



Management Science

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To cite this article:

Brian Rubineau, Roberto M. Fernandez (2013) Missing Links: Referrer Behavior and Job Segregation. *Management Science* 59(11):2470-2489. <http://dx.doi.org/10.1287/mnsc.2013.1717>

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Missing Links: Referrer Behavior and Job Segregation

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The importance of networks in labor markets is well known, and their job-segregating effects in organizations is a given. Conventional wisdom attributes this segregation to the homophilous nature of contact networks, and leaves little role for organizational influences. Yet employee referrals are necessarily initiated within a firm by employee referrers subject to organizational policies. We build theory regarding the role of referrers in the segregating effects of network recruitment. Using mathematical and computational models, we investigate how empirically documented referrer behaviors affect job segregation. We show that referrer behaviors can segregate jobs beyond the effects of homophilous network recruitment. Furthermore, and contrary to past understandings, we show that referrer behaviors can also mitigate most, if not all, of the segregating effects of network recruitment. Although largely neglected in previous labor market network scholarship, referrers are the missing links revealing opportunities for organizations to influence the effects of network recruitment.

Key words: organizational studies; personnel; simulation; applications; behavior; labor; referral networks; screening

History: Received July 28, 2011; accepted December 29, 2012, by Jesper Sørensen. organizations. Published online in *Articles in Advance* June 14, 2013.

1. Introduction

Networks dominate labor market dynamics from both the job seeker's and the hiring firm's perspectives. Most job seekers use their personal contacts to look for work; personal contacts contribute to the recruitment of about half of those employed in the workforce (Franzen and Hangartner 2006, Granovetter 1995). Similarly, from the perspective of the hiring organization, recruitment through networks is common (Bewley 1999, Henly 2000, Marsden and Gorman 2001). A representative survey asking about metropolitan employers' most recent hire revealed network recruitment via referrals from current employees to be the single most frequently used mode of recruitment (DeVaro 2005).

Network recruitment has long been theorized as contributing to job segregation (Acker 2006, Doeringer and Piore 1971, Fernandez and Sosa 2005, Marin 2012, Marsden 1994, Marsden and Gorman 2001, Moss and Tilly 2001, Mouw 2002, Reskin et al. 1999). Job segregation contributes to wage inequality (Bayard et al. 2003, Bielby and Baron 1986, Petersen and Morgan 1995) and to labor market rigidities (Anker 1997, Kahn 2000, Padavic and Reskin 2002). Numerous calls to curtail job segregation in part by reducing or even eliminating network recruitment (Braddock and McPartland 1987, LoPresto 1986, Padavic and Reskin 2002, Roos and Reskin 1984) reflect the common wisdom that network recruitment necessarily segregates, and that other than reducing

the practice, organizations have no other ways to mitigate its segregating effects.

The problem with this common wisdom concerning network recruitment, job segregation, and the role of organizations is that its source is a literature with two major deficits. The first deficit is the almost exclusive adoption of the job seeker's perspective (Lin 2002). Network recruitment requires a dyad. The *referral applicant* (also simply the *referral*) is the job seeker using her networks to identify job opportunities. The other half of the dyad is the *referrer*, necessarily an organizational member aware of a job opportunity and who shares that information with the referral.¹ From the perspective of organizations, there is little an organization can do to influence either the network structure or job-search behaviors of the job seeker. For this reason, organizations have largely been absolved from any responsibility for the segregating outcomes of network recruitment (e.g., National Research Council 2004). This absolution is misplaced. Recent research has shown that labor market intermediaries can contribute to the gender segregation of jobs (Fernandez-Mateo and King 2011). In network recruitment, the intermediary is the referrer, an organizational member subject

¹ Although some definitions of referral recruitment are more broad, our dyadic definition is the most common realized form of referral recruitment (DeVaro 2005). Referral bonus policies are predicated on precisely this type of dyadic relationship.

to organizational influence. Some of this influence is evident when firms offer cash and other kinds of bonuses for successful referrals to encourage referring. Some firms also have informal policies to manage referrer behaviors. For example, one employer allowed all employees to refer except those whose previous referrals did not work out (Waters 2001, p. 106). Still, little research has addressed the demand-side dynamics of network recruitment, or how these dynamics affect job segregation.

The second deficit characterizing this literature is the lack of a process-based understanding of the segregating effects of network recruitment. Although some empirical work has established a link between network recruitment and job segregation (Braddock and McPartland 1987, Fernandez and Fernandez-Mateo 2006, Fernandez and Sosa 2005, Mouw 2002, Petersen et al. 2000), to the best of our knowledge, there has been no formal mechanism-based theory of how one is associated with the other. The prevailing explanation for this association is simplistic, and only considers a single source: the homophilous nature of contact networks. The tendency toward sociodemographic similarity among social contacts is one of the most robust findings in social science (Marsden 1987, McPherson et al. 2001, Newman 2003, Wimmer and Lewis 2010). It would be unreasonable to expect organizations to influence this tendency. Yet homophilous contact networks are not the only mechanism involved in network recruitment. Empirical findings document demand-side—that is, originating from within the organization—processes involved in network recruitment. Still the absence of a mechanism-based theory of demand-side network recruitment dynamics has prevented an integration of these processes and systematic analysis of their implications. Mechanism-based theories can serve as invaluable aids in designing organizational interventions and moving research forward (Davis and Marquis 2005, Hedström 2005, Reskin 2003, Schelling 1998). Without a better understanding of referrers' behaviors, and the mechanisms by which these behaviors contribute to job segregation, organization scholars can offer organizations little guidance on how to mitigate the segregating effects of network recruitment.

This paper addresses both these limitations. We identify referrer behaviors as the missing links in our understanding of the role of organizations in the job-segregating effects of network recruitment. We operationalize a mechanism-based theory of network recruitment as both formal mathematical and computational models. We focus on the firm's hiring yield from referring employees, and the impact of referrer-referral ties on referring and turnover behaviors. We use these models to address the following three questions: (1) How much job segregation results from network recruitment? (2) To what extent do refer-

rer behaviors contribute to these segregating effects? (3) To what extent can firms mitigate the segregating effects of referring through policies targeting referrer behavior? We answer these questions with an innovative, intuitive, and intersubjectively valid measure of segregation. Our answers challenge the conventional wisdom that segregation from network recruitment is primarily a supply-side mechanism and that organizations have few opportunities to mitigate these effects.

2. Background: Network Recruitment and Its Demand-Side Dynamics

Much of the research on network recruitment implicitly conceptualizes it as a supply-side mechanism operating independently of the firm. In numerous cases, this view is even explicitly stated (e.g., Calvó-Armengol and Ioannides 2008; Calvó-Armengol and Jackson 2004, 2007; Fernandez and Sosa 2005, p. 861; Kmec 2005, p. 343, 2006, p. 683; Loury 2006; Tomaskovic-Devey 1993, pp. 54–55; Van Hoye and Lievens 2009, p. 341). Less common, but not wholly absent, is an acknowledgement that network recruitment has both supply-side and demand-side aspects (e.g., Henly 2000, p. 154; Lin 2002, p. 96; Reskin and Roos 1990, p. 305). Still, the supply-side perspective dominates the scholarship on network recruitment (Lin 2002). The dominance of a one-sided perspective concerning a two-sided phenomenon has limited our understanding of how network recruitment contributes to job segregation.

Recent efforts to construct dynamic models of network recruitment to understand its segregating effects have made unrealistic and obfuscatory simplifying assumptions about demand-side processes. For example, Tassier (2005) assumes perfectly homophilous contact networks such that members of one group will never generate a referral applicant from any other group. That is, men will never refer women, and women will never refer men. As we show below, all available empirical estimates of mean contact network homophily in network recruitment show less than perfect homophily. In another case investigating network recruitment and job sex segregation, Stovel and Fountain (2009) assume that only a single individual per firm, the hiring manager, engages in network recruitment. As a result, for a given firm, all network applicants would be generated by one person, necessarily a man or a woman, and would thus generate referral applicants biased in a single direction. These simplifications would be reasonable if demand-side processes were known not to play much of a role in the segregating effects of network recruitment. Until now, to the best of our knowledge, the segregating effects of demand-side processes have never been explicitly investigated; their role is unexamined

and thus unknown. To reveal the segregating effects of network recruitment inclusive of demand-side processes, an investigation would need to allow less-than-perfectly homophilous contact networks among diverse referrers. Men may disproportionately refer men, but they may also refer some women, and vice versa. Similarly, both men and women employed in the same firm should be able to refer their contacts to vacancies in that firm. We build such a model to reveal the segregating implications of network recruitment's demand-side dynamics.

The most obvious demand-side factor of network recruitment is the organization's decision on whether to encourage or discourage network recruitment. This factor has largely been viewed as the organization's only real policy lever to affect the segregating effects of network recruitment. Yet many other organization-side processes affect network recruitment. For example, a second rather obvious demand-side factor is the relative rates at which different groups of employees engage in referring. If a group that was underrepresented in a firm relative to the labor market referred more than the overrepresented group, it is clear that network recruitment might contribute to that firm's desegregation. Despite both its obviousness and its clear implications for organizational action, we could find no mention in the current copious literature on how firms can address job segregation that raise this point. A small but growing body of scholarship has investigated the demand-side processes of network recruitment that may have consequences for job segregation. This scholarship has revealed a number of distinctive referrer behaviors, as well as organizational consequences for referrer-referral ties. Below, we provide a brief review of this scholarship.

2.1. Who Refers?

The Waters (2001) example discussed above illustrated an informal organizational policy influencing which employees can engage in network recruitment. Other research has suggested that the probability of engaging in network recruitment may differ across different groups of employees even without the influence of any formal or informal organizational policies. For example, there is some evidence that employees who were network hires are more likely to refer. That is, network applicants who are hired to the job are more likely to generate network applicants than job holders who were nonnetwork applicants. One empirical organizational case study illustrates this asymmetry. In their hazard-rate model estimating the factors affecting the risk of employees engaging in referring, Fernandez and Castilla (2001) found that having been a network hire increases a job holder's likelihood to refer by about 300% relative to comparable nonnetwork hires (Fernandez and Castilla 2001). In two different job categories (customer service

representatives (CSRs) and non-CSRs), nonnetwork hires had a probability of referring of about 0.06 and 0.04, respectively; whereas network hires had a probability of referring of about 0.25 and 0.16, respectively.

Ascriptive category membership such as gender or race/ethnicity may also influence referring behavior. In their study documenting the variety of mechanisms contributing to job segregation among the mostly female CSRs working in the call center of a large bank, Fernandez and Sosa (2005) found that female employees were 20% more likely than male employees to generate referral applicants (25.7% of women generated at least one referral applicant versus 21.4% of men [$p < 0.003$, likelihood ratio $\chi^2 = 8.753$, $df = 1$], $25.7/21.4 = 1.20$). In their study of network recruitment for entry level jobs in a majority minority manufacturing firm, Fernandez and Fernandez-Mateo (2006) did not find a similar gender effect (36.6% of women in the firm generated at least one referral applicant versus 34.6% of men [$p > 0.5$, likelihood ratio $\chi^2 = 0.228$, $df = 1$], $36.6/34.6 = 1.06$), but they did find that African American, Asian, and Hispanic employees were significantly more likely to engage in referring as compared with white employees. If network recruitment tends to generate applicants who are disproportionately demographically similar to their referrers, differing rates of referring behaviors by members of different demographic groups would likely directly influence the segregating effects of network recruitment.

2.2. Applicant and Job Factors Affecting Referring

Among those employees who do engage in network recruitment, further research shows that they do not broadcast their job opportunity information indiscriminately throughout their contact networks. Referrers may screen and withhold job opportunity information from members of their networks that may put at risk referrers' own work reputations (Smith 2005). This screening process could include the manifestation of biases and stereotypes that contribute to the segregation of jobs.

Referrers not only distinguish among the people with whom they elect to share their job opportunity information, but also share that information differentially based on the job itself. Referrers may share any job opportunity information with their strong-tie social contacts, but prefer to share job information with their weak-tie social contacts when the referrer is confident in the match between the contacts' skills and the job's credential requirements (Marin 2012). In their study of the hiring process during a four-month period at the headquarters of a large bank, Leicht and Marx (1997) found that referrers disproportionately share lower-level job opportunity information with opposite-sex contacts, while sharing same or higher-level job opportunity information

with same-sex contacts. This gendered sharing was itself gendered. Female referrers tended to refer their contacts to more gender-stereotypical jobs than did male referrers (Leicht and Marx 1997). Consistent with this finding, Mencken and Winfield's (2000) study of network recruitment in the Metropolitan Employer-Worker Survey (MEWS) data set found that female job seekers were more likely to be directed to female-dominated jobs by female referrers than by male referrers. These examples of differential referring behavior are further evidence that referrer behaviors may be an important component to the segregating effects of network recruitment.

2.3. Referrer–Referral Relationships, Performance, and Turnover

The influence of referrers' behaviors does not end with sharing their job opportunity information with their chosen referral. The referrer–referral relationship is entwined with both job performance and turnover. For example, Yakubovich and Lup (2006) showed that among the sales associates in a female-dominated virtual call center, the performance of the referrer was significantly associated with the hiring likelihood of that referrer's referrals. Performance effects are also manifest among network hires. In his study of the same CSR job from Fernandez and Sosa (2005), Castilla (2005) found that being a network hire was associated with initial job performance advantages, and that the performance of network hires declined upon the exit of the referral's referrer (Castilla 2005). In fact, when a network hire's referrer left the organization, the network hire's likelihood of exit almost doubled (Fernandez et al. 2000). Similarly, a network hire whose referrer remains with the organization is less likely to exit than a nonnetwork hire (Castilla 2005). An association between referrer–referral ties and turnover is consistent with existing theory and evidence on the effects of intrafirm social ties on turnover. An individual who exits an organization increases the exit likelihoods of others in the organization with whom the exiter had social ties (Krackhardt and Porter 1986, Popielarz and McPherson 1995, Felps et al. 2009). These exit chain (Sgourev 2011) processes operate for referrer–referral ties similarly to other intrafirm social ties such as friendship.

This brief review of current empirical findings on the behavior of referrers shows that differences in who engages in referring, whom referrers refer, and the effects from referrer–referral ties on job performance and turnover, are all processes that could contribute to the segregating effects of network recruitment. To the extent that this is true, these processes also introduce potential policy levers for organizations to influence these effects. Taking advantage of these opportunities for organizational

influence requires a dynamic understanding of the interworkings of these processes in the context of network recruitment. We use mathematical and computational modeling techniques to build such a dynamic understanding.

3. Preliminaries: Model Goals and Simplifying Assumptions

The goal of this paper is to explicitly study the demand-side dynamics of network recruitment and their contribution to job segregation. This will allow us to answer the question of whether the relative inattention to the demand-side aspects of network recruitment is justifiable. To achieve this goal, we develop and examine formal mathematical and computational models to evaluate the segregating effects of network recruitment when including the empirically documented demand-side processes of referrer behaviors, to estimate how much of these effects is attributable to referrer behaviors, and to investigate the extent to which the management of referrer behaviors can mitigate these effects. To be clear, the models we develop help us to build a better understanding of the segregation implications of network recruitment inclusive of demand-side dynamics. Our contributions derive from our analysis of the models and their implications. To successfully build theory using models, we build the simplest models that serve our goals, seeking to strike the important balance between parsimony and accuracy (Davis et al. 2007), while avoiding the "reality trap" (Burton and Obel 2011, p. 1196) of attempting to fully model social reality. In this section, we clarify the simplifying assumptions underlying our models.

First, although network recruitment may contribute to job segregation along the lines of gender, race/ethnicity, social class, national origin, and any number of other sociodemographic characteristics, we focus exclusively on job sex segregation. We constrain our focus for two main reasons. One reason is simplicity. Although the models we develop can readily be extended to more complex and multidimensional forms of job segregation, models limited to only male and female categories that are near parity in the population are simpler to construct, analyze, and describe. The other reason is availability. As the review above suggests, there are more instances of empirical scholarship documenting quantifiable demand-side network recruitment dynamics in the context of male–female differences than other social categories. By focusing on job sex segregation, we can ground our models using findings from multiple empirical studies of men's and women's referring behaviors.

A second simplification is the scope of referrer behaviors we consider in our models. To highlight the demand-side origins of these dynamics, we reserve

detailed scrutiny for those mechanisms that are likely to be subject to organizational influence. Other labor market and network recruitment mechanisms over which organizations have little control are set aside when possible, or when necessary are modeled as a constant contextual factor. For example, although the homophilous nature of personal contact networks is pervasive and well established (Marsden 1987, McPherson et al. 2001, Newman 2003, Wimmer and Lewis 2010), we concur with previous assessments that it would be difficult for an organization to affect the demographic composition of its employees' contact networks (National Research Council 2004). Because organizations cannot be expected to change the level of homophily in individuals' contact networks, we do not examine how such changes would affect job-segregation outcomes, even though they would certainly have an effect. Rather, we build in to our models empirical estimates of network homophily, and model this as a constant effect. Below, we describe in detail both the nature and justification for our operationalization of the effects of homophilous contact networks as a contextual constant.

Other mechanisms beyond the scope of our current efforts are the screening decisions referrers make when choosing who among their contacts (*alters*) will receive information about job opportunities. Systematic differences in these decisions—for example, referrer's concerns with reputation (Smith 2005) and credentials (Marin 2012)—can certainly influence the segregating effects of network recruitment. However, like the associational choices of referrers, these sharing choices of referrers are unlikely to be effectively managed via organizational policies. We therefore set such mechanisms aside in our models.

Other mechanisms beyond the scope of our current efforts are the screening decisions referrers make when choosing who among their alters will receive information about job opportunities. Systematic differences in these decisions are quite likely to influence the segregating effects of network recruitment, but like the associational choices of referrers, these sharing choices of referrers are unlikely to be effectively managed via organizational policies. We therefore set such mechanisms aside in our models.

Our analysis complements the existing literature on network recruitment by revealing the role of referrer behaviors in generating its segregating effects. To achieve this goal, we limit our modeling efforts to mechanisms that can be modeled simply. Some of the referrer behaviors identified above entail interactions with distinctive job queues, job performance, and other complicating factors. Operationalizing these mechanisms would require modeling internal labor markets, variations in worker quality, and

a host of other processes unnecessarily complicating our efforts. Thus, we model a firm where all employees share the same job title and are indistinguishable in terms of quality and performance. Apart from network recruitment with homophilous contact networks and the modeled referrer behaviors that are the focus of our study, there are no biases in screening, hiring, or turnover in our models. Also, consistent with our focus on the firm's perspective, we model a single organization rather than an entire market.²

The referrer behaviors we implement in our models include asymmetries in referring behavior by both sex and referral status, and the exit chains formed by referrer-referral ties. The composition of a job is the net result of hires (inputs) and exits (outputs). Thus job segregation—that is, a biased job composition—is similarly the net result of biases in personnel inputs and/or outputs (Sørensen 2004). The referrer behaviors we implement in our model are not hypothesized, but represent empirically documented mechanisms whereby referrers may influence job inputs via referring and job outputs via exit chain dynamics. Each mechanism is operationalized based on empirical findings, and we vary each mechanism's governing parameter to investigate its effects. We use the empirical evidence to set the initial values of the referrer behavior mechanisms' governing parameters, and experiment with variations in those parameters around the neighborhoods of their initial values. The results of our models represent the material consequences for job segregation of the operation of these empirically documented mechanisms.

4. A Firm-Centric Dynamic Model of Network Recruitment

We begin with a simple system representing a single firm composed of two stocks: male and female employees. The sum of these two stocks is the total number of firm employees. The flows in and out of these stocks are governed by hiring and exit, respectively. Men and women exit the firm at the same rate, x . To keep the size of the firm stable, the rate of hiring matches the rate of exit. The proportion of women among new hires is given by model parameter b . This parameter b represents the net effect of supply-side and other prior-to-application mechanisms that may yield a gender composition of applicants different from that of the labor market as a whole. Given that firm exit is unbiased and present,

²This choice is a simplification wherein we set aside the interdependencies between a single firm and its labor market. Such interdependence may be most visible in a large organization that dominates a local labor market. In such a situation, there may be limits on the segregation possible in the large organization, and the level of segregation can influence the composition of smaller organizations sharing the same local labor pool.

and that b gives the proportion of women among new hires, it is clear that regardless of the initial gender composition of the firm, and absent other biasing mechanisms, the proportion of females among firm employees will necessarily become b over time. For this reason, we call b the *baseline gender composition*. We also set the initial composition of the firm to b . For reasons discussed below, the range of b we explore in our model is between 0.1 and 0.9, exclusive.

The proportion of applicants generated by network recruitment is defined as p . The proportion of nonnetwork applicants is then $1 - p$. The gender composition of nonnetwork applicants is governed by b as above. The gender composition of network applicants is determined by the referring behaviors of firm employees and the homophilous nature of their contact networks. To determine how to operationalize this effect, we examine the relevant empirical evidence. Because our modeling efforts scrutinize mechanisms within an organization's scope of influence, and because the segregated contact networks of an organization's employees are arguably not within that scope (National Research Council 2004), our goal is an empirically justified and preferably simple operationalization for this mechanism. A pair of studies by Fernandez and colleagues described below provides the empirical evidence to operationalize this mechanism simply.

Noting that the effects of network recruitment are best studied by examining the referral status of prehire applicants rather than that of posthire employees who have been subjected to an additional organizational screening process, Fernandez and Sosa (2005) documented the surprising finding that male referrers generated majority female referral applicants. Rather than conclude heterophily in male referring behavior, they first constructed the counterfactual of referring in the absence of segregated contact networks. They concluded that network recruitment with representative contact networks would most closely resemble the composition of nonreferral applicants. That is, the set of labor market mechanisms that render the composition of nonreferral applicants unrepresentative of the labor market as a whole are also likely to similarly affect the composition of referral applicants. Thus, the composition of nonreferral applicants reflects the net effect of these mechanisms, while the composition of referral applicants reflects that effect plus the effect of network recruitment with homophilous contact networks. The difference between these two compositions thus provides an indicator for the effect of network recruitment with homophilous contact networks.

In Fernandez and Sosa's (2005) empirical case study of applicants to a CSR job at a large call-center, nonreferral applicants were 65% female. Referral applicants generated by female referrers were 75% female,

or 10 percentage points more female than nonreferral applicants. Referral applicants generated by male referrers were 44% male, or 9 percentage points more male than nonreferral applicants. So despite the observation that male referrers were generating majority female referral applicants, this case study provided evidence supporting a biasing effect from homophilous contact networks for both men and women. A second empirical case study of network recruitment yielded similar estimates for the effects of network recruitment with homophilous contact networks. In Fernandez and Fernandez-Mateo's (2006) empirical case study of applicants to entry level jobs at a large manufacturing firm, nonreferral applicants were 57% female. Referral applicants generated by female referrers were 68% female, or 11 percentage points more female than nonreferral applicants. Referral applicants generated by male referrers were 56% male, or 13 percentage points more male than nonreferral applicants.

Although additional research is needed to elucidate this mechanism more fully, in both of these empirical cases, the compositional effects of network recruitment with homophilous contact networks were very similar for male and female referrers. In the first case, the central percentage point change was 9.5 percentage points, with a slightly higher change (10 points) among women, and a slightly lower change (9 points) among men. In the second case, the central percentage point change was 12 percentage points, with a slightly higher change (13 points) among men, and a slightly lower change (11 points) among women. The gender differences in the magnitudes of same-sex referring do not show a consistently stronger tendency for either men or women. Based on these findings, we operationalize the effect of network recruitment as a constant 10 percentage-point shift in composition of network applicants relative to nonnetwork applicants for men and women. Although simple, this additive operationalization of the effects of network recruitment with segregated contact networks is wholly consistent with the current body of empirical evidence. We treat this shift as a constant rather than parameterizing it for two main reasons. First, as we previously noted, homophily in the contact networks of a firms' employees is beyond the purview of the organization. Second, the current empirical evidence is consistent with a near-constant shift (i.e., Fernandez and Sosa 2005, and the firm studied in Fernandez and Fernandez-Mateo 2006).³

With this set of model parameters— x for the exit rate, b for the baseline proportion of females of the

³This pattern of results is not limited to low-wage female-dominated jobs. Evidence of network recruitment among the nonentry-level jobs in a male-dominated high tech firm gives the same pattern of results. Nonreferral applicants to the job were 37% female and 63% male. Referral applicants from female referrers

firm and of nonnetwork applicants, p for the proportion of network applicants in the applicant pool, and a 10 percentage-point adjustment for the effects of segregated contact networks—we specify an initial mathematical model, and begin to answer our first question: How much segregation results from network recruitment? Using $w(t)$ to represent the stock of women in the firm over time, and $m(t)$ to represent the stock of men, we define our initial dynamic model of network recruitment with segregated contact networks as follows:

$$\begin{aligned} \frac{dw}{dt} &= (1-p)bx(w(t)+m(t)) + (b+0.1)pxw(t) \\ &\quad \text{Incoming nonnetwork female hires} \qquad \qquad \qquad \text{Women referred by women} \\ &\quad + (b-0.1)pxm(t) - xw(t) \\ &\quad \text{Women referred by men} \qquad \qquad \qquad \text{Exiting women} \\ \frac{dm}{dt} &= (1-p)(1-b)x(w(t)+m(t)) + (0.9-b)pxw(t) \\ &\quad \text{Incoming nonnetwork male hires} \qquad \qquad \qquad \text{Men referred by women} \\ &\quad + (1.1-b)pxm(t) - xm(t). \\ &\quad \text{Men referred by men} \qquad \qquad \qquad \text{Exiting men} \end{aligned} \quad (1)$$

The system of differential equations in (1) describes the basic population dynamics of a firm including effects of prior-to-application biasing mechanisms (via parameter b) and network recruitment with homophilous contact networks (the sex-specific 0.1 shifts to b).⁴ Notably, this model neglects referrer behaviors other than their unbiased participation in network recruitment. To measure the segregation resulting from these dynamics, we compare the behavior of this system with the behavior of the system in the absence of network recruitment (i.e., $p = 0$). Absent network recruitment, the gender composition of the firm would remain at b . So our measure of segregation from network recruitment is the area between the curves describing the proportion of females in the firm ($w(t)/(w(t)+m(t))$) in the presence of network recruitment and the baseline composition (b) from time t_0 to t_* . Equation (2) defines this segregating effect measure:

$$\text{Segregating Effect} = \int_{t_0}^{t_*} \left[\frac{w(t)}{w(t)+m(t)} - b \right] dt. \quad (2)$$

Figure 1 presents the segregating effects of our model for four different values of the proportion of network applicants in the applicant pool

were 49% female for a 12 percentage-point increase; referral applicants from male referrers were 74% male for an 11 percentage-point increase (data from the firm studied in Fernandez and Campero 2012).

⁴ For contexts with different shifts from homophily, the appropriate numerical substitutions may be made to system (4).

($p \in \{0.25, 0.5, 0.75, 1\}$), as both the exit rate parameter, x (in terms of the proportion of employees exiting each week), and the baseline job composition parameter b vary, and using a 10-year time horizon.⁵ All the surfaces in Figure 1 have the same shape, but with different scales. The segregating effects of network recruitment are commensurate with the proportion of network applicants in the applicant pool. That the segregating effects of network recruitment increase with the extent to which hiring depends on network recruitment is not surprising. The firm's ability to modify the extent to which it encouraged network recruitment is the one practical policy lever that networks in labor market literature acknowledge is available to organizations. Because the proportion of network applicants only moderates the magnitude of the segregating effects of network recruitment, in the interest of simplicity, we henceforth keep the proportion of network applicants in the pool parameter p constant at 0.5.⁶

Although Figure 1 shows the common shape for the segregating effects of network recruitment as modeled, it is not very informative beyond the model itself, and the segregating effect scores are not particularly meaningful in isolation. Issues of the generalizability and practical meaning of model results are common to model-based analyses (Burton and Obel 1995). We address this issue by using a different version of our model to develop a practical measure of segregation that exhibits intersubjective validity.

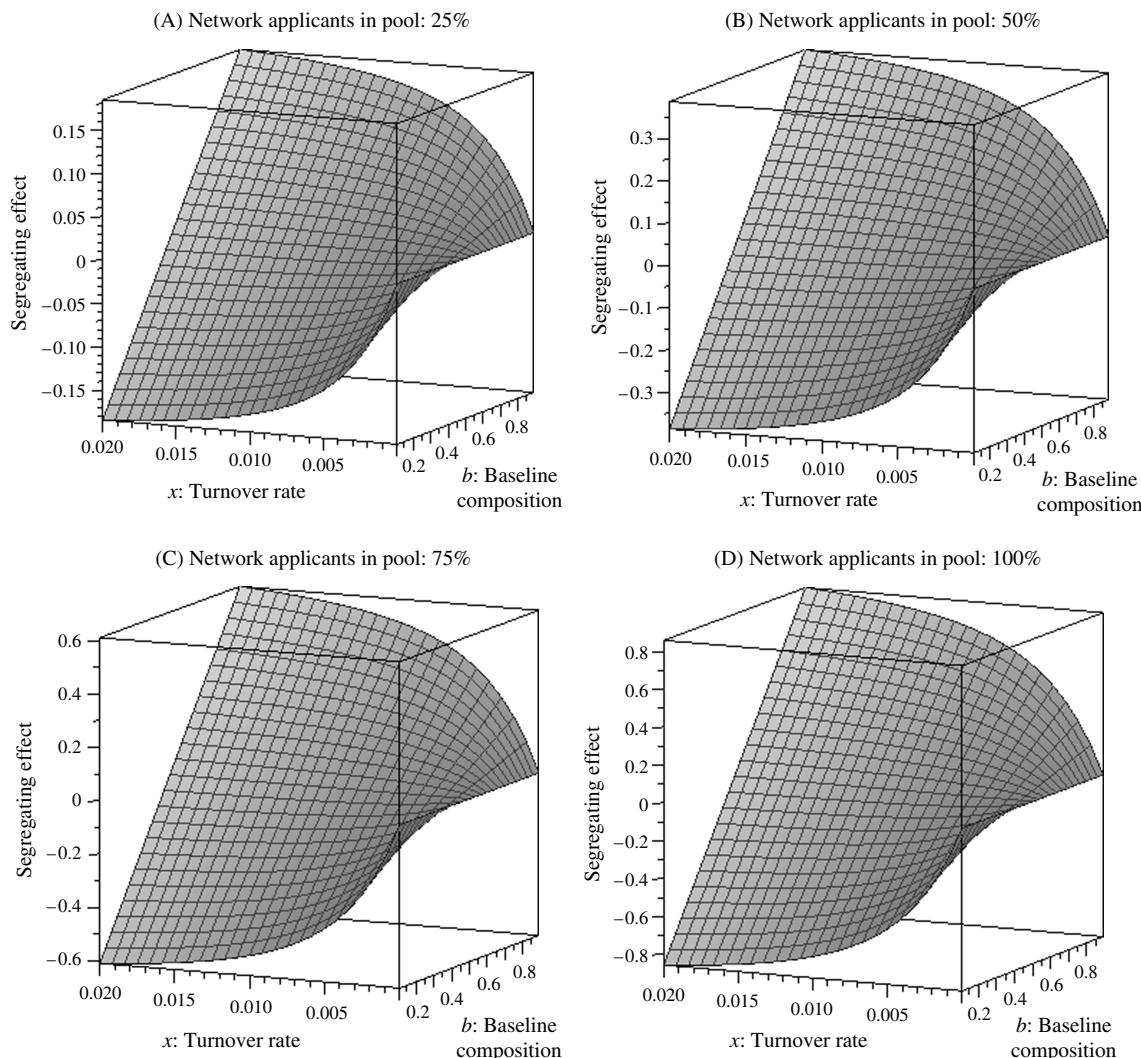
4.1. Interpreting Model Output

We modify our initial model to create a simple model of gender bias in applicant screening. Scholarship investigating how organizations contribute to job sex segregation has identified bias, stereotyping, and gender queuing as the most relevant and active mechanisms (Bielby 2000, Kaufman 2002, Reskin and Roos 1990), and identified the screening of job applicants as the stage where these mechanisms are most likely to manifest and contribute to segregation (Petersen and Saporta 2004, Reskin and Bielby 2005). Given the recognized importance of screening biases in the job-segregation literature, and the many efforts to measure these biases in organizational settings (e.g., Petersen and Togstad 2006, Bertrand and Mullainathan 2004, Neumark et al. 1996, Fernandez and Sosa 2005), we address the generalizability of our network recruitment model using a model of screening bias.

⁵ We sought a time horizon long enough to capture the effects of mechanisms that operate more slowly, but not so long as to require consideration of generational effects.

⁶ Note that the 50% figure commonly appears in the range of empirical estimates describing organizations' reliance on network recruitment.

Figure 1 Model Output: The Segregating Effects of Network Recruitment with Varied Levels of Turnover and Baseline Firm Composition over a 10-Year Window



Put simply, we ask what level of screening bias would be necessary to generate the same segregating effects observed in our network recruitment model, given a firm with the same baseline composition and turnover rate. The answer is the segregating effect of our model in terms of *sex bias units*. These units provide an intuitive and intersubjectively valid measure of segregating effects in a manner that has meaning beyond our model:

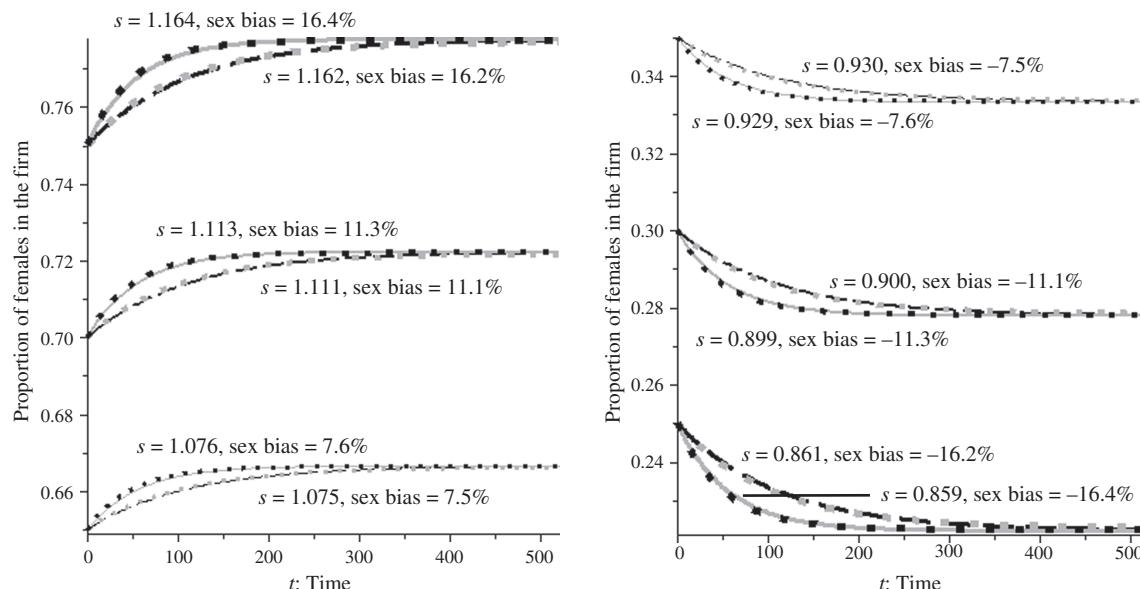
$$\begin{aligned} \frac{dw}{dt} &= \frac{sb}{1 - b + sb} x(w(t) + m(t)) - \frac{xw(t)}{\text{Exiting women}} \\ &\quad \text{Biased incoming female hires} \quad (3) \\ \frac{dm}{dt} &= \frac{1 - b}{1 - b + sb} x(w(t) + m(t)) - \frac{xm(t)}{\text{Exiting men}} \\ &\quad \text{Biased incoming male hires} \end{aligned}$$

The terms in (3) have the same meanings as defined above, with an added sex bias parameter, s . The system of equations in (3) implement this sex bias parameter such that when $s = 1$ there is no bias, when

$s = 0$ only men are hired, and as s approaches infinity only women are hired. The sex bias parameter s (which can have any nonnegative value) scales with baseline composition parameter b (valued between 0 and 1, inclusive, although as discussed above, we only explore values between 0.1 and 0.9) such that the proportion of women and men hired in the presence of bias are always between 0 and 1, and always both sum to 1. This sex bias term, s , can be interpreted as the relative likelihood that a female applicant is hired versus a male applicant. For example, when the baseline composition b is at parity (0.5) and $s = 2$, women are twice as likely to be hired. In this case women are hired with a probability of 0.67 and men are hired with a probability of 0.33.

The segregating effect of sex bias parameter s over time can be found using the same Equation (2) above. By calculating the value of s giving the same segregating effect as that from network recruitment (given the

Figure 2 Sex Bias Units Illustration of Equivalence of the Segregating Effects from the Network Recruitment Model (Lines) and the Corresponding Sex Bias Model (Dots)



Notes. Dashed lines: exit rate parameter, $x = 0.01$; solid lines: $x = 0.02$. Baseline parameter, b values: $\{0.25, 0.3, 0.35, 0.65, 0.7, 0.75\}$. In the network referring models, the proportion of network applicants parameter, $p = 0.5$.

same parameter values and range of time otherwise), we obtain the segregating effect of network recruitment in terms of sex bias. This novel solution to an enduring problem in model-based scholarship acts as an effect size measure for model results. We define the segregating effect of network recruitment via its equivalence to that from sex bias. To the extent that a particular value of the latter type of bias is nontrivial and of import, the bias from the former is of similar moment. Going forward in this paper, we report the segregating effects of network recruitment in terms of the equivalent level of sex bias.

Illustrating the use of sex bias units,⁷ Figure 2 graphs six pairs of curves describing the proportion of females in the firm over time from the model of network recruitment, and the matching curves from the models of sex bias in screening that produce the same segregating effects. The solid lines (turnover rate, $x = 0.02$, proportion network applicants, $p = 0.5$) and dashed lines (turnover rate, $x = 0.01$, proportion network applicants, $p = 0.5$) lines are from the dynamic model of network recruitment with the baseline proportion of females in the job and nonnetwork applicants, $b \in \{0.25, 0.3, 0.35, 0.65, 0.7, 0.75\}$. The dotted lines are the curves from the sex bias model with

the identified sex bias parameter that generates segregating effects identical to the matched (i.e., with the same values for b and x) network recruitment model. The fact that the matched pairs of curves appear to be on top of each other reflects not only that the segregation produced by one model is a good and reliable measure for the segregation produced by the other, but also that the time dynamics are similarly equivalent. That is, the segregating effects of network recruitment are dynamically equivalent to the segregating effects of the specified level of sex bias in screening.

Our models thus far allow us to give a meaningful initial answer to the question: How much segregation results from network recruitment? The segregating effects of network recruitment in the model scenarios from the top panel of Figure 2 are equivalent to otherwise identical scenarios without network recruitment where the relative probability of hiring a woman ranges from being 7% to 16% higher than the probability for hiring a man. Symmetrically, as there are no gender-asymmetric dynamics yet implemented in the model, the segregating effect of network recruitment in the model scenarios illustrated in the bottom panel of Figure 2 are equivalent to male-favoring sex biases in hiring ranging from 7% to 16%. This answer, however, has yet to incorporate the behaviors of referrers, and represents the segregating effects of network recruitment with homophilous contact networks if referrer behaviors had no impact.

4.2. Adding Referrer Asymmetries

We add to our dynamic model of network referring two empirically documented processes involving

⁷ The sex bias parameter, s , itself, is gender-asymmetric. The parameter ranges from 0 to 1 when favoring men, but 1 to infinity when favoring women. For clarity and symmetry, we present sex bias units as the percentage of female-favoring bias. That is, $s - 1$ when $s > 1$ (female-favoring bias), and $1 - 1/s$ when $s < 1$ (male-favoring bias).

referrer behavior: referring asymmetries by sex and by referral status. The dynamic model in (1) assumes referrers represent firm employees in all ways. As discussed above, studies have identified cases where referring employees differ significantly by gender and referral status (e.g., Fernandez and Sosa 2005). This distinctiveness of who refers could affect the segregating effects of network recruitment. Our augmented model examines the nature of these mechanisms separately and simultaneously.

Referring asymmetries by sex is a mechanism making men or women more or less likely to refer. Absent this mechanism, men and women engage in referring in a manner that represents their composition in the firm. In the presence of this mechanism, referring is no longer represented by sex, but is biased by parameter a . If the percent female in the firm is f , the proportion of females among referrers in the presence of this mechanism becomes $af/(1-f+af)$, and the proportion of males among referrers is $(1-f)/(1-f+af)$. This operationalization mimics that of sex bias above and shares its advantages. The parameter a can be any nonnegative number. For all possible values of the referring asymmetry parameter, a (nonnegative) and the proportion of females in the firm, f (between zero and one), the proportion of females and males among referrers remain between zero and one, and sum to one. When $a = 1$, referring is representative with regard to sex. In other words, the referring asymmetry by sex mechanism is effectively “off.” When $a > 1$, women are relatively more likely to refer than men, and when $a < 1$, men are relatively more likely to refer than women.

Referring asymmetries by referral status is a mechanism making employees who were themselves referral applicants more or less likely to refer. This mechanism is operationalized analogously to referring asymmetry by sex. Absent this mechanism, referring takes place independent of referral status and the proportion of referrals among referrers is expected to be the same as the proportion of referrals in the firm overall. In the presence of this mechanism, referring is biased by parameter r . If the proportion of referral hires among firm employees is \bar{h} , the proportion of referral hires among referrers is $r\bar{h}/(1-h+r\bar{h})$, and the proportion of nonreferral hires among referrers is $(1-h)/(1-h+r\bar{h})$.

The referring asymmetry by sex can be easily added to the system of equations in (1) by scaling the proportion of females and males among referrers by the above terms. To add the referring asymmetry by referral status, we must alter the structure of the model to accommodate four stocks so that we can separately keep track of men, women, network hires, and nonnetwork hires in the firm. The full system of equations for the revised model including both asymmetry mechanisms is provided below. In this model,

$w(t)$ represents the number of female network hires in the firm over time, $v(t)$ represents the number of female nonnetwork hires, $m(t)$ represents the number of male network hires, and $n(t)$ represents the number of male nonnetwork hires. As before, p is the proportion of network applicants in the applicant pool, x is the turnover rate, and b is the baseline proportion of females among nonnetwork applicants and the initial composition of the firm. The new parameters a and r govern the asymmetries in referring behavior by sex and referral status, respectively, as previously defined:

$$\begin{aligned}
 \frac{dv}{dt} &= -xv(t) + b(1-p)x(v(t) + w(t) + n(t) + m(t)) \\
 &\quad \text{Nonnetwork female exits} \quad \text{New nonnetwork female hires} \\
 \frac{dw}{dt} &= -xw(t) + (b+0.1)px(v(t) + w(t) + n(t) + m(t)) \\
 &\quad \text{Network female exits} \\
 &\quad \cdot \left(\frac{arw(t) + av(t)}{(av(t) + arw(t) + n(t) + rm(t))} \right) \\
 &\quad \text{Female network hires from female referrers} \\
 &\quad + (b-0.1)px(v(t) + w(t) + n(t) + m(t)) \\
 &\quad \cdot \left(\frac{rm(t) + n(t)}{(av(t) + arw(t) + n(t) + rm(t))} \right) \\
 &\quad \text{Female network hires from male referrers} \\
 \frac{dn}{dt} &= -xn(t) \\
 &\quad \text{Nonnetwork female exits} \\
 &\quad + (1-b)(1-p)x(v(t) + w(t) + n(t) + m(t)) \\
 &\quad \text{New nonnetwork male hires} \\
 \frac{dm}{dt} &= -xm(t) + (0.9-b)px(v(t) + w(t) + n(t) + m(t)) \\
 &\quad \text{Network male exits} \\
 &\quad \cdot \left(\frac{arw(t) + av(t)}{(av(t) + arw(t) + n(t) + rm(t))} \right) \\
 &\quad \text{Male network hires from female referrers} \\
 &\quad + (1.1-b)px(v(t) + w(t) + n(t) + m(t)) \\
 &\quad \cdot \left(\frac{rm(t) + n(t)}{(av(t) + arw(t) + n(t) + rm(t))} \right). \\
 &\quad \text{Male network hires from male referrers}
 \end{aligned} \tag{4}$$

We can solve this system numerically, and we examine the segregating effects of network recruitment over an empirically informed parameter space. As described above, for the referring asymmetry by sex parameter, a , we have empirical evidence for $a = 1.2$ (Fernandez and Sosa 2005), as well as for $a = 1$ (Fernandez and Fernandez-Mateo 2006). We examine values of a around both of these values, ranging from 0.8 to 1.4. Our empirical estimate for the asymmetry in referring by referral status parameter, r , is 4, representing the 300% increase in referring probabilities identified by Fernandez and Castilla (2001). We explore values for r ranging from 1 (no difference) to 7 (a 600% increase in probability). The other model parameters are the proportion of network applicants in the applicant pool, p , the turnover rate, x , and the

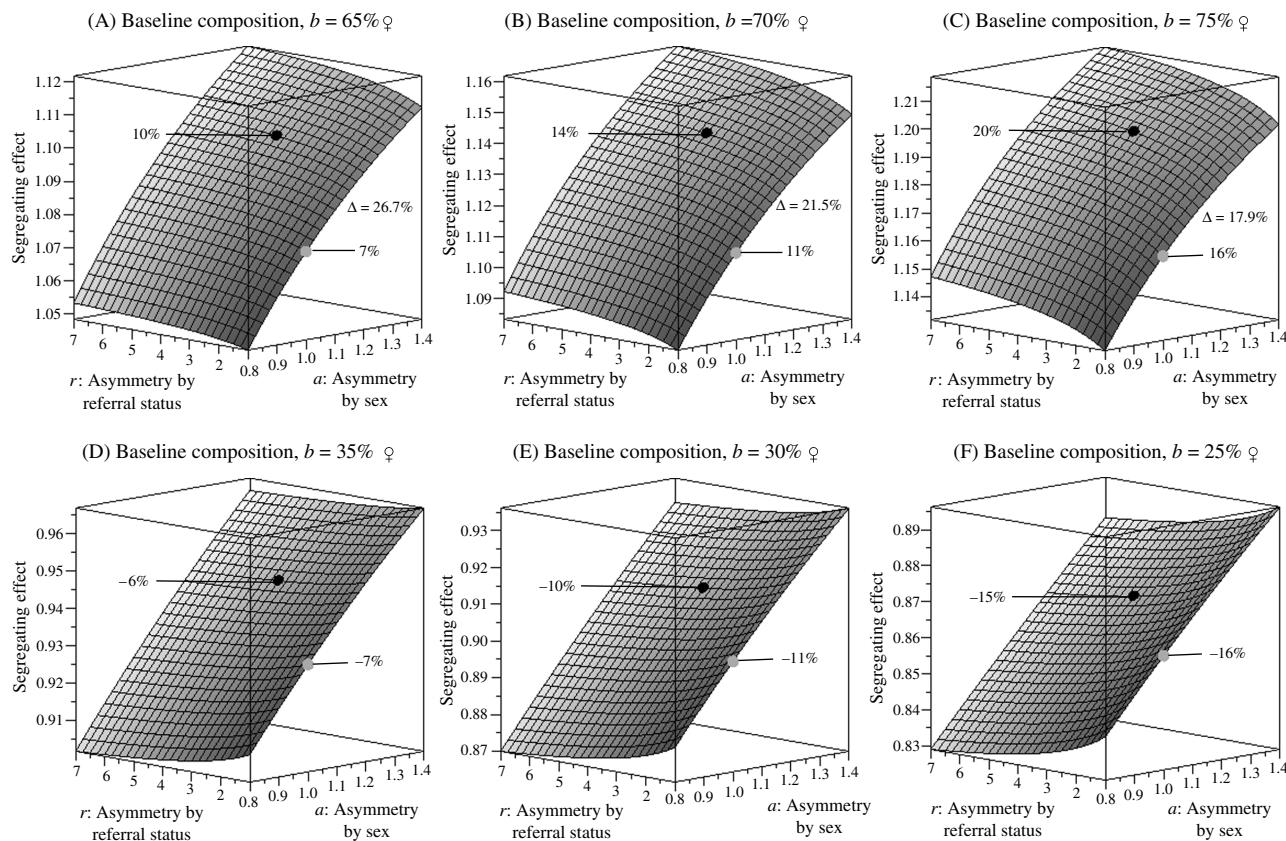
parameter defining both the baseline proportion of females among nonnetwork applicants and the initial gender composition of the job, b . The contributions of the turnover parameter x , and the proportion of network applicants in the applicant pool parameter p are rather trivial. For reasons discussed above, we set $p = 0.5$. As is clear from Figure 2, differences in turnover rates only affect the speed with which the firm attains its equilibrium proportion of females. We will set $x = 0.01$, the more conservative value for manifesting segregation from network recruitment, and the value closer to the empirical case that provides many of our estimates. This turnover rate is equivalent to an average employee tenure of 100 weeks, or approximately two years. For the baseline gender composition, we sample values from a set of female-dominated firms reflecting the empirical bases for our parameter estimates as well as male-dominated firms. That is, $b \in \{0.25, 0.30, 0.35, 0.65, 0.7, 0.75\}$.

The segregating effects of network recruitment with these two referrer behavior mechanisms are given in Figure 3. The vertical axis in Figure 3 is the segregating effect of network recruitment in terms of the sex bias parameter, s , from the equivalently segregating sex bias model scenario. Figure 3 shows that both asymmetries contribute to job sex segregation,

but in a manner showing no substantial interactions between the mechanisms. Asymmetries in referring by sex have strong, consistent, and direct effects on the sex composition of the firm. Of the two horizontal dimensions underlying the surfaces in Figure 3, the asymmetry in referring by sex—parameter a —generated the larger and consistently positive slopes. This result is as expected: The more women refer relative to men, the greater their eventual representation within the firm and vice versa. This effect is strong and independent of the initial composition of the firm.

Asymmetries in referring by referral status—parameter r —consistently exacerbate segregation. For female-dominated firms, greater values of r yielded increases in the proportion of females in the firm. For male-dominated firms, greater values of r yielded decreases in the proportion of females in the firm. The dominant group refers more and generates more of its own members. The referring asymmetry by referral status acts as a modest gender-neutral multiplier for the effect, advantaging the group in the majority, and conveying greater advantages as the level of dominance increases. In all cases, the slopes associated with changes in r were smaller in magnitude than the slopes associated with changes in a .

Figure 3 Segregating Effects (in Terms of Sex Bias Value, s , of the Corresponding Sex Bias Model) of Network Recruitment with Asymmetries in Referring by Sex (a) and Referral Status (r)



On each surface in Figure 3 are two highlighted points. One point (in gray) shows the segregating effects in terms of sex bias units—the percentage of female-favoring bias—when the two referring asymmetry mechanisms are “off,” that is, their parameters both equal one ($a = 1$ and $r = 1$). The second point (in black) shows those effects when the referring asymmetry mechanisms are “on,” with parameters from the values estimated from empirical case studies ($a = 1.2$ and $r = 4$). The former point indicates the segregating effects of network recruitment in the absence of any distinctive referrer behaviors. The latter point shows these effects in the presence of these empirically documented behaviors, and thus shows how much segregation results from network recruitment. This improves on our previous answer for our first research question. *In firms that would otherwise be 65%, 70%, or 75% female, network recruitment in the presence of empirically documented referrer behaviors generates the same levels of segregation that would result in otherwise identical firms without network recruitment in the presence of relative female-favoring biases in hiring of 10%, 14%, and 20%, respectively.* These effects are substantial. For comparison, among Fernandez and Sosa’s (2005) CSR applicants, the identified significant female-favoring biases for applicants getting an interview and a job offer were 4.6% and 4.2%, respectively.

The difference between the pairs of points on each surface in Figure 3 also provides an initial answer to our second research question. To what extent do referrer behaviors contribute to the segregating effects of network recruitment? The segregating effects shown by the black point at location ($a = 1.2$ and $r = 4$) that include some active referrer behavior mechanisms are arguably closer to the observed segregating effects of network recruitment than the effects shown by the gray point at location ($a = 1$ and $r = 1$), which neglects these mechanisms. Taking the segregating effects measure at location $a = 1.2$ and $r = 4$ as the indicator for the segregating effects of network recruitment, we estimate the contribution from referrer behaviors as the difference between the two segregating effects measures divided by the total measure. Calculating this measure for the first surface in Figure 3, we find $(10.2 - 7.5)/10.2 = 26.7\%$. *This means that a little over a quarter of the total segregating effects of network recruitment are generated by the distinctive behaviors of referrers.* As Figure 3 shows, this contribution declines as the job becomes more segregated by the set of prior-to-application mechanisms aggregated within the baseline composition parameter, b . As b approaches 0.9, the percent of network recruitment segregation attributable to these two referring asymmetries becomes 13.3%. As the job is less segregated by prior-to-application mechanisms, and b approaches 0.5, the percent of network recruitment segregation attributable to referring

asymmetries becomes 100% (as there is no segregation from network recruitment with homophilous networks when $b = 0.5$). Of the two referrer behaviors modeled, asymmetry by sex makes the more consequential contribution to the segregating effects of network recruitment.

As previously discussed, distinctive referrer behaviors are not limited to decisions about whether to refer. Referrers and their referral hires form networks within an organization that affect exit likelihoods. Our third and final referrer behavior mechanism is an implementation of these exit chain dynamics. Because network dynamics are poorly modeled by differential equation models, for this final component, we switch to a more appropriate agent-based approach (Rahmandad and Sterman 2008). The agent-based model implements network recruitment and the first two asymmetry mechanisms identically to the differential equation models above. In addition, it tracks referrer-referral ties and updates exit likelihoods as a function of the number of tied alters who remain in and who have left the firm.

This agent-based model operates as follows: A firm with 333 employees has an initial sex composition defined by the baseline parameter, b . At each time step, each employee agent exits the firm with a probability that is a function of the general exit probability parameter, x , and the number of referrer and referral alters who are in and have left the firm. Initially, this probability is just x for all employees. Firm vacancies are filled with network hires with probability p , and with nonnetwork hires with probability $1 - p$. Nonnetwork hires are female with a probability of b . When a vacancy is filled with a network hire, an employee within the firm is selected as the referrer. Implementing the asymmetry in referring mechanisms means that each agent’s chance of being selected as the referrer depends on their sex and referral status. Once the referrer is selected, the network hire is female with a probability of $(b + 0.1)$ if the referrer is female, and with a probability $(b - 0.1)$ if the referrer is male. After all vacancies are filled in this manner, the simulation advances to the next time step, each agent’s individual exit likelihood is updated to match any changes in turnover among their referrer and referral ties, and the next round of vacancies are generated. We record the number of male and female agents in the firm at each time step. Before we describe and examine the effects of this exit chain mechanism in detail, we first confirm that our agent-based model in the absence of this mechanism generates output congruent with our expectations and with the output of our differential equation model (4). The dynamics of this agent-based model closely replicate the dynamics of the mathematical models in this paper. The agent-based model is somewhat more conservative in predicting less segregation as a result of its discrete, rather than

continuous nature. The online appendix (available at <http://digitalcommons.ilr.cornell.edu/articles/840>) provides a detailed demonstration of the correspondence between the models.

The operationalization of the exit chain mechanism is necessarily more complex than the previous mechanisms. Letting t_{in} represent the number of ego's referring ties to alters (either ego's referrer or ego's referrals) within the firm, t_{out} represent the number of ego's referring ties to alters outside the firm, and c represent our exit chain mechanism governing parameter, and remembering that the weekly exit probability for job holders without ties is the exit parameter $x = 0.01$, we define an agent's exit probability as

$$\Pr(\text{an agent will exit in a given time step}) \\ = xc^{((t_{out}-t_{in})/\sqrt{\max(1, (t_{out}+t_{in}))})}. \quad (5)$$

The goal of this formulation was to implement the exit chain mechanism conservatively. Obviously, when $c = 1$, there is no biasing effect on exit likelihoods. Each referrer or referral tie who leaves the organization increases ego's likelihood of leaving, pulling them out via the exit chain mechanism. By the same token, each referrer or referral tie who remains in the organization decreases ego's likelihood of leaving, anchoring ego to the firm via the same mechanism. When $c > 1$ and an agent's $t_{in} > t_{out}$, that agent's anchors dominate, and the agent will be less likely to exit than the baseline likelihood of 1, as the exponent term will be negative. When $c > 1$ and an agent's $t_{in} < t_{out}$, the tug from alters to exit the firm dominates, and that agent will be more likely to exit than the baseline likelihood. The denominator in the exponent term serves two purposes. The first is to ensure that the increase (decrease) in exit likelihoods as $t_{out} - t_{in}$ becomes more positive (negative) at a decreasing rate (i.e., diminishing returns). That is, an agent's first alter to exit the firm increases that agent's exit likelihood more than that agent's fourth alter to exit. The second purpose is to ensure that the effect of an alter leaving (or staying) is scaled by a job holder's total number of ties. That is, the effect of an alter's exit on an agent will be larger for an agent with only two total ties than for an agent with four total ties. (For example, if $c = 2$, then an agent with 3 alters out and 2 alters in will have a smaller exit likelihood, 0.014, than an agent with 1 alter out and 0 alters in, 0.020, even though both exit likelihoods are greater than the initial exit likelihood of $x = 0.010$.) Because the actual functional form of this mechanism is not known, we tried to model the mechanism conservatively while maintaining the effects suggested by the theoretical and empirical findings.⁸ The one empirical

⁸ Although we do not know the functional form of this exit chain dynamic, we considered whether there should be some

Table 1 Model Parameters and Their Ranges of Simulated Values

	Simulated values
Referring process parameters	
b : Baseline proportion of females in job and nonnetwork applicants	{0.5, 0.55, 0.6, 0.65 , 0.7, 0.75}
a : Asymmetry in who refers by sex	{0.8, 1 , 1.2 , 1.4}
r : Asymmetry in who refers by referral status	{1, 2.5, 4 , 7}
c : Referrer-referral exit chains	{1, 1.5, 2 , 3}
Model parameters with fixed values	
in the simulations	
p : Proportion of hires coming via referrals	0.5
x : Turnover rate	0.01

Note. Parameter values representing the values from extant empirical research are shown in bold.

case study with some estimate of c found job holders whose referrals had left almost doubled their exit likelihood (Fernandez et al. 2000), or $c = 2$. Based on this finding, our simulations explore increases of 0%, 50%, 100%, and 200%, or $c \in \{1.0, 1.5, 2, 3.0\}$.⁹

5. Analysis

Our analysis proceeds by investigating the segregating effects produced by the mechanisms defined above over the set of parameter values indicated above. Table 1 summarizes the full set of parameters and the sets of their values we use in our study, defining the parameter space of our simulation. The parameter space entailed by the ranges of parameter values in Table 1 define 384 separate simulation scenarios (scenarios being defined as a particular set of values for the four model parameters). We explore the segregating effects of network recruitment in this parameter space to answer our three questions and present the answers in terms of the previously defined sex bias units.

5.1. Segregating Effects of Network Recruitment

The three questions we seek to answer in this paper are: (1) How much job segregation results from network recruitment processes? (2) To what extent do

time-dependent decay for this mechanism. The empirical evidence suggests that there is no decay in the effect of referrer exit on ego's exit likelihood (Fernandez et al. 2000).

⁹ Unlike the asymmetry mechanisms, this mechanism is not asymptotic to one, and could yield exit likelihoods greater than one. Our largest modeled value of c , 3.0, requires 18 alters to have exited the firm and no alters within the firm to exceed an exit probability of one. Given our implementation of our model, the probability that an agent has 18 alters is indistinguishable from zero. The likelihood of an agent having more than 10 referrer-referral alters is extremely small. Empirical settings also show the number of referral applicants a referrer generates tends to be quite small with very few exceptions (Fernandez and Fernandez-Mateo 2006, Fernandez and Sosa 2005).

Table 2 Segregating Effects of Referrer Behavior Mechanisms in Sex Bias Units

<i>b</i> : Baseline percent female	No referrer behaviors		Referrer behavior mechanisms in isolation			Paired referrer behavior mechanisms			All three	Referrer effects	Remediation	Percent reduction
	(1) <i>a</i> = 1	(2) Referring asymmetry by sex	(3) Referrals	(4) Exit refer more	(5) <i>a</i> = 1.2	(6) <i>r</i> = 4	(7) <i>a</i> = 1	(8) <i>r</i> = 4				
50%	−0.6	2.1	−0.1	0.5	1.9	3.5	0.4	3.6	116%	−5.6	256%	
55%	2.0	4.0	1.4	2.3	4.1	6.1	3.2	5.9	66%	−3.2	154%	
60%	4.4	7.2	4.6	5.0	7.0	9.0	4.9	9.1	51%	−0.5	106%	
65%	7.9	9.7	7.6	8.5	9.5	12.9	8.8	12.3	36%	2.6	79%	
70%	11.0	13.6	11.2	12.4	13.1	16.8	12.6	16.7	34%	6.8	59%	
75%	16.7	17.9	16.4	18.3	18.4	23.2	17.9	23.3	28%	12.5	46%	

Notes. Results are exclusively from the simulation model. Numbers represent the percentage-point bias favoring female applicants for hire yielding the equivalent segregating effects. Percentages compare the magnitude of the differences between the indicated columns. The highlighted row corresponds to the baseline composition of 65% women.

referrer behaviors contribute to these segregating effects? (3) To what extent can firms mitigate the segregating effects of referring through policies targeting referrer behavior? Our simulation¹⁰ results provide answers to all three questions.

Using sex bias units, we present our simulation results over a limited range of parameter space within a single table. Table 2 presents the segregating effects for network recruitment in the absence of referrer behaviors, the three referrer behavior mechanisms (referring asymmetries by sex and referral status, and exit chains) at their empirically observed levels in isolation, in each of the three possible two-mechanism combinations, and all three referrer behavior mechanisms simultaneously. These results are presented in Table 2 as column (1), columns (2)–(4), columns (5)–(7), and column (8), respectively. The rows in Table 2 correspond to different baseline job compositions ranging from 50% to 75% female.¹¹ The empirical case studies providing our initial parameter estimates are closest to the baseline composition of 65% women, so we will focus our discussion of our simulation results when *b* = 0.65. We highlight that row in Table 2. The other values of *b* illustrate the interaction dynamics among the referrer behavior mechanisms, as we discuss below. Having specific measures of the segregating effects of simulation scenarios, we can now give specific answers to our three research questions.

5.1.1. How Much Does Referring Contribute to Job Segregation?

Column (8) of Table 2 is our best estimate of the segregating effects of network recruitment

¹⁰The full code for the model, implemented using the RePAST agent-based modeling libraries for java (North et al. 2006), is available from the authors on request.

¹¹As with the mathematical model, we also examined the dynamics of a range of male-dominated firms in our model, and the results were symmetric as expected. These results are available from the authors on request.

in the presence of empirically documented referrer behavior mechanisms for the female-dominated jobs. Network recruitment in a firm getting half of its applicants from this method contributes as much to job segregation as a sex bias in hiring of 12% when the baseline composition is 65% women.¹² This segregating effect is almost three times as large as the segregating effect of sex bias documented in Fernandez and Sosa (2005). The amount of segregation from network recruitment is scaled by the firm's reliance on network recruitment, *p*. When *p* = 1 (total reliance), the segregating effect of network recruitment for a job with a 65% female baseline composition is equivalent to a sex bias of 27%. As is clear from the rows in column (8) of Table 2, the segregating effect also increases (decreases) as the baseline composition entails more (less) prior-to-application segregation.

5.1.2. To What Extent Do Referrer Behaviors Contribute to the Segregating Effects of Referring? Column (9) of Table 2 compares the total segregating effects with the effects when referrer behaviors are absent (column (1)), and finds that the modeled referrer behaviors are responsible for much of the segregating effects of network recruitment. In the case of a 65% female baseline composition, referrer behaviors contribute over a third of the segregating effects of network recruitment. The contribution of referrer behaviors to the segregating effects of network recruitment decreases (increases) as the baseline composition entails more (less) prior-to-application segregation, but remains substantial (over a quarter) even when the baseline composition is 75% female. In our model, as the baseline composition approaches 90% female, the segregating contributions

¹²As we also have an empirical case where *a* = 1, we could consider column (7) of Table 2, or about 9% sex bias, as another estimate of the segregating effects of referring in the presence of empirically documented referrer behavior mechanisms.

of the three modeled referrer behaviors does not go below 13%. For jobs that are near gender parity, most to all of the segregating effects of network recruitment are attributable to referrer behaviors. Network recruitment with homophilous networks does not have much of a segregating effect by itself in such situations. If the segregating effects of network recruitment in an actual firm were measured, this measure would include the effects of network recruitment with homophilous contact networks AND the various referrer behavior mechanisms. Neglecting the segregating effects of referrer behaviors neglects (in the case of the mechanisms implemented in this simulation with a baseline composition of 65% female) the mechanisms contributing about one-third of the total segregating effects of referring. Whereas previous scholarship has identified homophilous contact networks as the primary culprit in the segregating effects of referring, we find that referrer-behavior processes are also substantial contributors to this outcome.

Careful examination of the results presented in Table 2 also reveals that the three referrer behavior mechanisms interact in complex ways. For example, most of the increase in segregating effects over the “no referrer behaviors” scenario comes from the pairing of two referrer behavior mechanisms: referring asymmetries by sex and referrer-referral exit chains. The effects from just these two mechanisms (shown in column (6) of Table 2) are very close to the total effect from all three mechanisms in column (8). In these scenarios in column (6) when the referring asymmetry by referral status is off, the segregating effects range from 3.5 to 23.2 sex bias units, with a segregating effect of 12 when the baseline composition is 65% female. Interestingly, the exit chain mechanism does not have a large effect in isolation. In our referent $b = 65\%$ female scenario, the difference between all three referrer behaviors being off (column (1)) and turning only exit chains on is 0.6 sex bias units. In contrast, turning on exit chains in the presence of referring asymmetries by sex (comparing columns (2) and (6) of Table 2) increases the segregating effects of network recruitment by 3.2 units. Clearly, the exit chain mechanism interacts synergistically with the referring asymmetry by sex mechanism to yield more segregation.

This synergistic outcome illustrates how an initially gender-neutral mechanism such as exit chains can interact with another gendered mechanism such as referring asymmetries by sex to yield even greater segregation. Exit chains increase an agent’s exit likelihood for each of that agent’s referring alters who have left, but the mechanism also decreases an agent’s exit likelihood for each of that agent’s referring alters who stay. When a network hire joins the organization, they almost certainly (unless their referrer exits in the next round) have a lower exit likelihood than

a nonnetwork hire, and serve as an anchor making their referrer less likely to exit as well.¹³ When women refer more than men, they disproportionately accrue more anchors, and these anchors are disproportionately female. When all network hires refer more, the accrual of job anchors is more egalitarian. That is why adding the referring asymmetry by referral status can reduce the segregating effects of network recruitment. The ability of referrer behaviors to reduce the segregating effects of network recruitment outcomes reveals a potential policy lever: *Referrer behavior mechanisms can be used intentionally to reduce the segregating effects of referring.*

5.1.3. To What Extent Can Referrer Behavior Mitigate the Segregating Effects of Referring? We explore the parameter space of the simulation to find the scenario with the minimal increase in job segregation. For each value of the baseline composition parameter b , (given that reliance on network recruitment parameter, $p = 0.5$, and the initial exit rate parameter, $x = 0.01$), we look for the local minimum in the segregating effects over the subset of the parameter space defined by our three referrer behavior parameters (a , r , and c). This subset consists of 64 model scenarios for each value of the baseline composition parameter, b . This local minimum for the baseline composition, $b = 65\%$ occurs in female-dominated jobs when referring asymmetries by sex, a is 0.8 (i.e., men are more likely to refer than women), referring asymmetries by referral status, r is 2.5, and exit chains, c is 3. This minimal scenario represents the potential for mitigating the segregating effects of network recruitment through the management of referrer behaviors within our parameter space. By getting the underrepresented group (here, men) to refer more, by getting nonnetwork hires to engage in referring more equitably relative to network hires, and by enhancing the strength of referrer-referral ties relating to exit chains, the segregating effects of network recruitment can be greatly diminished (i.e., a 79% reduction) even without any changes in the amount of referring that takes place, or in the homophilous nature of referrers’ contact networks. As discussed above, the exit chain mechanism serves to reduce the exit likelihood of the group that refers more. When the dominant group refers more, the exit chain mechanism exacerbates job segregation; strengthening the mechanism would segregate the job further. If the underrepresented group can be

¹³ Consistent with this explanation, Kmec (2007) found that being a network hire as we have defined it—where there is an identifiable referrer who is employed within the same hiring firm—is associated with reduced turnover, whereas being a different kind of network hire is not.

induced to refer at a higher rate, this same mechanism reduces that group's exit likelihood. In that case, strengthening the exit chain mechanism would reduce the segregating effects of network recruitment. In this segregation-mitigating scenario, more than three quarters of the segregating effects of network recruitment can be eliminated; the segregating effects go from 12.3% to 2.6%. Based on our simulation results, organizations clearly have the potential to mitigate, eliminate, or even reverse the segregating effects of network recruitment. The opportunity for organizations to preserve the practice of network recruitment while mitigating its segregating effects is a key and novel insight provided by this research. Next, we suggest potential organizational policies to manage these referrer behaviors.

5.2. Potential Interventions: Managing Referrer Behavior

The segregating effects presented in columns (1)–(8) of Table 2 come from the referrer behavior mechanisms being either present or absent. Organizational policies are unlikely to be able to completely turn off any of these mechanisms as we can in a simulation. We now explore the biasing effects of various policy interventions targeting the three referrer behaviors by varying their governing parameters.

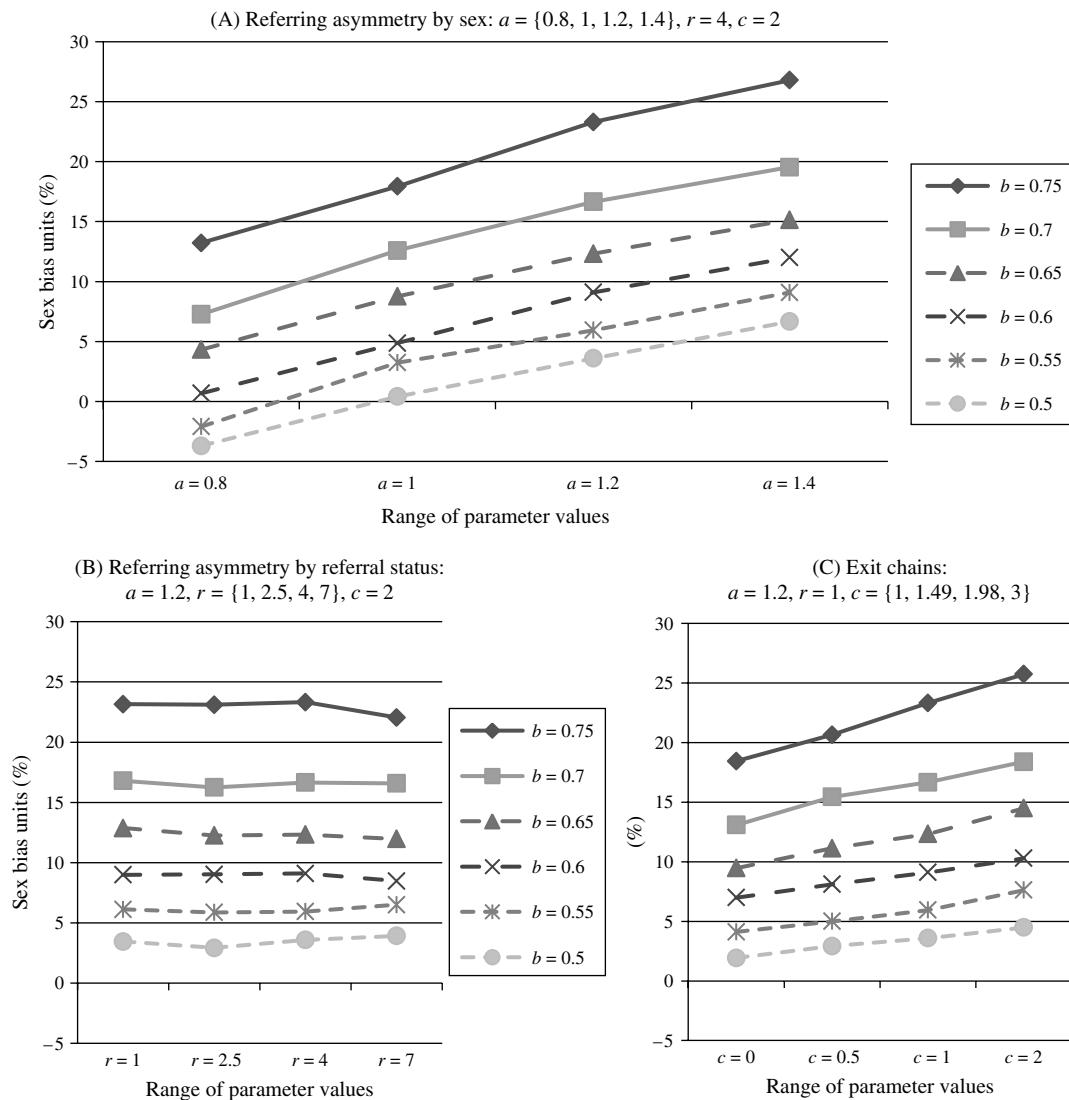
5.2.1. Changes in a : Referring Asymmetries by Sex. We found two case-study estimates of a , one with women referring more than men by 20%, and another with no sex differences. The fact that these two conditions both appear in low-wage female-dominated jobs suggests that this asymmetry is unlikely to be a strong general tendency. If so, approaches similar to those commonly suggested for Equal Employment Opportunity hiring (e.g., especially encouraging a particular group to apply for a job), might successfully be applied within an organization to encourage a particular underrepresented group to take advantage of the company's referral bonus policy, for example. It is thus plausible that such interventions could result in the underrepresented group referring more, thereby reversing the direction of the asymmetry.

Toward this end, we explore the range of values in a shown in Table 1, beyond the simple on or off values previously presented, looking for values that reduce the segregating effects of network recruitment. Figure 4(A) shows the effects in sex bias units of varying a across six values for the baseline job composition (parameter b), holding the other referrer behavior mechanisms at their observed values (asymmetries by referral status: $r = 4$, and exit chains: $c = 2$). Thus, the values plotted vertically when $a = 1.2$ on the horizontal axis correspond to the values in column (8) (all three referrer behaviors present) of Table 2. Across

all six series, there is a positive association between a and the segregating effects of network recruitment. Increases in the referring behavior of the underrepresented group (i.e., by reducing a , and moving from right to left on Figure 4(A), from reducing to reversing the asymmetry in referring), reduce those effects. The greatest reduction in segregating effects in Figure 4(A) occurs when $a = 0.8$, when the sex asymmetry in referring is reversed. This finding buttresses an intuitive but underexamined proposition in the literature on networks in labor markets: Getting the underrepresented group to refer more can reduce the segregating effects of network recruitment.

5.2.2. Changes in r : Referring Asymmetries by Referral Status. As is clear from column (3) (referring asymmetries by referral status in isolation) of Table 2, the impact of r alone is not appreciably different from the scenario with no referrer behaviors (column (1) of Table 2). Figure 4(B) shows further explorations of parameter r across six baseline gender composition values. All lines appear relatively flat. The referring asymmetry by referring mechanism does not by itself appear to be a particularly effective or strong lever in influencing the segregating effects of network recruitment. Although our mathematical model results illustrated in Figure 3 show that this mechanism makes a small contribution to segregation, the effects of this mechanism do not obviously exceed the stochastic noise present in the simulation where its effects were already reduced because of the discrete nature of the model. Because this mechanism contributes little to segregation, we do not attach much meaning to the range of values of r in the remediation scenarios (column (10) of Table 2).

5.2.3. Changes in c : Referrer–Referral Exit Chains. Figure 4(C) illustrates the effects of modifying c , the governing parameter for the exit chains mechanism, across six levels of baseline gender composition, while keeping the other parameters at their observed values (asymmetries by sex: $a = 1.2$, asymmetries by referral status: $r = 4$). As with Figures 4(A) and 4(B), the plotted values in Figure 4(C) when c takes its observed value (i.e., $c = 2$) correspond to the values in column (8) (all three referrer behaviors present) of Table 2. The exit chains mechanism also appears to vary directly with job segregation. As c increases, segregation increases, though the effect is not as strong as with the asymmetries in referring by sex. *The implication is that the ties among referrer and referrals do not create the situation where people involved in referring are being pulled out of the job at higher rates through this mechanism. Rather, these ties serve to disproportionately anchor people involved in referring to the firm.*

Figure 4 Segregating Effects, in Sex Bias Units, of Varying Each of the Three Referrer-Behavior Mechanisms in the Presence of the Other Two

Manipulating this mechanism could be attempted in several ways. First, efforts could be made to minimize its effects (desirable when the dominant group refers at a higher rate). An example would be working to retain employees whose referrer or referral left the organization via a retention bonus. Because the effectiveness of direct incentives for retention has been questioned (Capelli 2000), it is unclear whether such an intervention would work as desired. Another set of approaches is built on the assumption that exit chains matter because of the social relevance and salience of the referrer-referral tie. If so, strengthening the tie could strengthen the effect, while weakening the tie could weaken the effect. Strengthening referrer-referral ties would be relatively easy. One simple method is to share a referral bonus between the referrer and her referral hire. This shared reward could strengthen the dyad's relationship. In addition, the firm could promote interactions between referrers

and their referrals during their tenure in many ways including mentoring programs, organizational social activities, etc. Weakening the tie is a greater challenge, because the referrer-referral tie arguably is unlikely to have large salience and relevance even in the empirical setting used to identify these exit effects.

Despite the apparent direct association between the exit chains mechanism and job segregation, organizations seeking to reduce the segregating effects of referring are nonetheless likely to seek to *increase* the mechanism's effects. As we found when exploring the parameter space for segregation-mitigating scenarios, the greatest reductions in segregation come when c is large. The exit chain mechanism reduces the exit likelihood of the group that refers more. Thus, the largest reductions in the segregating effects of network recruitment come when the underrepresented group refers more and the exit chain mechanism is strong.

6. Summary and Conclusion

Current theory on segregation from labor market networks emphasizes the job seeker's perspective, focusing on the homophilous nature of the job seeker's information and contact networks, and leaves little role for organizational influence. We find this perspective to be misleadingly incomplete. Employee referrals are necessarily initiated from within a firm by referrers. This study builds theory about the dynamics of network recruitment in the labor market from the firm's and referrer's perspectives. The previously limited perspective of labor market networks has hidden opportunities to mitigate job segregation from network recruitment. Such opportunities are revealed by this study. Referrer behaviors are the missing link allowing organizations to manage the segregating effects of network recruitment without ending or reducing this important method of recruitment. Whereas previous scholars and practitioners seeking to reduce job segregation have made the impractical suggestion to end or dramatically reduce network recruitment, we show how managing referrer behaviors is a potentially effective way to achieve the same goal while preserving this integral labor market practice.

Network recruitment can have quantifiable and considerable segregating effects on a job even absent biases in screening. In docking our simulation model to a mathematical model, we developed a novel intersubjective measure of segregating effects, i.e., sex bias units. To the extent that sex biases where one group experiences a 12% advantage in its hiring likelihood would be considered nontrivial, our results show that the segregating effects of network recruitment are of a similar order. The degree to which a firm's applicant pool is stocked with referral applicants is an important factor in the segregating impact of network recruitment. Homophily in referrer-referral ties is a key driver of the segregating effects of network recruitment. Contrary to current understandings, however, homophily provides only a partial explanation for these segregating effects. Referrer behaviors help to complete the explanation. Empirically documented referrer behaviors substantially exacerbate the segregating effects of network recruitment, even for apparently gender-neutral referrer behaviors (e.g., exit chains). Contrary to conventional understandings, referrer behaviors can be managed by organizational policies to reduce the segregating effects of network recruitment.

This study reveals specific levers allowing organizations to manage the segregating effects of network recruitment. Asymmetries in which groups within the firm tend to be the most active in generating referral applicants are a key determinant, and potential lever, affecting these effects. Use of this lever first

requires that an organization attend to those employees who generate referral applicants, and consider how they resemble or differ from all job holders. In addition, attending to other aspects of the referral process observable by an organization, such as an individual employee's referral status and the referrer-referral network formed by referring ties, would assist an organization in managing the segregating effects of those referrer behavior processes that interact with other segregating mechanisms to either exacerbate or mitigate job segregation.

Although the mechanisms we have identified do not exhaust the list of possible policy levers, this study has shown that the management of referrer behaviors has the potential to mitigate most, if not all, of the segregating effects of network recruitment without eliminating the practice. Still, our study raises many questions about referrer behaviors. Are there overall differences in referring rates among different sociodemographic groups? Do these and other mechanisms operate similarly in male-dominated jobs and firms? What other factors influence referring likelihoods? Referrer behavior merits more systematic study so that the nature and extent of these and other referrer behavior mechanisms can be better understood. Using this understanding to inform organizational policies on referrer behaviors, the segregating effects of network recruitment can be mitigated, or conceivably, reversed.

Acknowledgments

The authors thank Lars-Erik Cederman; John Sterman; J. Bradley Morrison; Michael Macy; Ray Reagans; session participants at the 2004 International Conference on Complex Systems, 2004 American Sociological Association, Massachusetts Institute of Technology Organization Studies Group Seminar, and the Cornell Sociology Seminar; and the editors and anonymous reviewers at *Management Science* for valuable assistance, comments, and suggestions.

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