Hearing About A Job: Employer Preferences, Networks and Labor Market Segregation

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Abstract

We present a framework for simulating labor market matching processes in order to study mechanisms that generate segregation. Empirical evidence reveals that labor markets are often highly segregated with respect to the ascribed attributes of workers. Many occupations are sex-typed, while in heterogeneous societies certain fields are often dominated by specific ethnic groups. Various explanations have been proposed to account for segregation in labor markets. On balance, most of these explanations can be classified as essentially "supply-side" arguments, emphasizing differences in human capital distributions between groups, or "demand-side" accounts, based on employer preferences (either in-group or out-group biases). Yet the process of labor market stratification is not merely a matter of the human capital characteristics of workers or the preferences of employers; it also a function of the complex process by which persons are matched with one another, including the way that agents in the market find and evaluate information. In our research we address these oft-overlooked issues by considering two network-related aspects of the matching process explicitly: who knows about jobs, and how network structure relates to attributes. Using an agent-based simulation model, we show how network homophily can result in acute segregation by ascribed attribute, even in the absence of discriminatory preferences on the part of employers or supply-side human capital differences. Further, we consider how network dynamics, combined with workplace practices, can amplify or mitigate these effects. Implications for social policy are discussed.

1 Introduction:

Empirical evidence reveals that labor markets are often highly segregated with respect to the ascribed attributes of workers. Historically, many occupations are sex-typed, while in heterogeneous societies certain fields are often dominated by specific ethnic groups. In the US, one of the fundamental features of the labor market is the concentration of African American workers in the bottom tiers of the labor market (Reskin, Hargens and Hirsh 2004). Beyond these aggregate patterns, it has been observed that segregation is most pronounced within jobs (Baron and Bielby 1986), a finding that highlights the extent to which segregation is linked explicitly to employer-specific behavior. All of these forms of segregation are of concern to citizens and policy makers, not least because the existence of segregation appears to be at odds with our cherished political ideals of equality of opportunity and meritocracy.

Many explanations have been proposed to account for segregation in labor markets. On balance, most of these explanations can be classified as essentially "supply-side" or "demand-side" accounts. Supply side-arguments emphasize differences in human capital distributions between groups and link these differences to patterns in labor market outcomes, while demand side-accounts identify employer preferences (either in-group or out-group biases) as the mechanism that segregates labor markets by creating differential demand for different types of workers.

Yet which people are hired into which jobs is not merely a matter of the individual and human capital characteristics of workers or the preferences of employers; it also a function of the complex process by which persons and jobs hear about and are matched with one another (Granovetter 1981; Sørensen and Kalleberg 1981; Marsden and Gorman 2001). Among those interested in labor markets and stratification processes, how workers and employers learn about each other, and how information is evaluated once acquired, are often overlooked aspects of the matching process. This lacunae exists in part because it is extremely difficult to study the matching process empirically, let alone to evaluate the relative role of various information-based mechanisms in the allocation of persons to jobs (cf. Fernandez and Weinberg 1997). Nevertheless, as those who worry about "the old boys network" remind us, there is a lurking suspicion that this aspect of the labor market surely plays a key role in the level of segregation in the labor market.

We address these issues by considering two aspects of the matching process explicitly: simple constraints on information, and variability in the networks through which job-related information may flow. Rather than relying on empirical data drawn from real social settings (which are often the result of several competing mechanisms operating simultaneously), we proceed by isolating theoretically described mechanisms in an artificial laboratory to see how they operate under different structural conditions. Our goal is to provide some insight into the inter-play of mechanisms that produce, maintain, or reduce segregation by race, ethnicity, or sex, in the workplace.

We find that while discriminatory preferences of employers can generate substantial segregation in a labor market, other conditions can as well. Skill differences between groups and social segregation, in the form of biased or closed networks, are both also associated with high levels of segregation within firms. Further, we show that when workers incorporate co-workers into their networks, workplace practices may translate into more segregated networks. This feedback process suggests that interventions that focus primarily on employer behavior may be ineffective at reducing segregation, particularly in sectors where crucial job information flows through informal social relations.

We begin by summarizing the problem and identifying major theoretical and empirical themes in the study of labor market segregation. We then describe the simulation framework we use, and describe our experimental conditions. Next we present results from our simulator, first considering how employer preference regimes, combined with various social conditions, affect the level of segregation in an artifical labor market. These results show that segregated networks substantially increase labor market segregation, independent of employer preferences or behaviors. Building from this finding, we then consider how labor market activities might affect the level of homophily in social networks. We conclude by discussing the implications of this research for old and new economy jobs.

2 Labor Market Segregation

Labor market segregation and wage inequality are two of the most distinctive features of developed labor markets. Despite substantial expansion in the labor force participation of women over the past fifty years, US women who work full-time currently earn on average 76 cents for each dollar of men's wages (IWPR 2005), and remain concentrated in female-dominated occupations. Blacks and several other racial and ethnic minorities also suffer a wage penalty, and are over-represented in some occupations and sectors, and under-represented in others. With some variation, similar fundamental patterns hold in most European countries as well (Pettit 2005). Recently Barbara Reskin and her colleagues have documented the extent of occupational concentration by remarkably fine-grained race/sex/ethnic-origin categories; they find that sex-segregation remains extremely prevalent, and that within sex-typed occupations, racial and ethnic groups are arrayed into a stable prestige hierarchy (Reskin, Hargens, and Hirsh 2004).

Understanding the processes that generate segregation in labor markets–and devising policies to ameliorate this form of inequality–has been an important research topic for social scientists from a variety of disciplines. Two primary ideas dominate the research on what generates segregation (or occupational sex- or race-typing) in labor markets: that differences in skill translate into different labor market outcomes, and that discriminatory preferences on the part of employers are the culprit.

First, there is a set of explanations that focuses on the supply side of the equation. Commonly associated with economists (by sociologists, at least), the ideal-typical supply-side model posits that the market mechanism accurately rewards the skill or value of workers. Thus variation in the distribution of skills in a population will be reflected as variation in wages or other rewards associated with jobs (Mincer 1974). According to this logic, if two (or more) groups have different job-relevant skill profiles (i.e., whites receive, on average, higher levels of education than blacks), the groups will have different labor market experiences. To the extent that occupations or jobs require similar skills, this mechanism may channel certain types of workers into certain types of jobs, and labor market segregation will occur as a by-product of a legitimate selection process. For this mechanism to generate segregation, two key elements must exist: (1) there are differences between groups in the distribution of job-related skills; (2) the hiring process evaluates potential candidates exclusively in terms of skill.

While the supply-side argument has predominantly used to account for wage differences between groups, it is also applicable to segregation, especially in contexts where similarly rewarded jobs are clustered into occupations or workplaces. However, empirically testing whether this mechanism explains observed segregation in the labor market is a challenge, largely because it is extremely difficult to observe the hiring process directly. Often researchers work around this by estimating a regression equation predicting wages or occupational prestige as a function of human capital characteristics. The idea is that if the human capital variables fully account for differences between groups in wages or occupation, the hiring process is assumed to be neutral with respect to illegitimate characteristics, and any observed labor market segregation is a result of differences in the supply of skill between groups.

A second class of explanations is demand-based, in that it works via employers' preferences for specific types of workers. Unlike the supply-side mechanism described above, when the demand-side mechanism operates employers are not indifferent to traits other than human capital characteristics. Rather, employers prefer workers of type X (or prefer workers who are $\sim$ Y), and potential workers who have the desired characteristic (or who do not have the undesired characteristic) receive preferential treatment in hiring.[1] The essential feature of this mechanism is the explicit preference of an employer for (or against) a particular type of workers, a preference structure Becker refers to as a "taste for discrimination" (Becker 1957). When employers prefer workers with particular attributes, independent of skill qualifications, such preferences can produce segregation at the level of the workplace, job, or occupation. For example, employers may feel that women are more suited to be elementary school teachers, men are better at working in nuclear power plants, or that salesmen should share the ethnicity of their customers.[2] If employer-based preferences are strong enough, only those workers with the trait will be hired: if there are no qualified workers with this trait, the job may remain unfilled. This mechanism underlies the idea of a labor queue (Reskin and Roos 1990).

Many people believe, and some social science suggests, that discriminatory preferences play a major role in producing (and maintaining) labor market segregation. However, empirically evaluating the content of preferences is notoriously difficult; in the contemporary US setting, few employers would admit to discriminatory preferences (Moss and Tilly 2001, Pager and Quillian 2005), and so evidence concerning discriminatory preferences is often indirect. Two types of research dominate: Experimental studies such as those used in housing discrimination studies have been used in an attempt to directly assess employer bias, but these findings are not particularly generalizable (Pager 2003). At the aggregate level, researchers often resort to an indirect logic when attempting to reveal this mechanism: after controlling for human capital factors, residual differences in the labor market experiences of groups are interpreted as evidence of discrimination. However, this strategy is well-recognized as inadequate, since many other institutional factors influence the hiring process; further, it is theoretically possible that both (a) groups have different skill

[1] Of course in the supply-side model employers also have preferences for certain types of workers: in that framework these preferences are called job qualifications. For example, when hiring for a position in a sociology department, it makes some sense to prefer candidates with background or skills in this field, rather than, say, physics, or bricklaying.

[2] A twist on this model considers also the preferences of workers for types of jobs: if women, for instance, prefer part-time or flexible work, they may self-select into or out of the pool of applicants in ways that affect segregation levels by occupation or work-place. Shelly Correll has done some very nice work exploring how such preferences might develop (Correll 2004).

profiles and (b) employers have discriminatory preferences, yet this analysis strategy cannot detect the magnitude of these effects or how the two processes interact.

While these two dominant accounts and their refinements continue to attract scholarly interest and debate, many have observed that other features of labor markets influence who finds what jobs, how jobs link together, and–by implication– how segregated the labor market becomes (Granovetter 1981, Sørensen and Kalleberg 1981; Marsden and Gorman 2001). The third class of mechanisms is rooted in the way information about labor-markets is disseminated and interpreted. If the labor market is a matching arena, how workers find out about jobs, and how employers find out workers, are crucial links in the chain of employment.

A fundamental information-based mechanism operates directly through constraints on access to information about jobs. Normally, to get a job one must know about a job. Jobs that are not known about might as well not exist. Thus constraints on the flow of information about open jobs will limit workers labor market opportunities. The basic neoclassical model recognizes this: full and perfect information is typically considered a condition for the proper functioning of markets. Deviations from perfect information may result in sub-optimal sorting of sellers and buyers. In the labor market setting, information about potential jobs may flow through a variety of socially structured channels, including organizational or occupational associations, newspapers, headhunters, and word-of-mouth. Each of these channels constrains access to information-both in terms of the number of persons who might hear about vacant jobs, and which particular persons hear about them. One potentially important channel through which information about vacant jobs can flow is the personal contact network of a worker.[3]

If a worker's personal contact network is disproportionately composed of others who share a particular trait, then this worker may disproportionately hear about jobs held by (or known about by) other workers with the same trait. From the

[3]Personal contact networks may work in conjunction with other information channels: for example, organizations may post listings of open jobs on a bulletin board, and employed workers may tell their friends about promising openings.

employers perspective, this creates a pool of potential employees that mirrors the (extended) contact network of current employees; selection from this pool will amplify the level of segregation in employment. Thus in and of itself, a constraint on the flow of information-combined with a segregated network structure–could produce and maintain segregation within jobs or firms, without any discriminatory action on the part of individual employers.[4]

For this mechanism to produce segregation, two conditions must hold: (1) personal contact networks must be an important channel through which information about jobs flows; and (2) networks must tend toward homophily with respect to some attribute. However, there has been very little systematic investigation of this mechanism to date, perhaps because both of these conditions are difficult to measure on a broad scale. It is generally recognized, however, that recruiting through personal networks may have important implications for the diversity of organizations, since homophily in contact networks may be reproduced in the socioeconomic make-up of organizations (Doeringer and Piore 1971, Fernandez, Castilla and Moore 2000, Granovetter 2005).

Most of the work on networks and job searching treats Granovetter's finding that weak ties are a good source of information about jobs (1973, 1985) essentially as a sociological truism, despite the fact that Granovetter's original study examined a very restricted sample of skilled professionals who actually found jobs. Subsequent studies find some evidence weak ties help individuals find jobs, that having a rich network helps find better jobs, and that spells of unemployment are shorter for those with broad networks. But we also find evidence of some people being trapped; that some networks are connected only to bad jobs, and that these "bad networks" may translate into poorer labor market outcomes for some individuals. Further,

[4] It is perhaps worth noting that policies that require public employers to actively and widely disseminate information about all vacancies are designed to counteract the potentially segregating (and individually discriminatory) consequences of this sort of information constraint. These policies, however, increase screening costs, and may provide employers with a great deal of information that is difficult to interpret or evaluate. Therefore, in spite of bureaucratic rules designed to keep an "old boys" network from excessively influencing hiring decisions, applicants with personal referrals may still have an advantage, since employers have more trustworthy information about these workers and may have lower monitoring costs once referrals are hired.

there are real questions about selectivity into networks and into jobs, which raises important issues about the mechanism underlying associations between networks and jobs. In the few nationally-representative samples of workers we find that the aggregate effects of networks on job-related outcomes are a wash (Mouw 2003). Nevertheless, it is clear that in many contexts–particularly smaller firms and firms without well developed HR departments–informal networks are a important conduit for employees to find candidates, and for workers to hear about jobs. More progress has been made analytically, most notably Montgomery's (1992, 1994) work showing that those with more extensive networks have access to a richer pool of employment potential, and may end up with higher wages, even if weak ties do not lead them to their ultimate job (see also Boorman 1975). Further complicating research on this aspect of the hiring process is that we know very little about the empirical distribution of the composition and structure of personal contact networks, though some reasonable bounds on these distributions have recently been proposed (e.g., Watts 1999b; Barabsi 1999; McPherson, Smith-Lovin and Cook 2001).

3 Our Laboratory: A stochastic, dynamic agent-based model

Previous research has documented that variations on the supply-side, demand side, and information-based mechanisms all play a role in structuring the level of segregation in employment. However, it is extremely difficult to tease apart how powerful the mechanisms are, particularly because the effect of one mechanism may be contingent on structural features of the labor market itself, or on the composition of networks that are maintained for other purposes (and are not well understood anyway).

Given these substantial limitations, our approach rests on a developing a dynamic agent-based model that is flexible enough to incorporate various preferences and structures consistent with specific abstract descriptions of labor-market behavior. In adopting this approach we build on computational advances and our own previous work using a similar framework that emphasizes the two-sided nature of a matching problem. In Stovel and Fountain (2003) and Fountain (2006) we examine how socially structured access to information about jobs can influence macro-level characteristics of the labor market such as unemployment rates, mobility, and turnover. We modify this by operationalizing various theoretically described mechanisms as sets of structures and rules; we then use the model to simulate artificial labor markets, and examine the effect of the mechanisms in isolation and in conjunction with each other. The simulation technique is a useful way to address empirically intractable problem such as ours, and helps focus subsequent empirical work as well suggests strategies that might effectively reduce concentration in the labor market.

Agent-based approaches are still not widely used, although they are rapidly gaining acceptance in sociology and other social science disciplines (Macy, Clark, Mark, Kitts, Chiang). In a typical agent-based model, the researcher specifies the micro-level rules of interaction, and observes the macro-level patterns it produces. This provides a way to directly model the mechanisms that produce particular outcomes, rather than indirectly studying associations. However, models are often quite simple and stylized many things are left out or held constant in order to isolate how concepts of theoretical interest operate under distinctive conditions. From this perspective, agent-based models offer a tool for theory building and refinement, rather than hypothesis testing (Davis, Bingham, and Eisenhardt 2006). The goal is to use patterns that emerge in data simulated from the model to suggest new questions to ask of empirical data. Some of the problems that have been studied via agent-based models include collection action, the production of order, and diffusion. We treat the problem we study as a type of diffusion process (information spreads over networks), although one that is complicated by the two-sided decision to hire (outcomes rest on the union of information and competitive processes). Increasingly, agent based models and other formalisms have been brought to bear on related questions concerning the hiring process (Calvo-Armengol and Jackson 2004;

Rubineau and Fernandez unpublished ms 2006; Tassier JMS 2005, 2005; Fountain and Stovel 2005, Fountain 2006.)

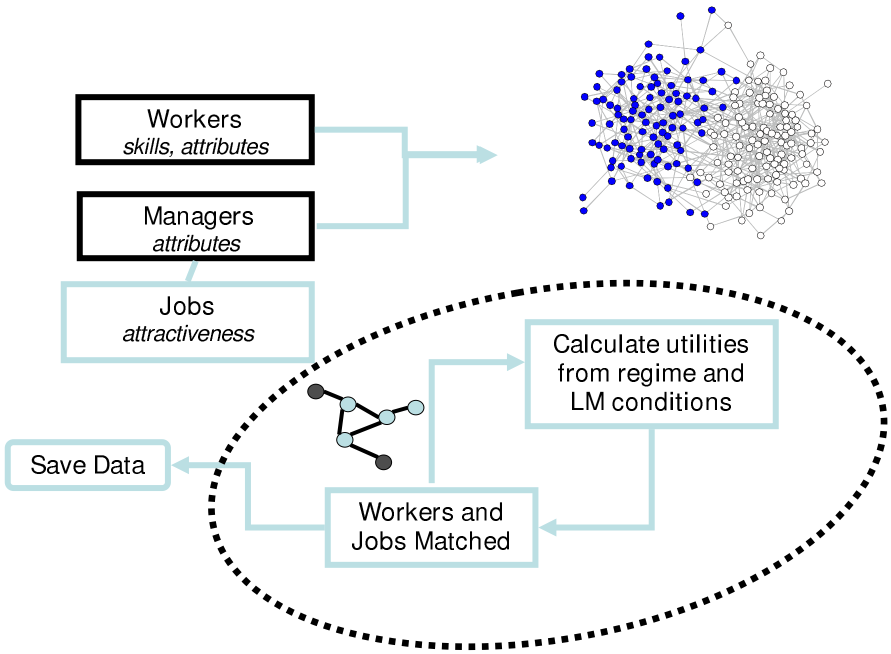

Figure 1: Schematic Diagram of Simulation Flow

Our basic strategy is to build an artificial world populated by workers who want to find jobs and managers who want to staff jobs. While real labor markets are extremely multi-dimensional and complex, our goal in designing the artificial world is to capture (and vary) core features of theoretical interest. Thus our workers are heterogeneous with respect to two characteristics: a binary attribute (think sex, or race) and a quantitative measure that captures variation in qualification (think education, or skill). Managers' preferences about potential workers are reflected in utility equations that operationalize various employer-based decision rules. The primary source of information about job vacancies is a (dynamic) social network that links workers and managers. Within each iteration of the model, workers become aware of a set of job openings, and managers select among their pool of available candidates. Using a well-known many-to-many matching algorithm (Gale-

Shapley 1969), workers are assigned to a job or are left unmatched; networks and other labor market features are adjusted in response to the new conditions, and the process begins again. A schematic diagram of the basic flow of the model is shown in figure 1. Additional details about the model can be found in Appendix A and in Fountain and Stovel 2005.

We use this basic simulation framework to conduct experiments contrasting different labor market conditions. We vary three families of parameters: employer preferences; characteristics of populations; and the information regime. A summary of our experimental structure is reported in Table 1.

Employer Preferences		**Population Characteristics**		**Information Regime**
• Indifferent • Skill-based • Taste for Discrimination	X	• ρ (skill,attribute) = 0 • ρ (skill,attribute) > 0	X	• Full information • Correlated Network • Dynamic Network
Outcomes Labor Market Segregation (Index of Dissimilarity) Network Homophily				

Table 1: Experimental Structure

3.1 Employer Preferences

As discussed above, employer preferences for- or against- certain classes of workers are often identified as an important source of labor market segregation. We compare employers who are indifferent to workers' characteristics to two distinct types of employer preferences: a preference for more skilled workers, and a discriminatory preference. These preferences are controlled in the utility calculation: in the most general form, an employer i's utility for a worker j is a linear function of characteristics of the worker, the employer, and the current labor market conditions.[5]

[5]We also calculate an analogous set of utilities from the workers' perspectives. This allows us to use the two-sided matching algorithm.

$$U_{ij} = \alpha X_{ij} + \beta LM_t + \epsilon_j \quad (1)$$

In this conceptualization, X_{ij} includes a variety of worker and job characteristics, LM_t contains current labor market conditions, and ϵ_j is a small employer-specific noise term. The sets of parameters α and β can be thought of as weights on the characteristics: a higher relative value of a parameter means a stronger employer preference for this characteristic. In most of our experiments all employers are governed by the same utility calculation, though in the final section of the paper we relax this assumption.

In the first preference condition, all workers are fully equivalent in the eyes of employers and selection among candidates is essentially random.[6] In practice, this means that the αs associated with workers' skill and attributes are set to zero.

The second condition is designed to capture employers' preferences for more skilled workers. Here we set the α associated with workers' skill to a value > 0, while keeping the α associated with workers' attribute equal to zero.[7] This means that *ceteris paribus*, workers who present with higher skills will be preferred over workers who present with lower skills. While empirically it may be the case that employers actually prefer workers who are *appropriately* skilled, such fine-grained targeting introduces too much additional complexity into this model to be easily interpretable.

The third condition introduces a discriminatory preference. The general thinking here is that employers may prefer to hire workers who are like them in salient ways: women managers prefer women employees, Irish foremen prefer Irish workers, and black business owners prefer black employees (get refs on this). We call this an

[6] In all trials reported here, the model does include a slight preference for previous employees; this is included to reduce the overall amount of turnover in the labor market and serves to crystallize observed patterns more quickly. Examinations of the effects of reducing this preference are discussed in Fountain and Stovel 2005.

[7] Sensitivity analyses designed to uncover scaling effects in the model reveal that this and most of our other preference parameters act in an essentially binary fashion: macro-level effects are evident when weights are set close to one, and there are only trivial changes as they rise above one. We suspect that this is a result of setting the stickiness parameter to one.

in-group bias, and operationalize it by introducing a binary X_{ij} term that indicates whether the worker and manager are in the same attribute category. When this preference is operative, the α assigned to this indicator variable is set > 0, so that managers will select same-group candidates over candidates who do not share the attribute. This operationalization also allows us to easily consider an *out-group bias*; results of trials including an out-group bias are reported *in passim*.

3.2 Population Structure

While employer preferences may be an important source of labor market segregation, there is reason to believe that their significance is contingent on the structure and characteristics of the supply of labor that employers confront. At the most basic level, a highly skewed population distribution could make it very difficult for some employers to exercise a discriminatory preference–simply because workers matching their desired profile are scarce in the population.[8] Things are potentially more interesting when considering the dependence of skill-based preferences on population characteristics, and this is what we focus on here. Drawing from the logic of economists' arguments concerning human capital, we compare scenarios where workers' skills and attributes are correlated with each other to scenarios where these two characteristics are independent of one another.

There is ample justification for being concerned with group-level differences in the stocks of human capital in the US labor market. For example, Figure 2 shows the relative distribution (Handcock and Morris 1998) of educational attainment for adult blacks and adult whites, based on 2002 CPS data. The top panel reports differences for men, the bottom for women. Within each panel, the height of the bars shows the relative portion of blacks at each educational level over the portion of whites in that category. If there is equal composition within a level of attainment (e.g., 25% of black men and 25% of white men have graduated from high school),

[8] We do not report results for skewed group sizes here, though results are available from the authors.

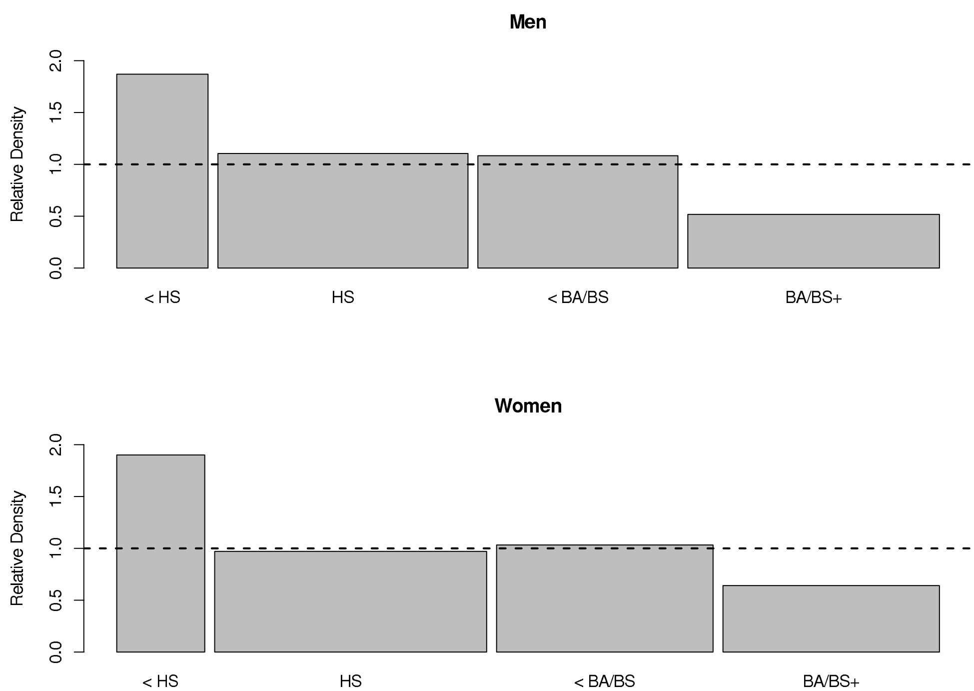

Figure 2: Relative Educational Distribution of Blacks and Whites, 2002 CPS Data

the ratio is one. Higher bars mean more black in a category, lower bars mean more whites. The width of each bar reflects the portion of whites in the category. The empirical data reported in Figure 2 clearly show that in the US, blacks are substantially over-represented at lower levels of education, and under-represented among college graduates.

Translating the basic idea of group-level differences in job-related preparation or skills into the limited building blocks of our model is not completely straightforward. What we do is specify a mean and standard deviation for the distribution of skill within each group, and assign skills from a normal distribution with these moments: when the means and standard deviations for each group are equal, there is no difference in skill between the groups (though there is individual heterogeneity in skill). When the means differ, groups differ in their average skill. Figure 3 depicts density plots for two different scenarios, one in which there is no skill difference

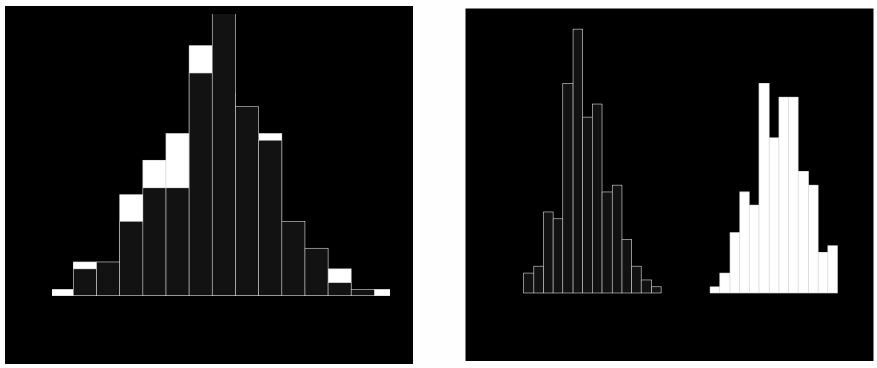

Figure 3: Simulating various associations between skill and attribute. Left panel (no association): $\bar{X} = 50, s.d. = 10, \bar{X}_1 = 50, \bar{X}_2 = 50$; right panel (strong association): $\bar{X} = 50, s.d. = 10, \bar{X}_1 = 30, \bar{X}_2 = 70$

between the groups, and one in which there is a relatively strong skill difference between the groups.

3.3 Information Regimes

While employer preferences and the association between skill and attribute dominate discussions of labor market segregation, we are particularly interested in how access to information about vacancies and candidates affects labor market processes. We have two aims here: first, as a simple baseline, we are interested in the effects of restricting the amount of information available to all actors in the labor market. Second, and more importantly, we want to examine the relationship between the structure of networks through which information flows and labor market outcomes.

As a baseline comparison, we evaluate the model under a condition of full information. Full information is an important assumption of neoclassical micro-economic models of markets, and while it is empirically unrealistic, it offers a theoretical benchmark against which we can compare outcomes derived from models capturing key features of social processes that influence labor markets.

Once we move away from a full information regime, agents in the model have access to jobs primarily via a social network linking workers and managers.[9] A substantial body of research shows that informal social networks are an important vector for the diffusion of information about jobs; here we concentrate directly on whether network homophily translates into labor market segregation. By homophily we refer to the tendency of like to choose like as a relationship partner (McPherson, Smith-Lovin, and Cook 2001). The primary question we ask is, are there levels of network homophily that can generate substantial segregation in employment, even absent explicitly discriminatory preferences on the part of workers.

We begin by fixing the network at the outset, and varying the level of homophily (in-group bias) across trials. We control the level of homophily in the network with a simple function that governs the probability P_{ij} of a tie between two actors i and j.

$$P_{ij} = (1 - 2p)\left((1 - \theta) H_{ij} + \theta (1 - H_{ij})\right) + p \tag{2}$$

The key parameter here is θ, which controls the strength and direction of the network bias. H_{ij} a binary measure that indicates if i and j share an attribute, and p is a very small underlying probability of a tie. When $\theta = .5$, the probability of in- and out-group ties are equal, and the graph approximates a Bernoulli random graph. As θ approaches zero, most ties will cross group boundaries, while as θ approaches one, in-group ties will dominate.[10] Figure 4 depicts networks generated

[9] We also distribute a small amount of random information, to simulate non-network recruitment strategies.

[10] Beyond the in- or out-group preference, there is no structure in the graph. In other work we explore the implications of more- or less-clustered graphs on labor market outcomes (Fountain and Stovel 2005, Fountain 2006).

with θ values of .5, .9, and 1.0. One nice feature of this expression is that in the case of equally sized groups, θ can be interpreted as the proportion of all ties that are within the group.

In our network restricted information scenarios, workers have access to information about any jobs controlled by managers they are tied to directly, as well as about those jobs controlled by managers connected to their network partners.[11]

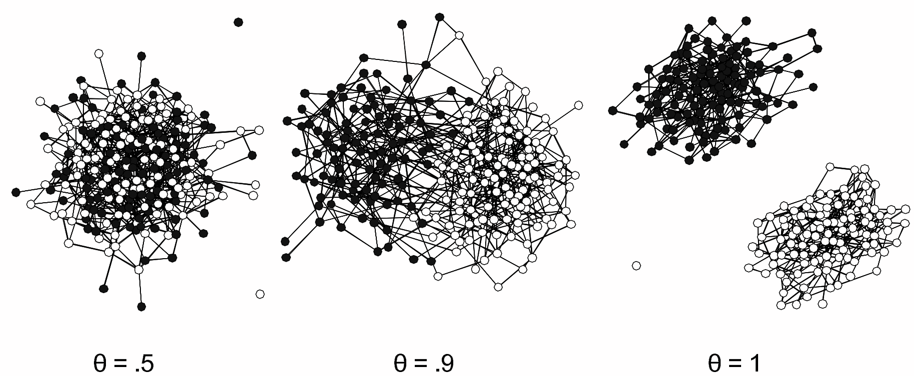

Figure 4: Simulated networks with various levels of θ. Group membership is indicated by node shading

We also consider what happens when networks are dynamic. There are many ways to make networks dynamic: they can simply be re-drawn according to a fixed probability structure, or they can evolve in response to endogenous changes in the circumstances of the agents. We adopt the latter strategy, and consider the

[11]Sensitivity analyses show that for the population sizes and densities we use, going beyond second degree ties essentially duplicates the full information regime.

possibility that over time, agents shift their network ties *toward* co-workers and *away from* non-coworkers. There is some empirical justification for imagining that people incorporate co-workers into their social networks. For example, data from the General Social Survey shows that in the US, adults' networks are quite likely to contain co-workers (Marsden 1986). Figure 5 shows that of the network partners with whom adult respondents "discussed important matters," over 20% were co-workers, while among employed respondents the figure is closer to 27%.

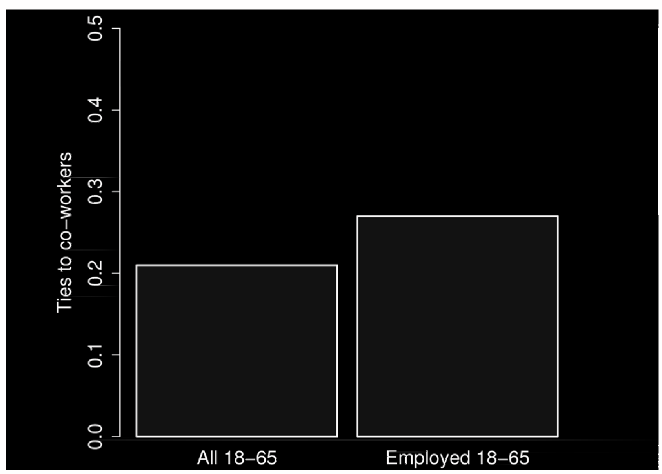

Figure 5: With whom do people discuss important matters? Proportion of ties to co-workers. Data from GSS network modules.

Since our model treats networks in a fairly simplistic fashion, and focuses on networks through which job-relevant information might pass, we figure it is reasonable to believe that if networks change over time, one direction in which they might change is toward long-standing co-workers. Specifically, in our dynamic network trials, we rewire a fixed percentage (typically 5%) of all ties at each iteration, such that new ties are formed according to the following equation:

$$P_{ij} = (1-p)\left(\frac{C_{ij}}{t}\right)^{\phi} + p \tag{3}$$

The key parameter in this formulation is ϕ, which governs the extent to which agents who work together are likely to form a tie. This parameter operates on a variable C_{ij} that measures the length of time (in iterations) that worker i and j have worked for the same manager. Lower values of ϕ are associated with a stronger preference for co-workers. As in the homophily model, p is a small underlying probability. To reduce the effects of changes in the overall availability of information in the network, we drop an equal number of ties with a probability of $1 - P_{ij}$. In our dynamic network experiments, we set $\phi = 2$ and apply this endogenous drift model to different starting networks.

3.4 Outcomes

Our primary outcome of interest is the level of segregation by attribute in the simulated labor market. Because we have implemented a simple two-group model, we use the familiar index of dissimilarity to measure segregation (Reardon and Firebaugh 2002). Since we do not explicitly identify firms, occupations, or spatial units in our model, we use the cluster of jobs controlled by a single manager as our unit of aggregation.

$$D = .5\sum_{k=1}^{m}\left|\frac{G_{1k}}{G_1} - \frac{G_{2k}}{G_2}\right| \tag{4}$$

This index is calculated as in equation 4, where k indexes managers, m is the number of managers, G_1 is the proportion of the population in attribute category 1, G_2 is the proportion of the population in attribute category 2, and G_{1k} and G_{2k} are the proportions of group 1 and 2 members, respectively, hired by manager k. Substantively, the index of dissimilarity measures the proportion of workers who would have to shift from one manager to another in order make the distribution in across managers proportional to the distribution in the population. A value of zero means that workers are distributed in proportion to their representation in the population; higher values mean greater segregation.

A second, intervening outcome that we examine in a subset of our analyses is the level of group-bias in the network. When the information networks are static, the level of in-group (or out-group) bias is fixed by the parameter θ. However, when the networks themselves are dynamic, the level of in-group bias may change over the course of the simulation trials. Therefore, we calculate the proportion of all ties between alters who share attributes. When group sizes are balanced, this measure is analogous to the parameter θ described above.

3.5 Additional Model Details

4 Results

As described above, our experimental design calls for us to vary three families of parameters. First, to establish a baseline, we consider how employer preference regimes interact with different population structures under conditions of full information. We then restrict information, and consider what happens when networks are more or less structured by our attribute variable. We find that several combinations of parameters generate substantial levels of segregation in our artificial labor market, including scenarios in which employer are indifferent to workers' characteristics. Because our model suggests that highly biased networks are a sufficient condition for high levels of segregation, we then explore whether labor market conditions themselves can affect the level of homophily in networks. We find that several patterns of employer preferences can affect the network, and that even if a minority of employers engage in discriminatory behavior, sufficient network segregation is produced that we observe unequal opportunities even at "fair" firms.

4.1 Full Information Regime

We begin by examining situations in which all actors have full information about each other, but employer preference regimes vary. This allows us to verify that the model is operating as advertised, and reveals some preliminary comparisons about the mechanisms of interest.

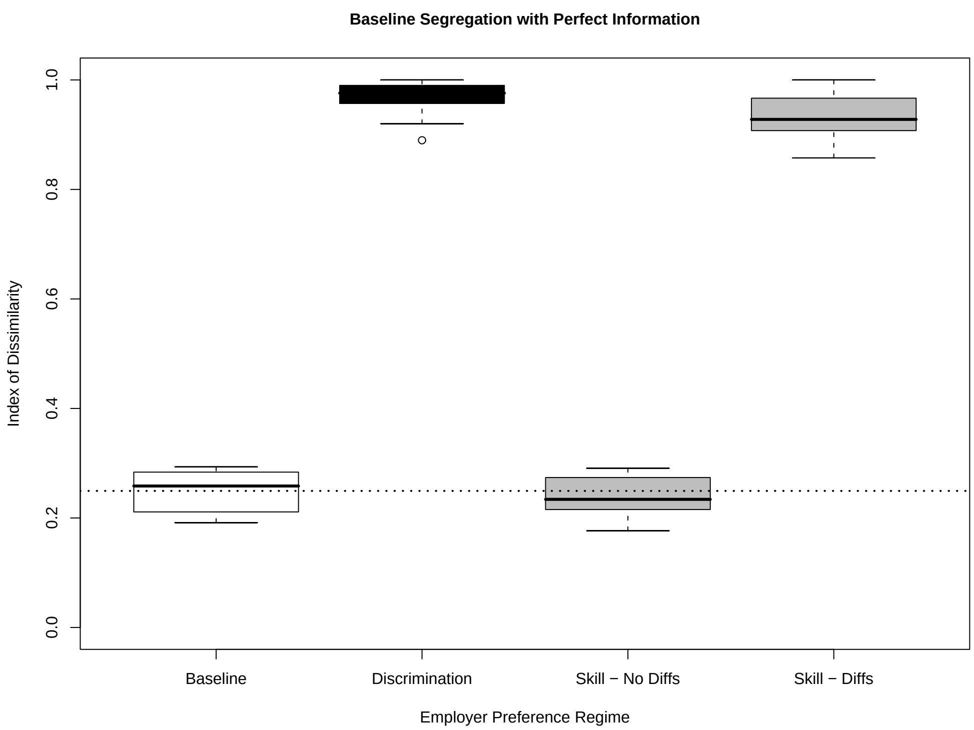

Figure 6: Full Information, Employer Preference Regimes, and Labor Market Segregation

In Figure 6 we plot the results of 50 trials for each of four distinct employment preference/population structure scenarios. Each unique constellation of parameter values is arrayed along the X-axis, while the level of labor market segregation from the resulting trials (measured with the dissimilarity index) is plotted on the Y-axis. Variability within each scenario comes from the stochastic aspects of the model.

In the first employer preference regime, managers are completely indifferent to all types of worker heterogeneity (skill and attribute). Further, since this is the full information set-up, they are aware of all workers. We consider this scenario a baseline; it produces a dissimilarity index centered around about 25%, with very little variability. We consider this the minimum level of segregation possible in our model; what segregation remains is driven largely by small numbers and technical features of the model.

The second scenario adds in a taste for discrimination. In the absence of any other structure in the model, when managers prefer workers who share their attribute over workers who don't, segregation becomes extremely high. In trials run under this scenario, close to 100% of workers are employed in fully segregated firms. Again variability is relatively low.

In the third scenario, employers prefer higher skilled workers and are indifferent to attribute. However, worker skill and attribute are independent of one another. This scenario represents what some would consider a labor market 'ideal,' in the sense that employers are seeking the most competitive workers, but whatever process produces skill in the population is not associated with ascribed attribute. In our model, this scenario produces levels of segregation that are statistically indistinguishable from the baseline model. That is, this scenario produces no more (or less) segregation than the minimum expected in our model.

The final scenario combines an employer preference for higher skilled workers with an association between skill and attribute. This set of parameter values generates substantially higher levels of segregation than the baseline model, though there is a bit more variability than in the discriminatory regime. In this scenario, human capital is rewarded, but since it is unevenly distributed between the two groups, one group enjoys better labor market outcomes.

4.2 Network Information Regimes

We now turn to scenarios in which information flows primarily through a social network that links workers and managers. We once again begin with our baseline scenario: Figure 7 shows boxplots for sets of 50 trials when employers are indifferent to worker characteristics. While the index of dissimilarity is still plotted along the Y-axis, the X-axis now arrays trials characterized by various levels of network homophily. On the far left the graphs are random with respect to attribute $\theta = .5$; as we move toward the right, networks' in-group biases become more pronounced. This figure reflects the baseline association between network homophily and labor market segregation in our network restricted models. It is evident that when networks are integrated, the level of segregation is comparable to our full-information baseline. However, as networks become more homophilous ($\theta \geq .7$), the level of labor market segregation begins to rise quite dramatically. When networks are largely segregated into two distinct clusters, the average level of segregation in the simulated data is almost four times greater than in the baseline model. The implication of this result is that high levels of segregation are possible even when employers are indifferent to any worker characteristics. The mechanism generating segregation when networks have a strong in-group bias is a selective pool: if job-relevant information flows through networks, and networks are disproportionately composed of those in the same attribute category, workers will predominantly hear about jobs controlled by in-group managers, and managers will be forced to choose from a pool that disproportionately reflects their own attribute identity.

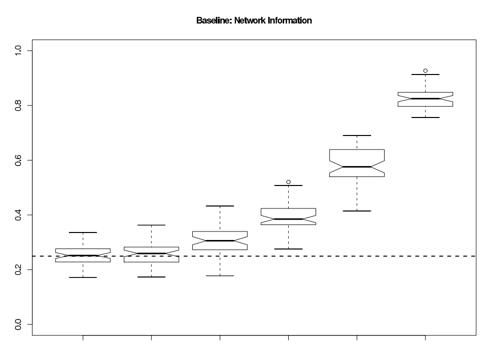

Figure 7: Network Restricted Information: Baseline model

Figure 8 shows an analogous figure for trials when employers exhibit an ac-

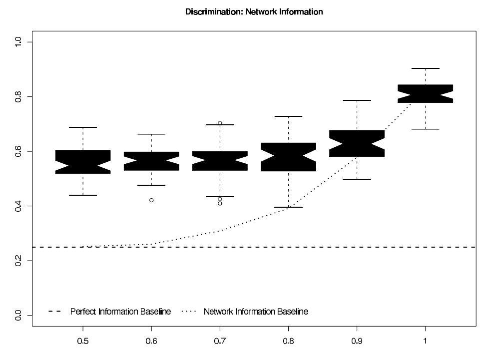

Figure 8: Network Restricted Information: Taste for discrimination

tive preference for workers who share their attribute. Again we vary the level of network homophily, and calculate the index of dissimilarity across 50 trials. For reference, we indicate the level of segregation for the full information baseline as well as the segregation trajectory for the baseline model under varying network conditions. Results here are substantially different from the baseline: When networks are random, discriminatory preferences increase labor market segregation substantially over baseline levels (D is roughly three times higher than the baseline). However, the index of dissimilarity for these trials is not as high as in the full information-discrimination regime, because the restriction on information means that some employers are 'forced' to choose workers they don't prefer, simply because there are no others in their randomly generated pool. As the network bias gets stronger, the level of labor market segregation rises. However, even at the highest levels of in-group bias, segregation does not rise above the network-restricted baseline levels. This suggests that when networks are highly segregated ($\theta \geq .9$), the network itself is the cause of extremely high levels of labor market segregation, rather than any existing employers' discriminatory preferences.

Next we consider the effects of employer skill preferences and network homophily. Figure 9 reports results of trials where employers prefer higher skill workers, but skill and attribute are independent, while Figure 10 considers contexts where there are skill differences between groups. When skill and attribute are independent, the

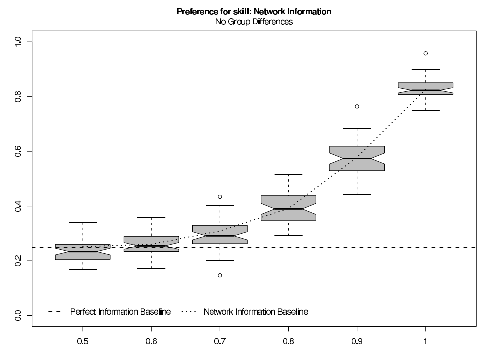

Figure 9: Network Restricted Information: Skill preference, no between-group differences in skill

pattern in the level of segregation is identical to our network baseline mode. While segregation does rise, it is purely as a result of changes in the level of in-group bias in the underlying network through which job-related information flows. In contrast, when groups differ in their average skill, the pattern is closer to that generated by the discriminatory preference regime–though the level of segregation observed for low levels of θ is somewhat lower. As in the discriminatory case, when networks have a strong in-group bias the level of labor market segregation is substantially higher, though again the values do not rise above those generated in the baseline model.

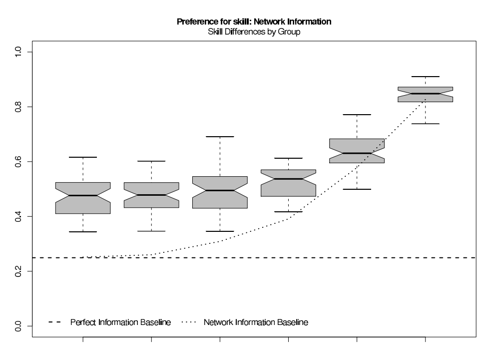

Figure 10: Network Restricted Information: Skill preference, between-group differences in skill

When comparing the impact of employer preferences and population characteristics on segregation, the results from the network restricted information trials mimic the crude pattern observed in the full information trials. Specifically, discriminatory preferences are extremely effective at generating segregated labor markets, while the combination of skill preferences and group differences in skill-levels are almost as effective. However, the network restricted scenarios reveal that these well-known mechanisms for creating segregation are not necessary conditions: When networks themselves reveal strong in-group biases, these biased networks themselves are a sufficient condition to segregate the artificial labor market. In fact, adding either of the segregating mechanisms to a homophilous network does not result in an increase in labor market segregation above the level observed with the homophilous network alone.

4.3 Dynamic Networks

Thus far our model has demonstrated that segregated networks can be as a powerful force toward segregation. But this raises an interesting question: where do segregated networks come from? Identifying sources of bias in networks has been the topic of a great deal of well-known and important research, much of which points to propinquity and explicit homophily preferences as crucial (Moody 2005, McPherson, Smith-Lovin, and Cook 2001). What we aim to do next is consider how the workplace itself might contribute to increasing segregation of networks. That is, if networks are dynamic, can workplace exposures shift the level of homophily in significant ways? To answer this we now turn to our second outcome of interest: the level of network homophily.

We now report results from sets of trials that incorporate our dynamic network model, in which over time, workers are likely to form ties with co-workers and drop ties to those they don't work with. In Figure 11 we plot the effects of various employers' preference regimes on the level of in-group bias in the social networks of workers over time. The Y-axis shows the change in network segregation (% of edges that are in-group) from the initial condition, and the X-axis shows time, in iterations. At each iteration, 5% of network ties are added and dropped, according to probabilities that depend on co-worker status and random noise, so that as levels of workplace segregation change, so does network composition. In these trials, we begin with a completely random network ($\theta = .5$), and ask whether any of our scenarios is able to generate a highly segregated network. It turns out that when employers have a taste for discrimination (the solid dark line), networks become progressively more homophilous over time: in our trials, networks go from fully integrated to approximately 90% in-group biased. In other words, when managers prefer to 'hire their own,' the network may evolve from being completely integrated to a point of nearly total homophily. This happens because when employers discriminate, workplaces become segregated (even if the original networks are integrated); if network evolution is influenced by the composition of the workplace, early (and moderate) levels of workplace segregation may be sufficient to stimulate in-group bias in an evolving network. The insidious part is that network segregation feeds back into workplace, accelerating and bolstering workplace segregation beyond the initially moderate levels. This suggests that even if employers' behavior changed at some later date (as a result of affirmative action or some other pro-active policy), it is possible that the consequences of their previous discriminatory behaviors could linger, via the segregated networks that these early preferences generated.

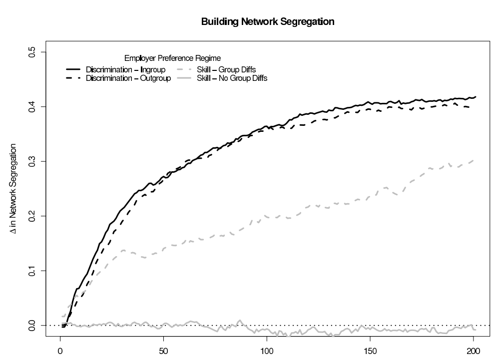

Figure 11: Building segregated networks from random networks: The effects of workplace conditions on network homophily

The dotted dark line shows what happens to random networks when employers discriminate in favor of the out-group (rather than preferring members of their own group, managers prefer workers who do not share their attribute category): under this preference regime, workplaces, and thus networks, still become segregated. [12] The lighter dotted line shows the change in network homophily when employers hire on the basis of skill, and skill is associated with attribute. We saw in the previous section that this mechanism results in substantial workplace segregation, although not as extreme as in the discrimination case. Similarly here, supply-side group differences in skill can contribute to network segregation through the intervening workplace segregation. Finally, the solid light line shows that if there are no skill differences by group but employers hire according to skill, workplace-influenced dynamic networks remain integrated.

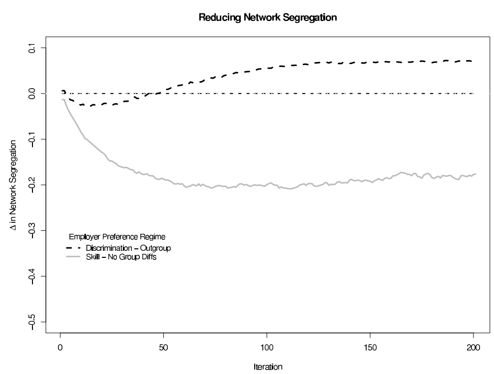

Figure 12: Deconstructing segregated networks: The effects of workplace conditions on network homophily

In Figure 12, we begin with a highly segregated network ($\theta = .9$), and explore whether it is possible to *reduce* network segregation via a workplace-based dynamic process. Our results show that when employers select according to skill, and skill is not correlated with attribute, allowing networks to respond to workplace conditions has the effect of reducing network segregation, through the intervening

[12] This is because any singular preference will lead to a dominant group in the workplace; with an out-group preference segregation cannot be complete (due to the presence of the manager), but it can be severe.

mechanism of a trend toward lower workplace segregation (which we saw in a previous graph).[13] Although networks never become completely random, homophily does decline substantially: from a 90% in-group bias at the outset to 60% over time. This is a significant decline, and moves the network from the range where network homophily dominates all other mechanisms to a range when the level of in-group bias has no independent effect on the level of segregation.

The dotted line shows the effects of an out-group preference. Here we initially see a small decline and then a slight rise again, indicating that network segregation actually increases. Rather than breaking segregation, out-group hiring just changes its form. In this case, employers tend to hire the out-group workers that they are tied to. As networks respond to this workplace diversity, there is an initial drop in segregation, however around the 20th period there has been complete turnover in ties and new ones have been made within the now segregated workplaces. In these units, most workers are of the same group, although a different group than their manager.

4.4 Mixed Regimes

5 Discussion

Need to write this section

Several mechanisms are sufficient to produce segregation in labor markets When networks are segregated and job-relevant information flows through nets, labor market segregation is substantial Workplace practices can increase network segregation

Mobility up, turnover up, career instability up Institutions that organize careers are being dismantled Puts additional pressure on job-seeking and hiring strategies

issues associated with changing the level of segregation in networks, changing association between skill and attribute implications of mixed regimes findings for

[13] It is worth noting, however, that this combination of circumstances is quite unlikely to appear in empirical settings, since whatever social process results in a equal skill profiles between group is likely to result in relatively integrated job-related networks.

interventions

Some new hiring strategies will increase access of information, and may minimize the segregating effects of homophilous social worlds. But, when information becomes more prevalent, it becomes harder to sort and sift through. Under these conditions, informal screenslike networks and referralsmay re-emerge.

If there is more turbulence in careers, trans-organizational networks become more important.

When people spend shorter periods of time in one job, over the course of a career it means they hold more jobs, and/ or they spend more time unemployed. This means that not only do workers have to look for jobs more often, but employers must hire more often and much of this action is occurring between rather than within firms. This can be quite costly and time-consuming for both workers and employers. Second, the organizational channels that once organized careers seem to be disappearing. Where once a young worker might have taken an entry-level job in a vertically integrated firm and worked their way up the career ladder as a route to upward mobility, now workers must rely on other extra organizational resources, such as labor market intermediaries, the internet, professional organizations, and social networks, to cobble together an upwardly mobile career by moving between firms.Taken together, these trends put a lot of pressure on the labor market it has a lot of work to do so frequently allocating workers to jobs.