offer fully output-contingent contracts to workers. For simplicity, I assume below that firms must offer wages in advance; see Montgomery (1991) and Greenwald (1986) for defense of this assumption.

[5] I will examine the symmetric equilibrium in which workers do not condition upon their types.

the correlation of productive traits across acquaintances, which provides firms with more accurate evaluations of referred individuals than those seeking employment through market. An alternative (albeit less tractable) assumption on workers such as firm-specific match quality which is correlated across acquaintances would thus yield similar qualitative results.

If the reservation wage r is sufficiently greater than zero, firms hire only educated workers in equilibrium. Representing the opportunity cost of employment, this reservation wage might be interpreted as the wage offered by a second type of firm in which output is not contingent upon type nor education. Assuming that output is equal to r, free entry of this type of firm will drive profits to zero and the wage to the assumed reservation level. One might thus imagine that uneducated workers do enter the labor force, but are employed in another sector of the economy.

Timing (in Period t+1)

(1) Firms make referral offers which are transmitted from generation-(t-1) employees to their (potential) generation-t acquaintances; referred generation-t individuals accept the highest offer.[6]

(2) Generation-t individuals receiving no referral offers are hired through a formal market.

(3) Firms choose between technologies A and B.

(4) Production by generation-t workers; firms learn employee's type.

(5) Generation-(t+1) individuals make education decisions.

(6) Social ties are assigned between generations t and t+1.

Note that each worker makes his education decision before his social

[6] In equilibrium, all referral offers exceed the market wage; only those receiving no offers seek employment through the market. Note that workers providing referrals merely convey information; their actions are assumed to be non-strategic.

network is determined; this decision is not contingent upon the realization of his social ties to workers in the previous generation. Instead, the education decision depends upon the individual's *expected* social network, determined by the fraction of workers educated (and employed) in the preceding generation. (As shown below, the education decision depends upon the expected wage earned by educated workers, which is also determined by the fraction of workers educated in *subsequent* generations.)

B. Equilibrium

I now examine the steady state of the preceding model. Suppose that a firm offers a referral wage w. If this offer is accepted, the firm's expected profit is equal to $(\alpha - w + \beta V)$ where β is the discount factor and V is the value of the firm the next period. Note that the firm chooses the technology corresponding to the previous employee's type; a referred worker thus produces one unit of output with probability α. If the referral offer is not accepted, the firm must hire through the market; free entry implies zero expected profit for firms hiring through this channel. Assuming a lower bound on the reservation wage (to be discussed below), firms hire only educated workers. Conditional upon its employee possessing a social tie to an educated individual, the firm's referral offer is accepted if this individual receives no higher offers. As shown in the appendix, the (conditional) probability that the firm's offer is accepted may be written

$$a(w) \quad = \quad e^{-\tau n(1-F(w))}$$

where $F(\cdot)$ is the equilibrium distribution of referral wage offers and $n \in [0,1]$ is the steady state fraction of educated workers. Since the firm's current employee knows an educated worker with probability τn, the firm's expected profit may thus be written

$$E\Pi(w) = \tau n e^{-\tau n(1-F(w))}(\alpha - w + \beta V) \quad .$$

To maintain equilibrium wage dispersion, firms must earn the same expected profit on each wage offered to referred workers.[7] Given an upper bound on the reservation wage (to be discussed below), the minimum wage offered is equal to the market wage w_M. The expected profit of all firms making referral offers is thus equal to

$$E\Pi(w_M) = \tau n e^{-\tau n}(\alpha - w_M + \beta V) \quad .$$

Setting $E\Pi(w) = E\Pi(w_M)$ for all referral wages offered, we obtain

$$F(w) = (1/\tau n) \; [\; \ln(\alpha - w_M + \beta V) - \ln(\alpha - w + \beta V) \;] \quad ,$$

$$f(w) = 1 \; / \; [\tau n(\alpha - w + \beta V)] \quad ,$$

and $$a(w) = e^{-\tau n}[(\alpha - w_M + \beta V)/(\alpha - w + \beta V)]$$

for all $w \in [w_M, \bar{w}]$ where $F(\bar{w}) = 1$.

Since firms hiring through the market lack knowledge of worker type, they randomize over technologies, choosing each with probability one half. Given free entry, expected profit is driven to zero and $w_M = 1/2 + \beta V$. Since $V = E\Pi(w_M) = E\Pi(1/2 + \beta V)$,

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[7]Applying Theorem 4 in Burdett and Judd (1983), wage dispersion arises because the probability that each job seeker receives exactly one referral offer is strictly between 0 and 1. Proposition 2.2 in Butters (1977) guarantees that the support of the wage distribution will be connected: if no wages were offered between w_1 and w_2 (where $w_M < w_1 < w_2 < \bar{w}$), then a firm offering w_2 could reduce its wage offer without reducing the probability that the offer is accepted, thus increasing expected profits.

$$V = \tau n e^{-\tau n}(\alpha - 1/2)$$

and $$w_M = 1/2 + \beta\tau n e^{-\tau n}(\alpha - 1/2) \quad .$$

Given $F(\bar{w}) = 1$ and substituting for V and w_M, we obtain

$$\bar{w} = \alpha - e^{-\tau n}(1-\beta\tau n)(\alpha - 1/2) \quad .$$

To simplify characterization of the model, the preceding analysis has implicitly assumed $r \in [\beta V, 1/2]$. The upper bound guarantees that educated workers accept the market wage if they receive no referral offers; the lower bound insures that firms will not be willing to hire uneducated workers.[8] Since βV never exceeds 1/2, the specified bounds are sufficient to guarantee the existence of the specified equilibrium. (These bounds are not necessary, however, for all parameter values.)

As in Montgomery (1991), increases in network density (τ) and inbreeding bias (α) increase competition for referred workers and generate greater wage dispersion: more offers are received as network density rises; expected productivity increases with inbreeding bias. In contrast to Montgomery (1991), however, an increase in either social-structure parameter increases the market wage. In my earlier model, workers were of either high or low ability; increases in τ or α ameliorated a market "lemons effect." In the present model, workers may be well-matched or poorly-matched to specific jobs, but none are of strictly higher ability than others; there is no lemons effect in the formal market. Instead, a second effect operates: increases in the social-structure parameters increase the expected profits

[8]Rather than requiring a lower bound on r, I could assume that an uneducated worker's output is (sufficiently) negative.

of firms making referral offers; these profits are captured by workers through increases in the market wage.

Note that a change in the fraction of educated individuals (n) is equivalent to a change in network density. Since only educated individuals are employed and refer acquaintances in the next generation, only these ties are relevant for individuals in making their education decisions. Following Montgomery (1991), the product τn might thus be interpreted as *effective* network density.

An individual will choose to become educated if the expected wage earned exceeds his cost of education. The expected wage is a weighted average of the market wage and *accepted* referral offers. Since a fraction $e^{-\tau n}$ of educated individuals receive no offers and must find employment through the market,

$$Ew = e^{-\tau n} w_M + \int_{w^M}^{\bar{w}} w \, \tau n \, a(w) f(w) \, dw \quad .$$

After substitution and integration by parts, we obtain

$$\int_{w^M}^{\bar{w}} w \, \tau n \, a(w) f(w) \, dw = \bar{w} - e^{-\tau n} w_M - \tau n e^{-\tau n}(\alpha - 1/2)$$

and thus

$$Ew(n;\alpha,\tau,\beta) = \alpha - e^{-\tau n}(\alpha-1/2)[1+(1-\beta)\tau n] \quad .$$

One can show that $Ew(\cdot)$ is increasing in each of its arguments; I will focus upon the positive relationship between this wage and the fraction of educated individuals. Note that $Ew(0) = 1/2$.

To close the model, note that the supply of educated workers given an expected wage w is equal to $S(w-r)$ where $S(\cdot)$ is the cumulative distribution of education costs. The labor market is thus in steady state when

$$n = S(Ew(n) - r) .$$

Graphically, an equilibrium exists when the supply curve for educated workers crosses the expected wage curve. Given that both curves are non-negatively sloped, multiple equilibria are possible. Figure 1 shows the possible equilibria given two different distributions of education costs. Note that an equilibria is unstable if (and only if) the expected wage curve is crossed from above: a small change in the wage would alter the education decisions of many individuals in the present (and ultimately future) generations. Thus, if all individuals have the same cost of education c as depicted in the first graph, only the corner equilibria $\{n = 0\}$ and $\{n = 1\}$ are stable. Similarly, the S-shaped (cumulative) distribution of education costs underlying the second graph generates a stable low-n equilibrium, a stable high-n equilibrium, and an intermediate unstable "tipping point" equilibrium. Alternative assumptions on the distribution of education costs (uniformity for instance) might, of course, generate a unique equilibrium.

When multiple equilibria exist, those equilibria with higher fractions of employed workers are more efficient, generating higher net output. To prove this, let $q(n)$ represent the average output of educated workers. This may be written

$$q(n) = 1/2\, e^{-\tau n} + \alpha\, (1 - e^{-\tau n})$$

since workers on the market produce an expected output of 1/2 while the expected output of those hired through referral is α. Welfare, defined as average output net of the opportunity cost of employment and education costs, may be written

$$W(n) = nq(n) + (1-n)r - \int_0^{Ew(n)-r} cs(c)\, dc \quad .$$

Now consider two equilibria, one with a high fraction of educated workers ($\bar{n}$) and a second with fewer educated workers ($\underline{n}$). The difference in welfare between these two equilibria is

$$W(\bar{n}) - W(\underline{n}) = \bar{n}q(\bar{n}) - \underline{n}q(\underline{n}) - (\bar{n}-\underline{n})r - \int_{Ew(\underline{n})-r}^{Ew(\bar{n})-r} cs(c)\, dc \quad .$$

Since the preceding integral is no more than $[Ew(\bar{n})-r](\bar{n}-\underline{n})$, we obtain

$$W(\bar{n}) - W(\underline{n}) \geq (\bar{n}-\underline{n})[q(\bar{n})-Ew(\bar{n})] + \underline{n}[q(\bar{n})-q(\underline{n})] > 0 \quad .$$

Intuitively, an increase in the fraction of educated workers generates two effects, both of which increase efficiency. First, newly educated workers are more productive, even after subtracting education costs and the opportunity cost of employment (equal to $Ew(\bar{n})$ for the marginal worker). Second, a higher fraction of educated workers generates more referrals and thus better job matching: the expected output of previously educated workers increases by $q(\bar{n})-q(\underline{n}) > 0$.

C. Omitting the Education Decision

In the above model, the use of employee referrals implies that the expected wage is increasing in labor-force participation; this externality may induce multiple equilibria. Several assumptions were made merely to simplify the analysis and presentation; alternative assumptions would not affect this central result. In particular, I could have omitted the education decision (and the technological requirement that only educated workers are productive). (Equivalently, I could have altered the model's timing so that the education decision is made *after* wage offers are received.) In this revised model, an individual's labor-force participation is determined by his *realized* (rather than *expected*) social network and wage offers. All workers with reservation wages below the market wage are employed; some workers with higher reservation wages accept employment through referral. Since higher labor-force participation generates a higher market wage and greater wage dispersion (which in turn encourage a higher participation rate), the potential for multiple equilibria persists. But while this revised model might be more appropriate for some of the applications discussed in the next section, it is more difficult to characterize because firms' referral offers and the market wage now depend upon the underlying distribution of reservation wages as well as the participation rate n. I will thus retain my earlier assumptions in the extended model below.

III. Persistent Differences Between Demographic Groups

A. Group Inbreeding and Inequality

The preceding model generates multiple equilibria for reasons similar to those identified by Diamond (1982): higher labor-force participation increases the probability of referral, improving job matching and wages, which in turn encourages higher labor-force participation. But while the literature on coordination failures has emphasized macroeconomic implications, I wish to address a microeconomic question: might the widespread use of employee referrals explain the observed inequality in labor-market outcomes across demographic groups? If group members tend to refer others within their own group, employee referrals might generate persistent differences in wages and labor-force participation between blacks and whites or males and females.

As an important special case, one might consider whether the use of employee referrals contributes to the persistence of an inner-city "underclass." According to Wilson (1987), one reason for the recent growth of the underclass is the exodus of the black middle class from the inner city and the resulting breakdown of job-referral networks. Because black youth lack connections to older workers in "good" jobs, they often drop out of school and remain only marginally attached to the labor force. Restated within the context of the preceding model, the middle-class exodus may have "tipped" the equilibrium, thus reducing the expected wage, the rate of education (and labor-force participation), and number of employee referrals.

The fact that social ties tend to occur among individuals with similar characteristics is well established in the social network literature. Examining General Social Survey data on individuals with whom the respondent discusses important matters, Marsden (1988) reports strong inbreeding biases between individuals of the same race/ethnicity, religion and (to a lesser extent) sex, age, and education level.[9] (While inbreeding by sex is weaker than by race or religion, this is due to the large number of opposite-sex kin alters--spouses, parents, siblings, etc.--cited by respondents. Inbreeding by sex is quite strong among non-kin pairs.) While providing

[9] See Marsden (1987, 1988) for references to other studies.

only indirect evidence, network research thus suggests that individuals might refer in-group members for jobs more often than out-group members.

More direct evidence on referrals is provided by the National Longitudinal Survey of Youth; see Tables 1 and 2.[10] As in the PSID data analyzed by Corcoran, et al. (1980), males are more likely than females (41% vs. 29%) to have obtained their jobs through employee referral. (The overall referral rate (36%) is lower than reported elsewhere because a worker is counted as referred only if the referring friend or relative worked for the hiring firm; approximately two-thirds of all referred workers meet this criteria.) Table 1A also supports the finding in Rees and Shultz (1970) and Corcoran, et al. (1980) that blue-collar workers are more often referred than white-collar workers. Note, however, that the male/female difference in referral rates can not be explained by the smaller percentage of females in blue-collar jobs: Tables 1A and 1B show that this difference tends to exist even within (one-digit) occupations or industries.

Tables 2A and 2B offer direct evidence that workers tend to receive referrals from others of the same sex: 87% of referred males obtained their jobs through a male; 70% of referred females received the referral from a female. Again, this result is not an artifact of occupational segregation since it holds even within (one-digit) occupations or industries. Even in male-dominated occupations such as craft worker or machine operator, most referred females receive these referrals from other females. Conversely, most referred males in clerical positions--an occupation dominated by females--are referred by other males. A more refined breakdown of occupations might yet demonstrate that these results are an artifact of

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[10] I am grateful to Doug Staiger for providing these tabulations; this sample was used in Staiger (1990). Unfortunately, the NLSY asks only the sex (and not the race, education, etc.) of the individual making the referral.

occupational segregation. But combined with the evidence from the social network literature of strong inbreeding biases on a variety of characteristics, these results seem likely to hold even within very narrowly specified occupations. Moreover, while no direct evidence is available on referrals between members of different races, a similar pattern--whites referring whites, etc.--should be expected.

Returning to the model, consider the extreme case where inbreeding within groups is complete. Since the outcome of each group is independent of the others, the comparison of two groups is essentially an exercise in comparative statics. Labor-market outcomes will vary across groups if network parameters differ: an increase in network density (τ) or inbreeding by ability (α) generates a steeper expected-wage curve, increasing the fraction of individuals educated at each stable equilibrium. Alternatively, the group with the worse (i.e., stochastically dominating) distribution of education costs will have a smaller supply of educated workers at each wage and thus inferior (stable) equilibria. But even if these underlying parameters are constant across groups, outcomes may vary if the groups are at different equilibria--if *effective* network density varies across groups.

In the analysis below, I will maintain the strong assumption that the network parameters τ and α and the distribution of education costs $S(\cdot)$ are constant across groups; group differences thus rely upon the existence of multiple equilibria. But as sociologists have observed significant differences in the social networks of different groups, some of the observed variation in labor-market outcomes might be explained in this manner. While men and women tend to have networks of similar size, network composition differs: most notably, women hold more ties to kin (and thus fewer to non-kin) even after controlling for employment status.[11] If these family ties reflect the caregiving and kinkeeping roles of women,[12] they are likely to be less instrumental in obtaining referrals, thus reducing the effective network density of women.[13] While fewer cross-race network comparisons are available, Marsden (1987) reports that whites have significantly larger networks than blacks (while Hispanics and others are intermediate).

B. The Model with Cross-Group Ties

I now extend the model to consider observationally distinct groups (males and females) with social ties between the groups. For convenience, I will assume equal numbers (more precisely, an equal measure) of each group in each generation. In addition to the inbreeding by type (A or B) assumed previously, I now assume inbreeding by group: conditional upon holding a tie, an individual knows someone of his own group with probability $\gamma \geq 1/2$. Thus, an individual holds a social tie to someone of his own type and group in the next generation with probability $\alpha\gamma\tau$; the probability of other social ties are calculated similarly.

Since the groups are observationally distinct, the equilibrium distribution of wage offers (as well as the market wage) may differ across groups. As derived formally in Appendix 2, the expected wage for males may

[11]See Fischer (1982), Fischer and Oliker (1983), Marsden (1987), and Moore (1990). Moreover, Campbell (1988) shows that among employed workers, women with young children and whose spouse is transferred have less diverse networks (measured by alters' occupation and socioeconomic status) than similar men.

[12]See the discussion in Moore (1990).

[13]Stepping outside the model, women may also be disadvantaged because connections to kin are likely to be strong ties. Granovetter (1973, 1974) argues that weak ties are more likely to generate new information on job openings.

be written

$$Ew^m(n^m;n^f,\gamma) \;=\; \alpha - (\alpha-1/2)\left\{ e^{-\tau\tilde{n}^m}[1+\tau\tilde{n}^m] - \beta\tau\,[\gamma n^m e^{-\tau\tilde{n}^m} + (1-\gamma)n^f e^{-\tau\tilde{n}^f}] \right\};$$

the analogous expression for females is

$$Ew^f(n^f;n^n,\gamma) \;=\; \alpha - (\alpha-1/2)\left\{ e^{-\tau\tilde{n}^f}[1+\tau\tilde{n}^f] - \beta\tau\,[\gamma n^f e^{-\tau\tilde{n}^f} + (1-\gamma)n^m e^{-\tau\tilde{n}^m}] \right\}$$

where n^m and n^f are the fractions of males and females educated (and employed), $\tilde{n}^m \equiv \gamma n^m + (1-\gamma)n^f$, and $\tilde{n}^f \equiv \gamma n^f + (1-\gamma)n^m$. As before, the expected wage is increasing in labor-force participation: both $\partial Ew^m/\partial n^m$ and $\partial Ew^f/\partial n^f$ are positive.

Given that the expected wage for each group depends upon both n^m and n^f, the labor market is in steady state equilibrium only when both of the following equalities hold:

$$n^m \;=\; S(Ew^m(n^m;n^f,\gamma) - r)$$

$$\text{and}\quad n^f \;=\; S(Ew^f(n^f;n^m,\gamma) - r)\quad .$$

Unfortunately, the equilibrium outcome of this extended model can no longer be easily characterized by a two-dimensional graph. Several results, however, follow from inspection of the expected wage equations. First, if $n^m = n^f = n$, both equations collapse to the single-group expected wage equation:

$$Ew^m(n;n,\gamma) \;=\; Ew^f(n;n,\gamma) \;=\; Ew(n) \quad \forall\,\gamma\quad .$$

Any equilibrium in the single-group model thus remains a viable equilibrium for both groups. Since the expected wage and education rates are constant across groups, the level of group inbreeding bias γ is irrelevant. Second, given $n^m > n^f$, one can show that

$$Ew^m(n^m;n^f,\gamma) \quad > \quad Ew^f(n^f;n^m,\gamma) \qquad \forall \quad \gamma > 1/2 \quad .$$

Thus, for some distributions of education costs, there exist steady state equilibria in which a larger fraction of males are educated and employed.

Given complete inbreeding within groups ($\gamma = 1$), expected wages depend only upon the group's own education rate:

$$Ew^m(n^m;n^f,1) \quad = \quad Ew(n^m) \quad ;$$

$$Ew^f(n^f;n^m,1) \quad = \quad Ew(n^f) \quad .$$

As already noted, each group may be analyzed independently in this case; n^m and n^f may differ if multiple equilibria existed in the single-group model. At the other extreme, given no inbreeding within groups ($\gamma = 1/2$), the expected wage is the same for both groups:

$$Ew^m(n^m;n^f,1/2) \quad = \quad Ew^f(n^f;n^m,1/2) \quad = \quad Ew(n^{avg})$$

where $n^{avg} = (n^m+n^f)/2$. Given the above conditions for steady state equilibrium, n^m must equal n^f. A difference in the equilibrium outcomes of males and females thus requires some inbreeding within these groups (i.e., $\gamma > 1/2$).

More generally, one might expect that increased inbreeding within groups (higher γ) would generate larger differences in expected wages and education rates; decreased inbreeding might reduce differences between groups. While the potential multiplicity of equilibria makes a general statement problematic, partial differentiation of the expected wage function implies that $\partial Ew^m(\cdot)/\partial\gamma > 0 > \partial Ew^f(\cdot)/\partial\gamma$ given $n^m > n^f$. To interpret these inequalities, consider an initial equilibrium where $n^m > n^f$. Holding n^m and n^f constant, an increase in γ will raise the expected wage for males and decrease the expected wage for females. Intuitively, the resulting change in network composition favors males, who now possess more ties to educated workers; females will now possess fewer of these ties. As a result of the change in expected wages, more men (and fewer females) are likely to become educated and enter the labor force--the difference between male and female outcomes is exacerbated. Conversely, a decrease in γ reduces the male expected wage and increases the female expected wage; the resulting changes in education rates will mitigate the difference between male and female wages. Indeed, as γ falls, such differences may become impossible to sustain.

For concreteness, consider the example depicted in Figure 2. As in the first graph in Figure 1, all individuals have the same cost of education c. Given $\gamma = 1$, there are four possible (stable) equilibria: n^m and n^f may be either 0 or 1. Consider the case $\{n^m = 1, n^f = 0\}$. As γ falls to γ', the expected wage for males falls for all $n > 0$; the female expected wage rises for all $n < 1$. But if γ' is sufficiently close to 1, the initial equilibrium remains viable: the female expected wage remains below r+c while the male expected wage remains above. This illustrates the more general result that a small number of cross-group social ties will not necessarily eliminate persistent differences between groups. As γ falls further to γ'', however, the initial equilibrium fails. Since $Ew^f(n^f;1,\gamma'') > r+c$ for all n^f, each female would always choose to become educated if all males were educated. Note, however, that $\{n^m = 0, n^f = 0\}$ remains a potential equilibrium regardless of γ.

As I have emphasized, the model can generate persistent differences in labor-force participation and wages between males and females even if both groups have the same network parameters and distribution of education costs. But beyond reproducing these observed facts, the model also generates the two major results found in Tables 1 and 2. Given an equilibrium where $n^m > n^f$, a larger percentage of employed males are hired through referral:

$$\Pr\{\text{referred}|\text{employed male}\} = 1 - e^{-\tau\tilde{n}^m} > \Pr\{\text{referred}|\text{employed female}\} = 1 - e^{-\tau\tilde{n}^f} \quad .$$

Moreover, conditional upon having received a referral, males are more likely to have been referred by someone of their own sex:

$$\Pr\{\text{referred by male}|\text{referred male}\} = \gamma n^m / \tilde{n}^m > \gamma > \Pr\{\text{referred by female}|\text{referred female}\} = \gamma n^f / \tilde{n}^f \quad .$$

Intuitively, each of the preceding probabilities depends upon the opportunities for contact between job holders and job seekers. Since a smaller percentage of females are employed (and given inbreeding bias by sex), female job seekers are less likely to know an employed worker and are thus more likely to be hired through the market. Since γ is constant across sexes and more males are employed, females are more likely to receive (and accept) offers from males than vice-versa.

C. Discussion of Policy Implications

The widespread use of employee referrals and resulting potential for persistent wage differentials across groups provides one rationale for affirmative-action legislation. If low female wages and labor-force participation reflect an inferior equilibrium outcome, firm hiring quotas (or alternatively educational subsidies) might induce a superior equilibrium. (Indeed, males would benefit as well since social ties to females would more often generate job referrals.) Since the program would induce a movement between equilibrium states, it could be temporary (i.e., a single period in the model). But to succeed, the program must be large enough to push n^f beyond the "tipping point" separating the high and low (stable) equilibria. A small (exogenously induced) increase in the current labor-force participation of females may have no lasting effect on the equilibrium outcomes of either group.

Of course, any discussion of public-policy implications must recognize the special assumptions underlying the current model. If individuals possessed multiple social ties (which could result in multiple referrals and job placements), a small exogenous increase in labor-force participation might be more likely to generate lasting effects. (Indeed, multiple ties might reduce the potential for any steady state difference between groups.) If entry of firms was restricted (thus limiting the number of positions available), an increase in the labor-force participation of one group might require a decrease in participation among another group; the net change in welfare resulting from affirmative-action legislation is unclear. Given these limitations of the present model, further generalization is required for a more complete analysis of such programs.

IV. Conclusion

The widespread use of employee referrals, coupled with the observed inbreeding bias in social networks, provides one plausible explanation for the persistent inequality of labor-market outcomes across demographic groups. While (for the sake of tractability) the model incorporates a variety of special assumptions, it suggests that equilibrium differences in wages and labor-force participation between groups may indeed be a byproduct of referral hiring. Such differences depend upon the existence of inbreeding by group, an empirical regularity well established in the social network literature. Beyond reproducing observed differences in wages and participation, the model also predicts the greater use of referrals by males and the pattern of own-sex referrals reported in NLSY data. Continued study of social networks in the labor market should provide a better understanding of inequality between groups and potential policy interventions.

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Appendix 1: Determination of Acceptance Probability

First consider the single-group model in Section II. Conditional upon its current employee knowing an educated individual in the next generation, a firm's offer is accepted if this individual receives no higher offers. Thus, if a firm offers a wage w to some individual X in generation t+1, the (conditional) probability that the offer is accepted may be written

$$a(w) = \prod_{i} [1 - \Pr\{X \text{ receives offer} > w \text{ from } i\}]$$

where n is the steady state fraction of educated workers and i indexes individuals in generation t. Further,

$$\begin{aligned} &\Pr\{X \text{ receives offer} > w \text{ from } i\} \\ &\quad = \Pr\{i \text{ knows } X\} \cdot \Pr\{i \text{ makes offer}\} \cdot \Pr\{i\text{'s offer} > w\} . \end{aligned}$$

The probability that i knows X depends on i's type (A or B): $\Pr\{i \text{ knows } X\} = \alpha\tau/N$ if i and X are of the same type; $\Pr\{i \text{ knows } X\} = (1-\alpha)\tau/N$ if i and X are of opposite types. Since a fraction n of all individuals are educated, $\Pr\{i \text{ makes offer}\} = n$. Finally, symmetry implies that firms employing either type-A or type-B workers will generate the same equilibrium referral offer distribution $F(\cdot)$: $\Pr\{i\text{'s offer} > w\} = 1-F(w)$ for all i. Given N individuals of each type,

$$a(w) = \left[1 - \left(\frac{\alpha\tau n}{N}\right)(1-F(w))\right]^N \left[1 - \left(\frac{(1-\alpha)\tau n}{N}\right)(1-F(w))\right]^N .$$

(Since one generation t individual is employed by the firm and is referring X, one of the exponents should be N-1. This becomes irrelevant, however, as N grows large.) In the limit, as $N \to \infty$,

$$a(w) = e^{-\tau n(1-F(w))} .$$

To determine the acceptance probability in the two-group case, note that individuals may now be catagorized in four ways: same sex/same type, same sex/other type, other sex/same type, other sex/other type. The probability that i knows X is equal to $\alpha\gamma\tau/N$ if i and X are of the same sex and type; the remaining probabilities are derived analogously. Moreover, Pr{i makes offer} now varies according to the sex of individual i: the fractions n^m of males and n^f of females are educated. Given N individuals in each of the four catagories, the (conditional) probability that a male accepts the firm's offer is thus

$$a^m(w) = \left[1 - \left(\frac{\alpha\tau\gamma n^m}{N}\right)(1-F^m(w))\right]^N \left[1 - \left(\frac{(1-\alpha)\gamma\tau n^m}{N}\right)(1-F^m(w))\right]^N .$$

$$\cdot \left[1 - \left(\frac{\alpha\tau(1-\gamma)n^f}{N}\right)(1-F^m(w))\right]^N \left[1 - \left(\frac{(1-\alpha)(1-\gamma)\tau n^f}{N}\right)(1-F^m(w))\right]^N$$

where $F^m(\cdot)$ is the equilibrium distribution of male wages. As $N \to \infty$,

$$a^m(w) = e^{-\tau\tilde{n}^m(1-F^m(w))}$$

where $\tilde{n}^m \equiv \gamma n^m + (1-\gamma)n^f$. Analogously,

$$a^f(w) = e^{-\tau\tilde{n}^f(1-F^f(w))}$$

where $\tilde{n}^f \equiv \gamma n^f + (1-\gamma)n^m$.

Appendix 2: The Model with Two Groups

Let n^m represent the fraction of educated males and n^f represent the fraction of educated females. Conditional upon its current employee holding a tie to an educated male in the next generation, a firm's expected profit is equal to $a^m(w)\cdot(\alpha - w + \beta V^m)$ where $a^m(w)$ is derived in the previous appendix and V^m is the value of the firm given that a male is hired. Since the market wage for males is the lowest wage offered and all wages offered must yield the same expected profit, we obtain the distribution of male wage offers

$$F^m(w) \;=\; (1/\tau\tilde{n}^m)\;[\;\ln(\alpha - w_M^m + \beta V^m) - \ln(\alpha - w + \beta V^m)\;]$$

where w_M^m is the market wage for males. Similarly, the referral offer distribution for females may be written

$$F^f(w) \;=\; (1/\tau\tilde{n}^f)\;[\;\ln(\alpha - w_M^f + \beta V^f) - \ln(\alpha - w + \beta V^f)\;]$$

where w_M^f is the market wage for females and V^f is the value of the firm given that a female is hired.

The value of a firm employing a male is

$$V^m \;=\; \tau\gamma n^m\; a^m(w_M^m)\;(\alpha - w_M^m + \beta V^m) + \tau(1-\gamma)n^f\; a^f(w_M^f)\;(\alpha - w_M^f + \beta V^f) \quad .$$

Since $w_M^m = 1/2 + \beta V^m$ and $w_M^f = 1/2 + \beta V^f$, we obtain

$$V^m \;=\; \tau(\alpha-1/2)\;[\gamma n^m e^{-\tau\tilde{n}^m} + (1-\gamma)n^f e^{-\tau\tilde{n}^f}] \quad .$$

By symmetry, the value of a firm employing a female may be written

$$V^f \;=\; \tau(\alpha-1/2)\;[\gamma n^f e^{-\tau\tilde{n}^f} + (1-\gamma)n^m e^{-\tau\tilde{n}^m}] \quad .$$

The expected wage for males may be written

$$Ew^m = e^{-\tau\tilde{n}^m} w_M^m + \int_{w_M^m}^{\bar{w}^m} w\, \tau\tilde{n}^m\, a^m(w)\, f^m(w)\, dw \quad .$$

After integration by parts and substitution, this becomes

$$Ew^m = \bar{w}^m - \tau\tilde{n}^m e^{-\tau\tilde{n}^m} (\alpha-1/2) \quad .$$

Since $\bar{w}^m = \alpha + \beta V^m - e^{-\tau\tilde{n}^m} (\alpha-1/2)$, it is straightforward to derive the expected wage for males $Ew^m(n^m;n^f,\gamma)$ written in the text. The expected wage for females is derived analogously.

Table 1A: Percent of Workers Obtaining Job through Referral, by Occupation

	Males	*Females*	*All Workers*
All Occupations	41.4% (623/1504)	29.0% (391/1347)	35.6% (1014/2851)
By Occupation			
Managerial & Professional	30.9% (34/110)	20.3% (24/118)	25.4% (58/228)
Technical	25.0 (9/36)	15.0 (6/40)	19.7 (15/76)
Sales	36.2 (42/116)	27.7 (44/159)	31.3 (86/275)
Administrative Support/ Clerical	41.9 (52/124)	30.6 (158/517)	32.8 (210/641)
Service	39.3 (84/214)	26.0 (81/312)	31.4 (165/526)
Farming, Forestry & Fishing	36.7 (22/60)	40.0 (6/15)	37.3 (28/75)
Precision Production, Craft, Repair	45.5 (135/297)	55.0 (11/20)	46.1 (146/317)
Operators--Machine, Assemblers, Inspectors	48.6 (103/212)	34.1 (42/123)	43.3 (145/335)
Operators--Transport'n, Material Moving	40.0 (46/115)	20.0 (1/5)	39.2 (47/120)
Operators--Handlers, Helpers, Laborers	43.6 (96/220)	47.4 (18/38)	44.2 (114/258)

Data: NLSY Random Sample. The sample used here is from Staiger (1990). A worker is counted as receiving a referral if he/she answers yes to both (1) "Was there anyone specific who helped you get your job with your employer?" and (2) "Was this person working for this employer when you were first offered this job?". To enter the sample, the worker had to answer the questions on how his/her job was found, work at least 30 hours/week on 1982 job, hold a "regular" (as opposed to "odd") job, be working for pay and not self-employed, and not be enrolled in school nor unable to work.

Table 1B: Percent of Workers Obtaining Job through Referral, by Industry

	Males	*Females*	*All Workers*
All Industries	41.4% (623/1504)	29.0% (391/1347)	35.6% (1014/2851)
By Industry			
Agriculture, Forestry & Fisheries, Mining	42.5% (45/106)	40.7% (11/27)	42.1% (56/133)
Construction	46.4 (78/168)	61.5 (8/13)	47.5 (86/181)
Manufacturing	46.2 (165/357)	33.8 (77/228)	41.4 (242/585)
Transportation, Communication, Pub. Utilities	34.1 (31/91)	28.6 (14/49)	32.1 (45/140)
Wholesale Trade	43.4 (36/83)	34.0 (16/47)	40.0 (52/130)
Retail Trade	39.8 (142/357)	28.6 (93/325)	34.5 (235/682)
Finance, Insurance, Real Estate	36.4 (12/33)	25.5 (38/149)	27.5 (50/182)
Business & Repair Services	40.0 (42/105)	23.6 (13/55)	34.4 (55/160)
Personal, Entertainment & Recreation Services	35.5 (22/62)	25.3 (22/87)	29.5 (44/149)
Professional and Related Services	37.0 (34/92)	27.1 (82/303)	29.4 (116/395)
Public Administration	32.0 (16/50)	26.6 (17/64)	28.9 (33/114)

Data: NLSY; See Table 1A.

Table 2A: Percent of Referred Workers who Received Referral from Someone of Own Sex, by Occupation

	Males	*Females*
All Occupations	86.7% (540/623)	69.8% (273/391)
By Occupation		
Managerial & Professional	82.4% (28/34)	54.2% (13/24)
Technical	88.9 (8/9)	66.7 (4/6)
Sales	83.3 (35/42)	68.2 (30/44)
Administrative Support/ Clerical	76.9 (40/52)	69.6 (110/158)
Service	79.8 (67/84)	77.8 (63/81)
Farming, Forestry & Fishing	90.9 (20/22)	66.7 (4/6)
Precision Production, Craft, Repair	94.1 (127/135)	63.6 (7/11)
Operators--Machine, Assemblers, Inspectors	88.3 (91/103)	81.0 (34/42)
Operators--Transportation, Material Moving	87.0 (40/46)	0.0 (0/1)
Operators--Handlers, Helpers, Laborers	87.5 (84/96)	44.4 (8/18)

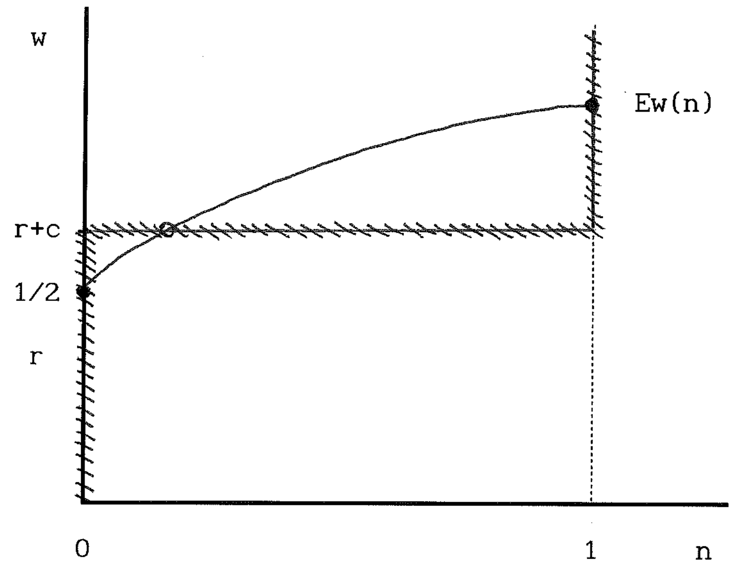
Data: NLSY; see Table 1A.

Table 2B: Percent of Referred Workers who Received Referral from Someone of Same Sex, by Industry

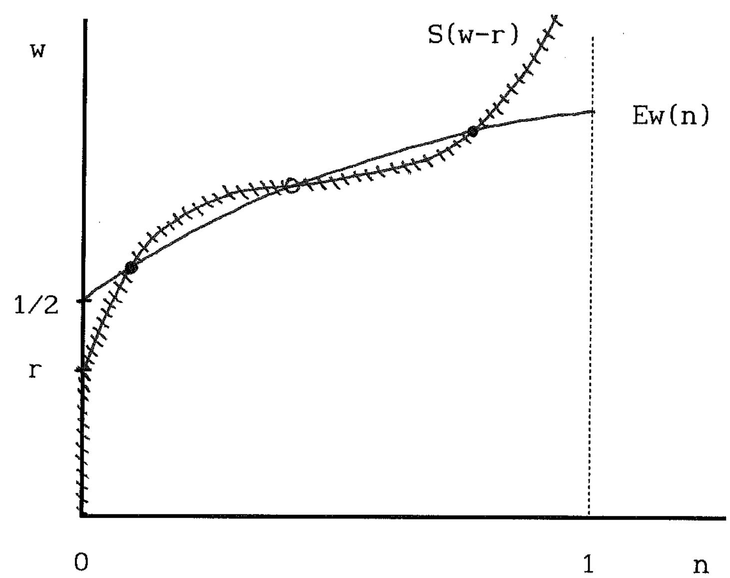
	Males	*Females*
All Industries	86.5% (540/623)	69.8% (273/391)
By Industry		
Agriculture, Forestry & Fisheries, Mining	91.1% (41/45)	45.5% (5/11)
Construction	100.0 (78/78)	25.0 (2/8)
Manufacturing	86.7 (143/165)	75.3 (58/77)
Transportation, Communication, Pub. Utilities	87.1 (27/31)	57.1 (8/14)
Wholesale Trade	80.6 (29/36)	81.3 (13/16)
Retail Trade	82.4 (117/142)	67.7 (63/93)
Finance, Insurance, Real Estate	66.7 (8/12)	68.4 (26/38)
Business & Repair Services	92.9 (39/42)	53.8 (7/13)
Personal, Entertainment & Recreation Services	81.8 (18/22)	77.3 (17/22)
Professional and Related Services	73.5 (25/34)	79.3 (65/82)
Public Administration	93.8 (15/16)	52.9 (9/17)

Data: NLSY; See Table 1A.

Figure 1

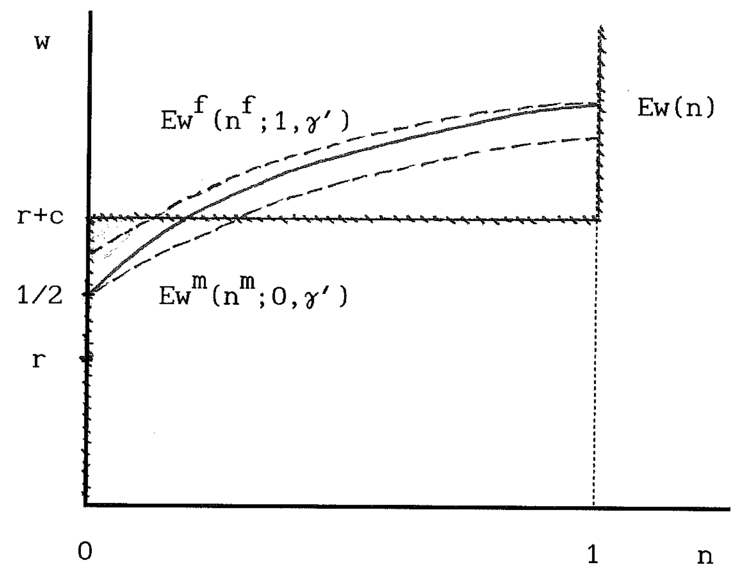


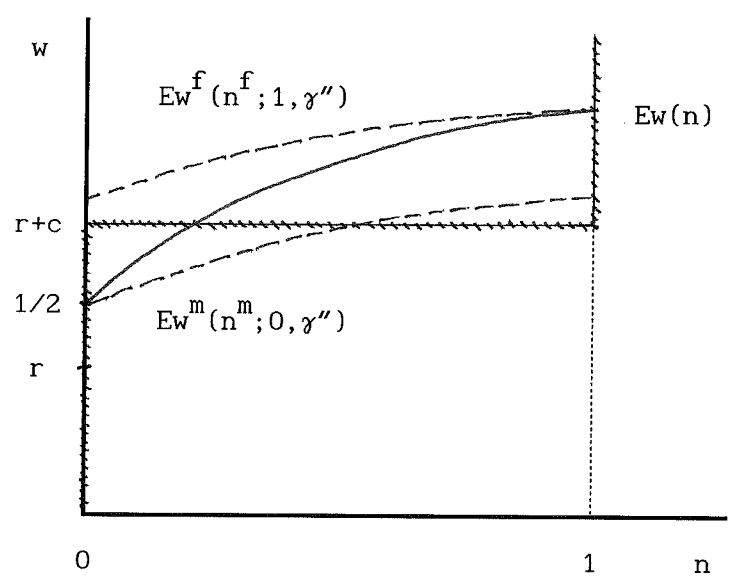
Education costs c for all individuals.



Education costs distributed S(c).

Figure 2





Graphs assume education costs c for all workers; $\gamma'' < \gamma' < 1$.