When Do You Put in a Word? Network Drivers of Racial Inequality in High-Stakes Work *

Sanaz Mobasseri † Mabel Abraham ‡ Elizabeth Linos §

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Abstract

Research consistently shows that White employees tend to have larger and more advantageous professional networks compared to their Black counterparts. However, less is known about how these differences in people's workplace networks emerge. Drawing on theory about the mechanisms underlying tie formation and racial bias in organizations, we propose that the effect of shared contacts—the process of forming connections through mutual contacts—drives racial disparities in networks beyond what can be explained by unequal access (structural homophily) or people's preferences to directly connect with similar others (choice homophily). We further predict that these disparities are most likely in high-stakes work contexts, where shared contacts face heightened uncertainty in their decisions to informally broker. To test our hypotheses, we leverage the random assignment of 2,984 new hires to initial project teams in a global professional services firm, conditional on office. This allows us to estimate the causal effect of shared contacts on project tie formation. We find that Black and White new hires form ties at similar rates when interacting directly with coworkers, in the absence of mutual contacts. However, Black new hires are significantly less likely to form ties through shared contacts. This racial gap is most pronounced in high-stakes work contexts, like client-facing projects, where the effect of shared contacts on the probability of forming ties is 39% larger for White new hires than their Black counterparts. Our findings contribute to the research on the network mechanisms driving racial inequality in the formation of intraorganizational ties and how routine network-based work practices perpetuate racial differences in organizations.

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†Boston University, sanazm@bu.edu, corresponding author

‡Columbia University, mabel.abraham@gsb.columbia.edu

§Harvard Kennedy School, elizabeth_linos@hks.harvard.edu

INTRODUCTION

Intraorganizational networks—connections among employees—are critical for providing people with access to valuable resources, strategic information, and job opportunities, fundamentally shaping career trajectories within their workplace (Podolny and Baron, 1997; Castilla, 2005; Fernandez and Sosa, 2005; Bidwell et al., 2013). Widespread belief in the importance of these network benefits motivates people to proactively form the types of connections they expect will support their career attainment (Ingram and Morris, 2007; Kuwabara et al., 2018; Vissa, 2012). However, extant research demonstrates that racial disparities persist in the size and composition of people's networks across social contexts and life stages (McPherson et al., 2001; Pager and Shepherd, 2008; DiMaggio and Garip, 2012). Though empirical evidence on racial differences in workplace networks is limited, these intraorganizational relationships generally advantage Black employees less than their White counterparts, as Black employees have fewer connections to White colleagues in positions to facilitate career benefits (Ibarra, 1995).

What remains less clear is how and under what conditions racial differences in people's workplace networks emerge. The most common explanations point to two processes of homophily—the tendency to connect with similar others—leading people to disproportionately form ties with same-race others (McPherson et al., 2001; Kleinbaum et al., 2013). The first relates to structural constraints whereby homophilous ties emerge because people tend to have more opportunities to form same-race than cross-race ties. However, within organizations, employees in the same jobs typically have comparable opportunities to connect with their colleagues, suggesting that structural constraints alone cannot explain racial differences in intraorganizational network formation. A second explanation centers on people's preference to directly connect with similar others, known as choice homophily. However, empirical evidence of such preferential attachment commonly comes from studies of more social, rather than professional, networks, such as ties among friends, neighbors, or college students (Moody, 2001; Kossinets and Watts, 2009; Currarini et al., 2010). By contrast, preferences for same-race connections are unlikely to be a primary driver of racial disparities in workplace networks for at least two reasons. First, unlike *social* relationships where two

people have more discretion to form ties based on their preferences, whether or not two people form an *instrumental*, or task-based, tie is governed more by workplace norms and needs than by personal preferences. Indeed, evidence suggests that in professional contexts, people often actively seek out connections across demographic differences to access diverse resources, knowledge, and opportunities, thereby limiting the role of choice homophily in workplace networks (Aldrich et al., 1989; Ibarra, 1997; Forret and Dougherty, 2004; Bensaou et al., 2014; Aten et al., 2017; Obukhova and Kleinbaum, 2022). Second, intraorganizational ties are often shaped by third-party decisions, such as mutual contacts or managers assigning project teams, not just by two individuals directly connecting based on their personal preferences about whom to work with.

We advance theory on racial inequality in elite intraorganizational networks by identifying a novel racializing mechanism of tie formation: the effect of shared contacts in informal network-based staffing practices for high-stakes projects. Elite knowledge-intensive organizations commonly rely on network-based staffing practices, such that employees' existing contacts shape their future opportunities to access projects and to form new connections with other colleagues on those projects (McGinn and Milkman, 2013; Woodson, 2023; Tippett, 2019). Unlike explanations based on choice homophily, which emphasize how people's preferences shape the direct person-to-person ties that employees form, we propose that these work practices positioning shared contacts as informal brokers will produce racial inequality in employees' project networks. Specifically, we argue that shared contacts deciding whether to connect an employee to project team members seeking new colleagues face uncertainty—stemming from the work context, especially in high-stakes projects—that amplifies racial bias, leading them to connect their Black contacts to others at a lower rate than they do their White contacts. In short, the routine work practice of informally relying on network intermediaries will produce racial inequality by disadvantaging Black employees in their access to valuable high-stakes projects, thereby constraining both their opportunities to form advantageous project ties and to demonstrate their work.

Using longitudinal network data from an elite professional services firm where we observe the formation of ties on projects (project ties) for new entrants, we estimate the causal effect of

shared contacts on project tie formation for these newly hired junior employees. Most central to our theoretical arguments, we identify racial differences in the effect of shared contacts on forming new project ties. We leverage two unique features of our setting to obtain such causal estimates. First, new hires are randomly assigned, conditional on the office they were hired into, to initial project teams by the firm, which results in the random assignment of initial network connections and allows us to compare otherwise identical Black and White new hires who have the same opportunities to form ties. Second, we have access to dynamic network data, allowing us to identify how these initial network connections shape subsequent tie formation.

We find clear evidence that shared contacts are the primary driver of racial differences in the project networks these employees form. Black and White new hires form new project ties at similar rates in the absence of shared contacts (direct, dyadic), but the impact of mutual connections significantly differs between racial groups. Shared contacts have a larger effect on project tie formation rates for White relative to Black new hires, especially in high-stakes work contexts. These differential effects of mutual contacts significantly and substantially drive racial differences in subsequent project ties. Moreover, considering that we do not observe meaningful differences in project ties formed person-to-person (in the absence of a shared contact), our results point to the effect of shared contacts as the chief mechanism perpetuating racial differences in the size and composition of employees' networks in this organizational context. Our findings thus contribute to the research on the network mechanisms driving racial inequality in ties formed, the organizational conditions under which racial bias emerges, and how routine network-based work practices perpetuate racial differences in organizations.

THEORY

Shaping Intraorganizational Networks: The Invisible Hand of Shared Contacts

While extant research has devoted considerable attention to identifying the consequences of social networks—namely, the ways that having connections to others increases access to valuable resources, jobs, and opportunities (Podolny and Baron, 1997)—substantially less scholarship has focused on the underlying drivers of tie formation, how people form the ties that constitute their

networks (Small, 2009). The prevailing notion of networking in organizations centers on direct person-to-person instrumental networking, whereby individuals engage in proactive behaviors to build relationships with others to achieve their professional goals (Lincoln and Miller, 1979; Ibarra, 1992). Such networking has become central in popular culture, fueled by the rise of enabling platforms like LinkedIn and the proliferation of firm-sponsored networking events (Casciaro et al., 2014; Kuwabara et al., 2018).

However, people do not form ties exclusively through their direct networking behavior. Instead, people also routinely form new ties through their existing contacts (Simmel, 1950). This is the idea of shared contacts (or brokers), who are people who have opportunities to connect two otherwise disconnected contacts (Burt, 2004). For instance, this is most famously studied in the context of referrals whereby a shared contact recommends someone they know to an employer—in many cases their current employer—who is looking to fill a job vacancy (Granovetter, 1995; Fernandez et al., 2000).

Shared contacts do more than just channel job referrals into organizations—they also forge relationships within them. Studies across diverse contexts—from universities (Kossinets and Watts, 2006) to workplace advice and friendship networks (Krackhardt and Kilduff, 1999; Lazega and Pattison, 1999)—demonstrate that shared contacts catalyze new connections among colleagues. Relatively less attention has been paid to the effects of shared contacts for breeding the instrumental workplace ties that are critical for individuals' career success (for an exception, see Obstfeld 2005; Tortoriello and Krackhardt 2010). Such seemingly neutral network processes—like networking with friends of friends, or triadic closure—can benefit organizations by facilitating cooperation and social cohesion and increase employees' willingness and motivation to invest time and effort into knowledge sharing (Coleman, 1988; Krackhardt and Kilduff, 1999; Reagans and McEvily, 2003; Dahlander and McFarland, 2013). Although seminal network scholars theorized shared contacts as universal facilitators of tie formation (Simmel, 1950), these mutual connections' ability to structure workplace relationships derives not from any inherent property of triadic relationships (Lin, 2002), but rather from specific features of the workplace context.

Relationship-based work practices are one key contextual factor through which shared contacts gain influence over their contacts' networks, especially in organizational settings that permit and promote these practices. In elite, knowledge-intensive organizations—where knowledge, skills, and connections among employees are the primary asset—cultivating connections among employees is particularly crucial for advancing the firm's work and for employees' career advancement (Sherer, 1995; von Nordenflycht, 2010; McGinn and Milkman, 2013). These types of organizations typically rely on informal network-based staffing practices, where employees' existing contacts shape their future access to working on new projects and forming new connections with other colleagues on those projects (Sturm, 2001; Woodson, 2023; Tippett, 2019). In short, through such informal practices, elite organizations create and staff informal brokerage positions, placing shared contacts in roles where they can informally facilitate relationships between others.

Shared Contacts and Racial Inequality: How Network-Based Staffing Disadvantages Black Professionals

Even when organizations create opportunities for shared contacts to informally broker connections, we know little about whether these contacts consistently favor White over Black employees and the underlying drivers of such racial bias. Research on personal networks and job referrals finds that Black people and other marginalized groups benefit less from their contacts than White, male, majority group members (Royster, 2003; Smith, 2005, 2007; Abraham, 2020). However, focusing solely on the racially disparate outcomes of triadic processes suggests that inequality may be inevitable when individuals must rely on others to forge connections for them. However, we propose that this is an overly simplified conclusion that masks how organizational contexts enable or constrain shared contacts' behaviors in ways that directly shape whether such racial differences emerge.

Drawing on research examining the effects of mutual contacts' on producing inequality in evaluations and research on the conditions that surface racial bias in organizations more generally, we theorize about how uncertainty—emerging from the work context rather than from individual biases—shapes shared contacts' decisions about whether to connect their Black or White contacts

to other members of their professional network. Shared contacts face three types of uncertainty that stem from organizational design choices: uncertainty about what performance criteria matter most, uncertainty about how to apply performance criteria, and uncertainty about whether and how much other people's perceptions of them will affect their own career advancement.

First, shared contacts can face uncertainty about what performance criteria can be used to evaluate (their own and other people's) performance because organizations often maintain subjective, ambiguous assessment criteria rather than formalizing clear standards. Research shows that when organizations leave evaluation criteria undefined, evaluators tend to rely on demographic stereotypes, disadvantaging Black people (Amis et al., 2020; Correll et al., 2020).

Second, shared contacts face uncertainty about how to observe and evaluate their contacts' capabilities in practice. For instance, in elite professional services firms with network-based staffing, shared contacts must assess less experienced colleagues' potential without clear metrics or sufficient opportunities to observe the quality of their work. Thus, when organizations leave performance qualities ambiguous and difficult to observe, evaluators tend to rely on demographic attributes as proxies for quality (Becker, 2010; Correll and Ridgeway, 2003), leading them to systematically underestimate Black contacts' capabilities.

Third, shared contacts face uncertainty about how their decision to connect two coworkers might affect their perception by others because organizations' reward systems create uncertainty about the career consequences of referral decisions. When organizations make career advancement dependent on others' subjective judgments, shared contacts are apt to become primarily concerned with how their informal referral decisions will be perceived by others. Consequently, shared contacts may hesitate to connect their Black contacts due to assumptions about others' racial biases and preferences (Correll et al., 2017), particularly when their own evaluations and career success could depend on maintaining a reputation for quality referrals.

In sum, we argue that these sources of uncertainty, stemming from ambiguities in organizational evaluation processes, make it more likely that racial bias will shape shared contacts' decisions about whether to connect their Black or White contacts to other members of their professional

network.

Hypothesis 1 (H1): Black employees will be less likely to form new project ties through shared contacts than will their White counterparts in high-stakes work contexts.

DATA AND METHODS

Study Setting

Our research site is a large, global, knowledge-intensive firm in the professional services industry, ConsultingCo. Professional services firms help clients maximize their profitability or effectiveness by providing them with knowledge and expertise related to management, law, strategy, finance, information technology, human resources (HR), and other domains (O'Mahoney and Markham, 2013; Morkes, 2023), and have been the subject of many studies (Sturm, 2001; Gorman, 2005; Roth, 2006; Turco, 2010; Gardner, 2012; Rivera, 2012; McGinn and Milkman, 2013; Woodson, 2023). ConsultingCo is well-suited to the study of the drivers of racial differences in tie formation in elite organizations because it offers several theoretical and empirical advantages.

First, ConsultingCo recruits at prestigious universities and rigorously screens candidates, which limits differences between newly hired junior employees' educational backgrounds and skills. Most entry-level hires are sourced through on-campus recruiting, with fewer than five percent of applicants receiving offers, as is typical in the industry (Morkes, 2023). The resulting cohort of junior employees enter the organization with relatively similar profiles, allowing for a more precise assessment of racial differences in drivers of project tie formation. Studying project tie formation for these new entrants to the ConsultingCo network thus minimizes the likelihood that any observed racial differences are driven by unobserved differences in new hires' human or cultural capital.

Second, ConsultingCo, like other elite professional services firms, formally and informally promotes networking to facilitate access to new project ties and highlights the importance of making project ties for success at the firm. Once hired, employees work on multiple projects simultaneously, which differ in size and duration, and are expected to work collaboratively to conduct research and analyses, draft and deliver presentations and written reports, develop solutions to var-

ious challenges, and make recommendations for clients (O'Mahoney and Markham, 2013; Indeed Editorial Team, 2023; Morkes, 2023; U.S. Bureau of Labor Statistics, 2023). Even though initial team assignment (and therefore initial coworkers) are determined by an HR manager with little control from new hires—a feature of the firm that we exploit for our causal identification strategy and explain in the Identification section—subsequent assignment to teams and projects depends on peoples' networks. Specifically, staffing on future projects becomes akin to an internal labor market where junior employees are eager to be placed on high-priority or client-facing projects to prove their value to the firm, and senior colleagues have flexibility and discretion in who they "recruit" or "select" to work on their projects. In ConsultingCo's formal onboarding program, networking is prominently featured in most sessions, and newly hired junior employees are urged to form project ties directly. For instance, they are encouraged to initiate contact with experienced colleagues (e.g., arranging informal meetings) and to attend networking events that facilitate building the connections necessary for future project allocation. This expectation is so salient that new hires are given time to practice networking strategies during their onboarding experience. In informational interviews with current employees and HR representatives, we consistently noted that employees felt near-constant pressure to maintain relationships in order to receive high-quality project placements. The importance of forming project-based ties is also made clear at ConsultingCo. One employee simply stated "You will get staffed on projects only if you know somebody." Another employee told us "It's not only the delivery of your job; it's who knows you and who can vouch for you." Employees also stressed the importance of identifying and nurturing relationships with mentors early on who could later connect them to their own network contacts. For instance, one respondent noted, "If you're staffed by someone who has a lot of pull, their recommendation has this great snowball effect..." As such, a new hire's ability to form ties with colleagues and leverage their colleagues' networks is baked into the practice of staff allocation. Taken together, the formal institution of working on collaborative projects with teams of employees that directly impact one's own career trajectory creates a high-stakes environment that underscores both the implicit (likeability, socialization) and explicit (staffing, promotion opportunities) significance of

networking to new hires.

Third, ConsultingCo provides an opportunity to develop theory about how racial differences in social networks emerge in elite workplaces, which are known to drive wage (Saez, 2008) and career disparities (Bertrand et al., 2010). This is particularly important because past research has primarily explored network effects on hiring into organizations or has been focused in low-wage work contexts (Smith, 2005; Fernandez and Fernandez-Mateo, 2006; Smith, 2007; RM Fernandez, 2013; Smith and Young, 2017; Silva, 2018; Pedulla and Pager, 2019). Like the broader industry, ConsultingCo offices are geographically dispersed across the U.S. in locations where professional services are in high demand (Dun & Bradstreet First Research Industry Profile, 2023). ConsultingCo represents an elite workforce with demographics similar to the industry, and with over 50,000 employees in the U.S., provides a suitable sample for our study. Though White and male employees are overrepresented in leadership positions, as is typical in elite organizational settings, there is comparatively more diversity at the junior level (Dean et al., 2020). Thus, ConsultingCo provides sufficient demographic diversity to explore racial differences in the evolution of intraorganizational ties in an elite context.

In sum, ConsultingCo is an ideal organizational context to study the dynamics of network evolution. ConsultingCo exemplifies the broader industry in numerous aspects, including the nature and structure of project-team-based work, demographic composition of employees, geographic distribution of their offices, and dynamics of intraorganizational tie formation. This typicality reduces our concern that idiosyncratic firm dynamics may influence our investigation but also highlight components of the industry as a whole that make ConsultingCo particularly well-suited to studying network processes underlying elite intraorganizational networks.

Identification

Empirical social network data consistently exhibit triadic closure, that is, if individuals A and B have a tie, and B and C have a tie, then it is more likely (than otherwise) that A and C also have a tie. One explanation of this pattern is that it is causal, which is our focus: If A and C share a contact, B, this makes it more likely that A and C will work together on a project, thus forming a project

tie, relative to when they do not share the contact B. Another explanation for this pattern is that it is purely correlational, caused by unobserved confounding factors: people might, for instance, be geographically segregated or share cultural interests, and thus be more likely to encounter and work on projects with others who are co-located or share those interests, respectively. The same reasons that made it more likely that both A and B form a project tie and that B and C form a project tie—such as geographic co-location or shared cultural interests—might also make it more likely that A and C work together. In this example, geographic co-location and shared cultural interests could be unobserved confounders driving project tie formation.

Furthermore, the causal effect of shared contacts on tie formation may also operate in the reverse direction, posing difficulties for identification. When we observe project ties between A, B, and C, we do not know the order in which each pair connected. It is possible that A and C as well as B and C were first connected on a project, which lead to the formation of a project tie between A and B. It is also possible that A and B, as well as A and C, were first working together on a project, which led to a project tie between B and C. In short, project ties forming can be both cause and effect in these feedback loops. Without network data over time, we cannot know whether the link between A and B caused the link between A and C, or whether it was the other way around.

Identifying the causal effect of shared contacts on project tie formations requires addressing both unobserved confounding variables and reverse causality.[1] That is, identifying this causal effect is difficult for the usual reasons that make it difficult to disentangle correlation from causation.

In this paper, we exploit a setting with two unique features that make it possible to solve these causal identification problems. The first feature is random assignment of new hires to initial project teams, within offices. Such random assignment means that the initial ties (initial coworkers, who become shared contacts between new hires and other employees) of new hires, who enter an ex-

[1] Our goal is to obtain a causal estimate of shared contacts, or triadic closure. This contrasts with estimation approaches that descriptively model network features and network generation. One popular class of such descriptive models are exponential random graph models (ERGMs), which yield a probabilistic model of network formation based on the degree of triadic closure and other network features (Quintane and Kleinbaum, 2011; Chen et al., 2022). ERGMs do *not*, in general, yield causal estimates of triadic closure.

isting intraorganizational network, are randomly assigned, conditional on the office they join. The second feature is the availability of dynamic network data, which enables us to observe project tie formation over time. We are able to observe who each employee works with, on which projects, for how long, over time, thus enabling us to construct the evolution of the intraorganizational network. The combination of these two features allows us to obtain the causal impact of shared contacts. These causal estimates, in turn, allow us to disentangle the extent to which shared contacts serve to amplify intraorganizational project tie formation, which in turn might serve to reproduce segregation and inequality in the workplace.

Data

Data for this study was sourced from seven years of ConsultingCo's administrative employment data and project staffing records. From ConsultingCo's administrative employment data, we observe employees' hiring dates, job details, geographic location, and the department to which they were assigned. Administrative data also contain employees' self-reported racial and ethnic identity, gender (male or female, as assigned at birth), and education history.

From ConsultingCo's staffing records, we observe the universe of projects on which employees report spending time each month—for instance, time reported on client-facing and non-client-facing projects. Project staffing data also includes a prioritization score for ConsultingCo which indicates how important the project is to the firm. Because we can observe all employees on a project and their corresponding job details, we can determine whether project ties are formed between new hires and more senior employees. These additional details allow us to identify different types of projects in which new hires form ties, such as in high-stakes contexts.

We also conducted 29 informational interviews to gain insight into how employees join project teams—initially through an HR process for new hires and subsequently relying on network-based staffing for all employees—and the extent to which these project-based ties and project networks matter for employees' career success.

Sample. ConsultingCo employs over 50,000 people, distributed across numerous U.S. cities and departments. Our study on the formation of intraorganizational project ties among new hires—

in other words, the evolution of the project network—relies on three types of employees: *new hires*, *initial coworkers*, and *potential coworkers*. *New hires* are full-time, inexperienced junior employees who join the firm during our study period. *Initial coworkers* are the employees assigned to work with the new hires on their first projects, which we assume (and support this assumption with empirical evidence) are randomly assigned, conditional on their office. *Potential coworkers* are prior coworkers of the initial coworkers, representing the set of intraorganizational project ties that new hires could potentially form through their shared contacts, via their initial coworkers. We take three steps to construct our dyadic relational data between new hires and their potential coworkers, based on a sample that includes new hires, their initial coworkers, and their potential coworkers. See Figure 1 for a visual representation of how the three actors of our network sample are related. Analyzing data at the level of these different types of employees is crucial for understanding the dynamics of project network formation, which an analysis of data focused solely on projects would not reveal.

We start by identifying a sample of new hires. From 2015-2020 (prior to the COVID-19 pandemic), the total sample of full-time junior professionals with the same job title in team-based departments in ConsultingCo's U.S. offices is 21,489. For this analysis, we excluded 13,525 employees who had prior experience with ConsultingCo (e.g., internships, rehires) that likely had existing networks. We also excluded 2 employees for whom all coworkers on their initial teams did not self-report their race or ethnicity and 10 employees who did not self-report their own race or ethnicity, which is not legally required in the U.S. We excluded 27 employees who worked in offices where all new hires in the cohort were connected to the same initial coworkers (in other words, employees in offices with no identifying variation). We excluded 447 employees who did not work for at least one year. Lastly, to ensure comparability of our results for Black and White new hires, we focus our primary analyses on offices where both Black and White new hires are present in the same cohort. This meant we excluded 4,494 employees in offices that did not have at least one Black and one White new hire. Thus, our sample of study consists of the intraorganizational ties for 2,984 full-time inexperienced new hires who joined the firm between 2015 and

2020 (and worked for at least one year) in offices with at least one Black and one White new hire.

Table 1 summarizes the project and employee characteristics of our full-time newly hired inexperienced sample. New hires are, on average, 24 years of age; all have an undergraduate degree; and 9% have degrees from a Top 20 ranked U.S. school. The average number of projects that new hires work on per month is 3 in the initial three months of work, and increases to 4 in the subsequent periods. On average, new hires initially spend 53% of their time on client-facing projects, and this increases to 83% of their time by the end of their first year. Table 2 further describes the study sample of new hires, which includes women (48.7%), White (56.9%), Asian (21.8%), Black (10.7%), and Hispanic (6.4%).

Next, we identified each new hire's set of initial coworkers on their initial project teams. Drawing on our assumption of new hires' random assignment, within office, to initial project teams detailed above in the Identification section, these 2,984 new hires worked with 49,397 initial coworkers during the study time frame. Table 2 details the demographic composition of new hires' initial coworkers: women (41.7%), White (48.4%), Asian (23.5%), Black (5.0%), and Hispanic (4.9%).

Third, we construct the risk set of potential coworkers with whom new hires in our sample could feasibly form a project tie by working on future projects together. We identify all prior project ties of the initial coworkers in an office (those with whom new hires were initially assigned to work with). We do this by constructing monthly intraorganizational network data based on project staffing records. For each randomly assigned initial coworker of a new hire in an office, we identify their coworkers from projects they worked on over the previous year—prior to the new hire's entry into the firm and onto a project with the focal initial coworker. Put simply, we identify new hires' initial coworkers' coworkers. Table 2 describes the demographic composition of 172,417 potential coworkers in our sample: women (40.3%), White (36.2%), Asian (21.1%), Black (4.4%), and Hispanic (4.2%). In each office, new hires are connected to potential coworkers through their unique set of initial coworkers. Though multiple new hires may join the same office simultaneously, they are not necessarily connected to the exact same potential coworkers as other new hires in their office. This difference in potential coworkers to which a new hire is indirectly

connected in an office is the key variation we use to identify the causal effect of shared contacts on future project tie formation. In other words, within each office, the set of potential coworkers represents the intraorganizational project ties that a cohort of new hires are at risk of working with in the future. In each office, a new hire is indirectly connected to a subset of those potential coworkers, those who have worked previously with their initial coworkers. Another subset of potential coworkers represents employees to whom a new hire's cohortmates are indirectly connected through their initial coworkers.

Our dyadic data set consists of 85,021,454 relationships between 2,984 new hires and potential coworkers across 193 offices.

Dependent Variables. Our main outcomes of interest are binary indicators of whether or not a project tie is present between a focal new hire and a potential coworker by the end of the new hire's first year of employment. We define a project tie as two employees working on the same project at the same time. Specifically, given that employees have flexibility in who they work with after the initial assignment to projects, we measure project ties formed between a new hire and each potential coworker in the nine months following the new hire's initial assignment to projects. *Overall project tie formation* takes a value of 1 in cases where the focal new hire formed any type of project tie with the potential coworker in the subsequent nine-month period. Beyond examining an aggregate measure of project tie formation, we also examine working together on different types of projects following the same binary coding procedure described above: *ties formed on non-client-facing projects*, a high-stakes work context, and *ties formed on client-facing projects*, a low-stakes work context.

Independent Variables. Our primary independent variable *shared contacts* captures whether a new hire has a shared contact to each potential coworker. For each new hire, we measure shared contacts by observing the number of initial coworkers of a new hire who connect them to other potential coworkers in the firm. Figure 2 depicts the distribution of our main independent variable in our sample of potential coworkers at risk to form project ties with new hires in a given office. Conditional on having a shared contact, the median number of shared contacts (via initial cowork-

ers) a new hire has to potential coworkers is 2. For our main analysis, *shared contacts* is coded as a binary variable taking a value of 0 in cases where the new hire has no shared contacts with a potential coworker, and a value of 1 otherwise (i.e., when new hire has 1 or more shared contacts to a potential coworker). This distribution also shows that in over 70 percent of these data, a new hire does not share a contact with a given potential coworker (0 shared contacts). On average, 0.20 pp of project ties are formed occur when new hires and potential coworkers do not share contacts.

Estimation

Our main outcome of interest is the formation of project ties between new hires i and potential coworkers k, at time t, $Y_{ik}^t \in \{0,1\}$. We aim to estimate whether such ties are more likely to form if i and k share a tie j in common and how this effect varies by new hire race and by potential coworker race.

Define

$$X_{ik}^t = \max_j \left(Y_{ij}^t \cdot Y_{jk}^t \right).$$

X_{ik}^t equals 1 if i and k share some tie j in common at time t; it equals 0 otherwise.

We conduct the following analysis for all new hires and for different subsamples, by new hire race, and by potential coworker race. Our main estimating equations are of the form:

$$Y_{ik}^2 = \delta_k + \beta \cdot X_{ik}^1 + \varepsilon_{ik}.$$

The coefficient β is a causal estimate of the effect of shared contacts on subsequent project tie formation—in other words, a causal estimate of triadic closure. This coefficient indicates how much more likely working together on a project becomes when a new hire and a potential coworker share a contact in common as compared to when they do not, all else equal. δ_k is a fixed effect for potential coworker k. Inclusion of this fixed effect ensures that our estimates are driven by the random variation of X_{ik}^1 across new hires i, due to random initial coworker assignment (via initial project teams), for fixed k. That is, this fixed effect controls for the endogenous variation of

connectedness across potential coworkers k.

Time 1 is the three-month period of initial employment, where new hires are randomly assigned to initial project teams. Consider all new hires i in a given office, and all potential coworkers k who are indirectly connected to *some* new hire in this office. By random assignment to project teams, X_{ik}^1 varies randomly (exogenously) across new hires i in a given office. Because X_{ik}^1 is exogenous, the coefficient β identifies the causal effect of having mutual connections on tie formation between a new hire and a potential coworker.

Because assignment to project teams is random within but not across offices, we run separate regressions for each office o, and obtain corresponding estimates $\hat{\alpha}_o$ and $\hat{\beta}_o$. We aggregate these estimates by averaging across offices, using the number N_o of new hires in given office as a weight,

$$\hat{\beta} = \frac{\sum_o \hat{\beta}_o \cdot N_o}{\sum_o N_o}.$$

As noted above, we calculate the estimator $\hat{\beta}$ for different subsamples, by new hire race and race dyad. We first calculate $\hat{\beta}^B$ and $\hat{\beta}^W$ for the subsamples of Black and White new hires separately, including potential coworkers regardless of their race. We then also calculate this estimator for the subsamples corresponding to different combinations of new hire-potential coworker race dyads. We get estimates $\hat{\beta}^{rs}$, where r and s denote new hire and potential coworker race, $r,s \in \{B,W\}$.

Because some offices offer more opportunities for forming project ties than others, we need to account for this office-level heterogeneity. For instance, if estimates for Black and White new hires were based on different sets of offices, they would not be comparable. Thus, to make estimates comparable across Black and White new hires as well as new hire-potential coworker race dyads, we base these estimates on data from the same offices. We estimate effects within offices that have both Black and White new hires, and then take a weighted average across these offices, where each office is weighted by the total number N_o of new hires in that office, regardless of race.

We denote the average rate of project tie formation (overall, and for these different subsamples)

by $\bar{Y}$, $\bar{Y}^B$, etc. We similarly denote the average of the independent variable by $\bar{X}$, $\bar{X}^B$, etc. Based on our point estimates for β and based on these averages, we can predict both the counterfactual rate of project tie formation absent shared contacts, as well as the rate of project tie formation in the presence of shared contacts:

$$r^0 = \bar{Y} - \bar{X} \cdot \hat{\beta}, \qquad\qquad r^1 = \bar{Y} + (1 - \bar{X}) \cdot \hat{\beta},$$

and similarly for the various subsamples.

Inference

Inference in our setting is somewhat complex and non-standard. The unit of observation for our regressions are project ties between new hires and potential coworkers *ik*. We consider a unit to be treated if $X^1_{ik} = 1$. Treatment assignment to units is clustered at the level of new hires and at the level of project teams, through which potential coworkers are connected to new hires.

One solution for this problem that has been proposed in the literature is two-way clustering (Cameron et al., 2011; Kleinbaum et al., 2013). However, neither conventional clustering of standard errors (Abadie et al., 2023) nor two-way clustering (Kleinbaum et al., 2013) at the level of new hires and project teams would result in correct inference in our setting. Conventional (and two-way) clustering assumes statistical independence of treatment assignment across clusters, even though it allows for correlated treatment assignment within clusters. Such clustering would result in incorrect standard errors and p-values because there is statistical cross-dependence across clusters in our setting. For instance, if a given new hire is (randomly) assigned to one project that takes up all their time, they are then not assigned to another project. Therefore, in this case, assignment to these different projects is negatively correlated. For another example, if a given project is assigned one new hire and only needs one new hire, then it is not assigned another new hire in that cohort. Therefore, in this case, the assignment of different new hires to this project is negatively correlated. Correct inference requires accounting for the statistical correlations that result from such cross-dependence.

Randomization inference for p-values. To obtain correct p-values in this context, we use randomization inference. We test the sharp null hypothesis that having a common contact has no effect whatsoever on subsequent project staffing and, thus, project tie formation. In other words, the null hypothesis that Y_{ik}^2 stays the same regardless of the value of X_{ik}^1. To do this, we construct random counterfactual assignments of new hires to projects. Our counterfactual assignments are based on randomly swapping the racial identity of new hires, which means swapping the projects (and, in turn, the initial coworkers) to which they are assigned. Each counterfactual assignment corresponds to a permutation $\pi(i)$ of new hires i within office, where the actual regressor X_{ik}^1 is replaced by the counterfactual regressor $X_{\pi(i)k}^1$. For each such counterfactual assignment, we can re-calculate our estimates, such as $\hat{\beta}$. Repeating this procedure 20,000 times results in a distribution of point estimates, $\hat{\beta}$—which is the sampling distribution under the null hypothesis. If the null hypothesis is true, then our actual point estimate, $\hat{\beta}$, is simply a random draw from this distribution. If our actual $\hat{\beta}$ lies in the tail of this distribution, then this provides evidence against the null hypothesis of no effect. We calculate p-values as the share of estimates from this distribution that exceed the actual point estimate (for the actual data). The null hypothesis is rejected for a small p-value, such as $p < 0.05$.

The procedure, as just described, allows us to test whether $\beta^r = 0$, and whether $\beta^{rs} = 0$, for $r,s \in \{B,W\}$/ We can also use the same procedure to test whether $\beta^W - \beta^B = 0$. For each permutation π of new-hire identities in an office, we can re-calculate the estimates for both β^W and β^B, and take their difference. Doing this repeatedly and aggregating across offices gives a distribution from which we can again calculate p-values[2].

Causal bootstrap for standard errors. Randomization inference results in correct p-values

[2] An alternative approach for inference using network data is the (MR)QAP approach (Hubert and Schultz, 1976; Krackhardt, 1988; Dekker et al., 2007; Lindgren, 2010). While the (MR)QAP approach uses permutations to construct a distribution for the test statistic under the null, like our approach, (MR)QAP is based on assumptions about the correlation structure of residuals, like the two-way clustering approach. In contrast, our design-based approach to inference relies solely on knowledge of the actual assignment of new hires to initial projects (i.e. study design), without any other parametric or non-parametric restrictions on the structure of regression residuals. Our approach relies solely on permutations that correspond to the actual assignment process of new hires to initial project teams that ConsultingCo used, rather than all possible permutations of new hires and initial project teams, as (MR)QAP does. Our approach to inference thus parallels our design-based approach to the identification of a causal model of network formation

under the strong null hypothesis. However, randomization inference does not allow us to calculate correct standard errors because they depend not only on realized tie formation outcomes but also on the counterfactual outcomes that would have resulted from a counterfactual assignment of X. Under the strong null these counterfactual outcomes are equal to the realized outcomes. Under the alternative hypothesis, where X, in fact, does have an effect on Y, it is not true that counterfactual outcomes are always equal to the realized outcomes. Thus, the correct standard errors differ from the standard deviation of the randomization distribution.

To address this problem, we modify the randomization inference approach described above to adapt a new procedure called "the causal bootstrap," combining insights from Menzel and Imbens (2021) and Abadie et al. (2023). In the Appendix Methods section, we describe in detail how we used the causal bootstrap approach to construct correct standard errors for our point estimates.

RESULTS

Randomization Check

Our study's identification strategy relies on the random assignment of new hires to project teams, which implies the random assignment of project ties with initial coworkers. This feature allows us to estimate the causal effect of *shared contacts* (via initial coworkers) on subsequent project assignments enabling project tie formation with potential coworkers. Random assignment implies that the presence of shared contacts with potential coworkers is statistically independent of new hire characteristics. In other words, if new hires are randomly assigned, we should observe no significant relationship between pre-determined (prior to their joining ConsultingCo) new hire characteristics and the likelihood of having mutual contacts with potential coworkers they could work with in the future.

To corroborate our identification strategy, we conducted a series of placebo tests, which build on our main model specification. In these tests, we replaced our dependent variable Y_{ik}^2 with new hire characteristics C_i that were determined prior to their entry to ConsultingCo—their racial/ethnic and gender identity, age, and education, which are all self-reported. For education, we constructed four binary variables—*Top 20, 21-100, 101-1,000, and 1,001+*—indicating the highest-ranked

university from which a new hire has a degree, based on rankings from Webometrics (Vernon et al., 2018). We also include a variable *Master's Degree* indicating whether the new hire has a master's degree and a variable *Technical Master's* indicating whether the new hire has a specialized technical master's degree. For these education variables, values are missing for a subset of new hires, so we restrict attention to the subset of offices where at least two new hires have non-missing values.

As with our main model specification, we use randomization inference to calculate p-values for the null hypothesis that new hires are randomly assigned to project teams within their offices. By definition of a p-value, if the null hypothesis is correct, then the p-value is a random draw from the uniform distribution ranging from 0 to 1.

Figure 3 shows the point estimates (left) and corresponding p-values (right) from these tests. We find no significant relationships between our independent variable X_{ik}^{1} (whether a new hire and potential coworker share a mutual contact) and observable new hire characteristics W_i: None of the p-values are below 0.05, and we therefore do not reject the null hypothesis of random assignment. Further, the p-values exhibit a nearly uniform empirical distribution across different covariates, which is exactly as expected under the null hypothesis.

In addition to these placebo tests, we also gathered qualitative evidence through informational interviews with 11 ConsultingCo managers, as described in Linos et al. (2024, pg.16). Our interview respondents indicated that new hires' assignment to their initial project teams was conditional on their office—defined by the geographic location, department, and hiring cohort—but orthogonal to additional project and team characteristics.

Taken together, our placebo test results and qualitative evidence strongly suggest that there is no relationship between new hires' observable pre-hire characteristics and whether new hires share contacts with potential coworkers. This provides support for the assumption that our sample of new hires is randomly assigned, conditional on office, to their initial coworkers and validates our identification strategy.

Effect of Shared Contacts on Forming New Project Ties for All New Hires

Figure 4 depicts the estimated effect of shared contacts on the probability of forming new project ties with potential coworkers *overall*, on *non-client-facing* projects, and on *client-facing* projects for all new hires. The right panel of the Figure shows the corresponding p-values for the null hypothesis that the effect of shared contacts on project tie formation is zero. The bracket indicates that the effect for client-facing projects is significantly different from the effect for non-client-facing projects, at a level of .01.

Across work contexts, we find positive point estimates for the effect of shared contacts: Having mutual contacts in common consistently increases the probability that new hires and potential coworkers will subsequently work together on new projects. Across all types of projects, the effect of shared contacts increases the probability that new hires will form new project ties with potential coworkers by 0.61 pp. Having at least one coworker in common increases the probability of project tie formation by 0.19 pp in non-client-facing projects, and by 0.42 pp in client-facing projects, which are high-stakes work contexts. This difference between the effect of shared contacts in non-client-facing and client-facing project contexts is statistically significant ($p < 0.001$). Mutual contacts have a larger effect on network formation in high-stakes work contexts characterized by greater uncertainty.

Corresponding to the estimated effect sizes in Figure 4, Figure 5 shows the predicted rate of project tie formation for all new hires with and without shared contacts. The tick marks displayed in the middle of each line denote $\bar{Y}$, the actual average rate of project tie formation in our data. Figure 5 furthermore depicts the predicted rates of project tie formation both in cases when a new hire does not have (left, denoted with triangle, written as r^0 in the Estimation Section) and has (right, denoted with diamond, written as r^1) a shared contact to a potential coworker, in projects overall, on non-client-facing projects, and on client-facing projects.

Mutual contacts increase the overall rate of project tie formation by 97%, relative to the rate at which project ties form absent shared contacts. We can interpret these rates in terms of the average number of ties formed by new hires, with and without shared contacts. New hires form 196 new

ties, on average, by the end of their first year. Of these new relationships, 46 (24%) would not have formed absent shared contacts. The impact of mutual contacts is most pronounced in client-facing project contexts, where having a shared contact increases the probability of forming ties by 1.5x (from 0.27 pp to 0.69 pp). In their first year, new hires form 102 new ties with potential coworkers in client-facing project contexts, with 32 (32%) emerging only because of shared contacts. In short, 1 in 3 client-facing project ties form because of shared contacts.

Effect of Shared Contacts on Forming New Project Ties, by New Hire Race

We turn next to racial differences in the effect of shared contacts across project contexts, illustrated in Figure 6. The brackets again indicate pairs of estimates that are significantly different from each other; in this case, estimates for the effect of shared contacts for Black and White new hires, within a given project context.

Across all types of projects, we find marginally significant differences ($p = 0.07$) between Black (0.38 pp) and White (0.59 pp) new hires in the effect of shared contacts on *overall* project tie formation. These effects imply that, due to the actual presence of shared contacts in our data, White new hires formed 45 new project ties with potential coworkers by the end of their first year that would not have formed in the absence of shared contacts. The corresponding number for Black new hires is only 27 new project ties that are due to shared contacts.

We hypothesized about racial differences in the effect of shared contacts on subsequent project ties in work contexts characterized by uncertainty. A closer examination of racial differences in the type of project tie context reveals a pattern of statistically significant differences that provide support for this hypothesis. We find statistically significant differences ($p < 0.05$) between Black and White new hires in the effect of shared contacts on forming ties with potential coworkers on client-facing projects. These client-facing projects are high-stakes work contexts in which shared contacts face greater uncertainty. Sharing a contact increases the probability that Black new hires will form new ties with potential coworkers working on client-facing projects by 0.31 pp, compared to 0.43 pp increase for White new hires. This effect is 39% larger for White new hires than their Black counterparts. Black new hires thus formed 23 new ties on client-facing projects due to the

presence of shared contacts compared to White new hires who formed 33 new such project ties. Consistent with our argument, we do not find statistically significant differences by race in the effect of shared contacts on forming ties with potential coworkers on non-client-facing projects (0.06 pp for Black vs. 0.16 pp for White new hires, $p = 0.21$).

The predicted project tie formation rates on the left side of Figure 7 reflect the rate at which Black and White new hires form new project ties without relying on shared contacts. In the absence of shared contacts, Black and White new hires form project ties with potential coworkers at similar rates: Both Black and White new hires exhibit a 0.63 and 0.61 percentage point probability of forming overall project ties, respectively. Further, there are no statistically significant racial differences in the rate of tie formation between new hires and potential coworkers across *any* of the types of project ties we observe, in the absence of shared contacts. For both ties formed with non-client-facing projects (0.34 vs. 0.34 pp) and in client-facing projects (0.29 vs. 0.27 pp), Black and White new hires form direct ties at similar rates.

Since Black and White new hires form new project ties with potential coworkers at similar rates when they do not have mutual contacts, differences in the effects of shared contacts *entirely produce* racial disparities in subsequent project networks. Substantively and statistically non-significant racial differences in the rates of forming new project ties on client-facing projects of 0.29 pp and 0.27 pp in the absence of mutual contacts are transformed into a White advantage of 0.11 pp (0.60 pp vs. 0.71 pp) in the combined rate of forming new project ties when shared contacts are present (see right side of Figure 7). Such racialized effects of shared contacts entirely produce an 18% advantage for White new hires in their rate of forming new ties with potential coworkers on client-facing projects. Consequently, Black and White new hires end their first year with different client-facing project networks, a difference that is entirely driven by new working relationships they formed through mutual contacts. Shared contacts facilitated 11 more client-facing project ties for White new hires compared to Black new hires.

Effect of Shared Contacts on Forming New Project Ties with White Potential Coworkers, by New Hire Race

We next consider the effect of shared contacts on Black and White new hires' probability of forming new project ties with (the same set of) *White* potential coworkers across work contexts. Figure 8 depicts the estimated effect of shared contacts on the probability that Black and White new hires will work with White potential coworkers on all types of new projects, non-client-facing projects, and client-facing projects.[3] The brackets again indicate pairs of estimates that are significantly different from each other, between Black and White new hires, for connecting with White potential coworkers within a given project context.

Shared contacts increase the probability of forming ties with White potential coworkers significantly more for White new hires than for Black new hires (0.60 pp vs. 0.36 pp, $p < 0.01$). Shared contacts facilitate 29 new project ties with White potential coworkers for Black new hires, compared to 51 for White new hires. This racializing effect of shared contacts is entirely driven by their influence in shaping networks among *client-facing* projects. Shared contacts increase the formation of client-facing project ties with White potential coworkers by 0.43 pp for White new hires, but only by 0.30 pp for Black new hires, a statistically significant difference ($p < 0.01$). This implies a difference of 12 new working relationships with White employees on high-stakes, client-facing projects, given the actual prevalence of shared contacts. In contrast, and consistent with our arguments about the role of uncertainty, we do not find statistically significant differences in the effect of shared contacts on forming project ties with White potential coworkers in *non-client-facing* work contexts.

Corresponding to the estimated effect sizes in Figure 8, Figure 9 reports predicted project tie formation rates (left, denoted with triangle), or the rate at which Black and White new hires are likely to work on projects with White potential coworkers when they share no common contacts. Across all types of project contexts, White and Black new hires have substantively similar probabilities of directly forming project ties with White potential coworkers (0.71 pp and 0.69 pp).

[3] Figure A2 depicts the estimated effect of shared contacts for all new hire-potential coworker race dyads.

Absent the effect of mutual contacts and consistent with our findings by new hires' race, we find nonsignificant differences between the probabilities that Black and White new hires will work with seasoned White colleagues. Although White and Black new hires have similar direct tie formation rates with White potential coworkers in client-facing projects (0.28 pp for White vs. 0.29 pp for Black), the benefit of shared contacts creates a 0.12 pp advantage for White new hires in their likelihood of working with White potential coworkers on high-stakes, client-facing projects. In the presence of shared contacts, White new hires are, on average, 20% more likely than Black new hires to form ties with White potential coworkers in client-facing projects (0.71 pp vs. 0.59 pp).

Robustness

We take several steps to probe the robustness of our findings. First, we explore how varying the time window in which we observe new hires working on subsequent projects and forming project ties with coworkers shapes our findings. We estimate the effects of shared contacts on future project ties formed (also by new hire race and new hire-potential coworker race dyads) in the subsequent three and six months, instead of nine months. We find substantively similar results. When examining project tie formation rates within six months, our marginally significant findings about the Black-White difference in the propensity for triadic closure through mutual contacts become statistically significant ($p < 0.05$). For project tie formation rates within three months, our findings fail to reach conventional levels of statistical significant, though our estimated coefficients remain similar in magnitude.

Second, we report results using two alternative measures of high-stakes work contexts in which new project ties with potential coworkers are formed: ties formed in *high-priority* projects and ties formed with *senior potential coworkers* across all projects. Figure A1 shows marginally significant racial differences ($p < 0.05$) in the effect of shared contacts on subsequent tie formation in two additional project contexts characterized as high-stakes, high-priority projects and with senior potential coworkers, lending some additional support for our argument. Having a shared contact increases the probability of forming new project ties for White new hires by 0.25 pp, but only by 0.19 pp for Black new hires ($p = 0.051$). Similarly, mutual contacts increase the probability of

forming project ties with senior potential coworkers by 0.49 pp for White new hires, but only by 0.31 pp for Black new hires ($p = 0.056$).

Third, we examine how the shared contact's race (race of the initial coworker) influences project tie formation for Black new hires. We estimate a variant of our main model that includes three regressors, instead of one. These three regressors correspond to whether there was any shared contact who identified as Black, as White, or as Other. For Black new hires, the point estimates suggest that initial coworkers whose race differs from the new hire's race are particularly helpful for joining future projects, while Black shared contacts confer a markedly smaller benefit on forming new project ties. One possible explanation of this finding is that Black shared contacts do not facilitate access to new projects and the formation of new project ties for Black new hires. Another, and maybe more plausible, explanation is that Black coworkers already facilitate access to new project ties for Black new hires in their office *regardless* of whether they are coworkers on initial project teams (which would make them a shared contact for Black new hires). This interpretation would be consistent with our findings because our coefficient estimates reflect the difference in the probability of project tie formation depending on whether or not the initial co-worker is in the same team, they do not reflect overall levels of forming new project ties.

Fourth, we examine how the shared contact's job level influences subsequent project tie formation for Black and White new hires by estimating a variant of our main model that includes multiple regressors corresponding to whether any shared contact identified as one, two, or three job levels above new hires. As expected for a hierarchical organization in which the number of employees decreases at each ascending job level, shared contacts one job level above new hires appear to drive our main findings.

Last, drawing on intersectionality research finding that people with multiple marginalized identities may have distinct experiences from people with one marginalized identity, we explore the possibility that shared contacts have a differential effect for new hires who are Black women compared to Black men. We estimate the effect of shared contacts for Black women new hires and Black men new hires separately and test for differences using our main model specification in a

sample of offices that included at least one Black woman and man new hire in a given cohort. We do not detect substantive or statistically significant differences, limiting our insight into how intersectionality shapes the evolution of project ties in this firm.

DISCUSSION

This study investigates racial differences in the causal effect of shared contacts on employees' subsequent project networks and the project ties they form. We find that in the absence of shared contacts, Black and White new hires form new project ties at similar rates, but that the impact of shared contacts significantly differs between racial groups. Shared contacts have a larger effect on project tie formation rates for White new hires compared to Black new hires, especially in high-stakes work contexts characterized by greater uncertainty about performance expectations. These differential effects of shared contacts produce racial disparities in subsequent project networks, even when racial differences in the rates of forming project ties without mutual connections are small.

Our research makes several contributions. First, we contribute to the literature on how social networks produce racial (dis)advantages by theoretically and empirically identifying racial differences in how ties form at work (Pager and Shepherd, 2008; DiMaggio and Garip, 2012). Past research has largely focused on the role of homophily—from people's preferences and from the constraints imposed by the demographic makeup of organizations—in reproducing inequalities (Ibarra, 1993; Kossinets and Watts, 2009; Wimmer and Lewis, 2010; Kleinbaum et al., 2013). We examine how intraorganizational ties form by comparing White and Black employees in the same jobs and with the same access to potential ties. Thus, by bringing together the literatures on network formation and network effects, we broaden beyond the limited focus on homophily to uncover a novel pathway through which racial differences emerge in intraorganizational networks. Furthermore, we show that racial differences in tie formation emerge *only* in the presence of shared contacts. We uncover that triadic closure (Simmel, 1908) is the primary driver of racial disparities in professional networks and not differences in networking behavior in person-to-person dyadic relationships.

Relatedly, while some prior work has theorized that triadic closure might act as a driver of tie formation, direct empirical evidence of its causal effect in any network context is scant (Moody, 2001; Asikainen et al., 2020; Abebe et al., 2022). Our study moves beyond correlational estimates to causal estimates of the effect of triadic closure on intraorganizational tie formation, and does so within a work environment where employees' full potential network can be observed and analyzed. In doing so, this paper reframes our understanding of the magnitude and the extent to which shared contacts produce racial disparities in intraorganizational networks. This is in contrast to the common focus in extant empirical research, which views triadic closure as an intrinsic, passive, ostensibly race-neutral network process. Our results show that organizational practices that permit and even promote individual reliance on mutual contacts can inadvertently activate racial bias in ways that produce disadvantages for Black people forming high-stakes project networks in elite organizations.

Second, our findings contribute to the literature on racial inequality. In any professional organizational context, the nature of the work varies, such that some tasks, projects, or clients are particularly critical and important to both the individual's and the firm's success. In our setting, we identify that it is precisely in such high-stakes situations that Black workers are most disadvantaged in forming ties through shared contacts. Racial differences in triadic closure in these situations doubly disadvantage Black employees: Black employees are less likely to form the high-stakes project ties that matter the most for their career attainment.

Third, our findings have implications for the practice of managing diversity in organizations. Our network approach shifts the focus from individual barriers in dyadic networking behaviors between two employees to subtle, often overlooked, decision-making of third parties, shared contacts, that yield racial (dis)advantages. Our findings call for interventions that proactively address the racialized effects of staffing models that rely on organic network evolution for career success and point to many potential testable interventions. For instance, a firm could test annual rotation programs that vary which employees work on high-stakes projects and with whom. Another possible intervention could involve instituting annual audits of project networks to make racial network

disparities visible—in terms of which coworkers an employee is working with, on what kinds of projects, and how those project relationships emerged (Sturm, 2001). Last, a possible intervention could re-think the overall project assignment processes, establishing clear guidelines on how, when, and why new project connections should be formed.

Despite the potential for numerous such network interventions, we argue that deeply-rooted and widely-held beliefs about top talent and who possesses it underlie persistent racial disparities in elite organizations (Correll et al., 2017). Any long-term, sustainable intervention must challenge these fundamental assumptions. Organizations that invest in clarifying their evaluation processes—for instance, what performance criteria matter, how those criteria will be applied, and who will be making these assessments—will also reduce the uncertainties that employees routinely face, such as when making informal brokering decisions. Organizations can also challenge assumptions about top talent by rewarding employees' efforts to mentor and develop junior talent alongside traditional metrics like revenue generation. For example, if a shared contact's work successfully connecting employees from diverse backgrounds or mentoring other employees was part of their own performance rating, incentives to adjust behavior may be clearer. These complementary strategies are essential for creating lasting change in organizational culture and practices.

These findings notwithstanding, the study has several limitations. First, there is the question of generalizability of our findings beyond ConsultingCo, the single organization in the professional services industry that we study. ConsultingCo exemplifies large firms in its industry through its project-team-based work structure, employee demographic composition, geographic distribution of their offices, and dynamics of intraorganizational tie formation (O'Mahoney and Markham, 2013; Dean et al., 2020; Dun & Bradstreet First Research Industry Profile, 2023; Morkes, 2023; U.S. Bureau of Labor Statistics, 2023). This typicality reduces our concerns that our findings rely on dynamics that are idiosyncratic to ConsultingCo itself or its employees—for instance, distinct demographic composition of employees or unique structures, policies, practices. Future research can explore the extent to which our findings generalize to other network, organizational, and industry contexts.

Second, we find racial differences in tie formation rates in the presence, but not absence, of shared contacts. We have argued that the presence of shared contacts introduces racial bias driving these differences, but we cannot definitely claim whether these differences are driven by the behavior of the shared contact, the presence of the shared contact leading to racial differences in behavior by the other two contacts (the new hire or the potential coworker), or some combination of both. To empirically disentangle this, we have focused on a sample of new hires for whom we do not find statistically significant differences in observable characteristics prior to their entry into the firm, and we included a fixed effect for potential coworkers to identify effects beyond differences in potential coworkers. More importantly, even after painting a compelling picture of how the shared contacts are the drivers, we are unable to observe the specific behavioral pathway within the shared contact leading to the observed racial patterns. For example, we cannot know if shared contacts' behaviors are based on their own racial bias or inferences about potential coworkers' racial preferences. Future research employing experimental methods is needed to more precisely isolate these pathways.

Third, our identification strategy relies on the assumption that subsequent project tie formation is driven by shared contacts on initial projects and not other characteristics of those initial projects or initial networks. Fourth, we find evidence of racial differences in the effect of shared contacts on tie formation, but we cannot know whether these results generalize to other dimensions of difference, such as those based on social class, nationality, or sexual orientation. Future research could expand on this by theoretically developing and empirically testing how triadic closure occurs for other underrepresented minority groups in elite organizational contexts. Last, our analyses rely on project staffing data, which captures self-reported time spent working on formal project team assignments rather than actual interactions. This data excludes informal workplace interactions and any interactions outside the organization. While it is possible that our findings reflect differences in how project work is reported rather than true differences in how project networks form, our understanding of ConsultingCo gives us no reason to believe that employees inaccurately report which projects they work on.

Network mechanisms implicit in organizational practices can produce and perpetuate racial disparities. That mutual contacts produce and perpetuate racial disparities in employees' workplace networks illuminates a critical, yet often overlooked, mechanism of inequality. Our research challenges scholars and practitioners to broaden their understanding of the drivers of inequality to include network effects at work, particularly in the context of informal staffing practices. These relational work practices, often viewed as neutral or even beneficial, can be conduits for the reproduction of racial inequalities. By unearthing their racialized effects on network formation, we underscore the need for a more nuanced and critical examination of seemingly inherent network processes in organizations. Looking forward, we call on researchers to build upon these findings to develop and test a suite of interventions that can disrupt such inequality-perpetuating processes.

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Tables

Table 1: Employee and Project Summary Statistics

Panel A: Sample Size						
	Total					
Number of Employees	>50,000					
Number of New Hires	2,984					
Time Span	2015 - 2020					
Panel B: New Hires Summary Statistics						
	N	Mean	Sd	Median	P25	P75
Age at Hire	2,984	24	3	24	23	25
Share in Top 20 U.S. Schools	2,668	0.09	0.29			
Share in Top 21-100 U.S. Schools	2,668	0.39	0.49			
Share in Top 101-1,000 U.S. Schools	2,668	0.38	0.49			
Share in 1,001+ U.S. Schools	2,668	0.14	0.34			
Share with a Master's Degree	2,754	0.19	0.39			
Share with a Technical Master's	2,754	0.09	0.29			
Panel C: Initial Project Summary Statistics						
	N	Mean	Sd	Median	P25	P75
Number of Projects	2,984	3	2	3	2	4
Project Team Size	2,984	26	16	23	14	35
Hours on Projects	2,984	141	23	141	130	152
Share of Client-Facing Hours	2,984	0.53	0.26	0.62	0.36	0.74
Panel D: Subsequent Project Summary Statistics						
	N	Mean	Sd	Median	P25	P75
Number of Projects	2,963	4	2	3	2	4
Project Team Size	2,942	28	15	26	18	35
Hours on Projects	2,963	155	34	161	151	170
Share of Client-Facing Hours	2,963	0.83	0.19	0.89	0.8	0.94

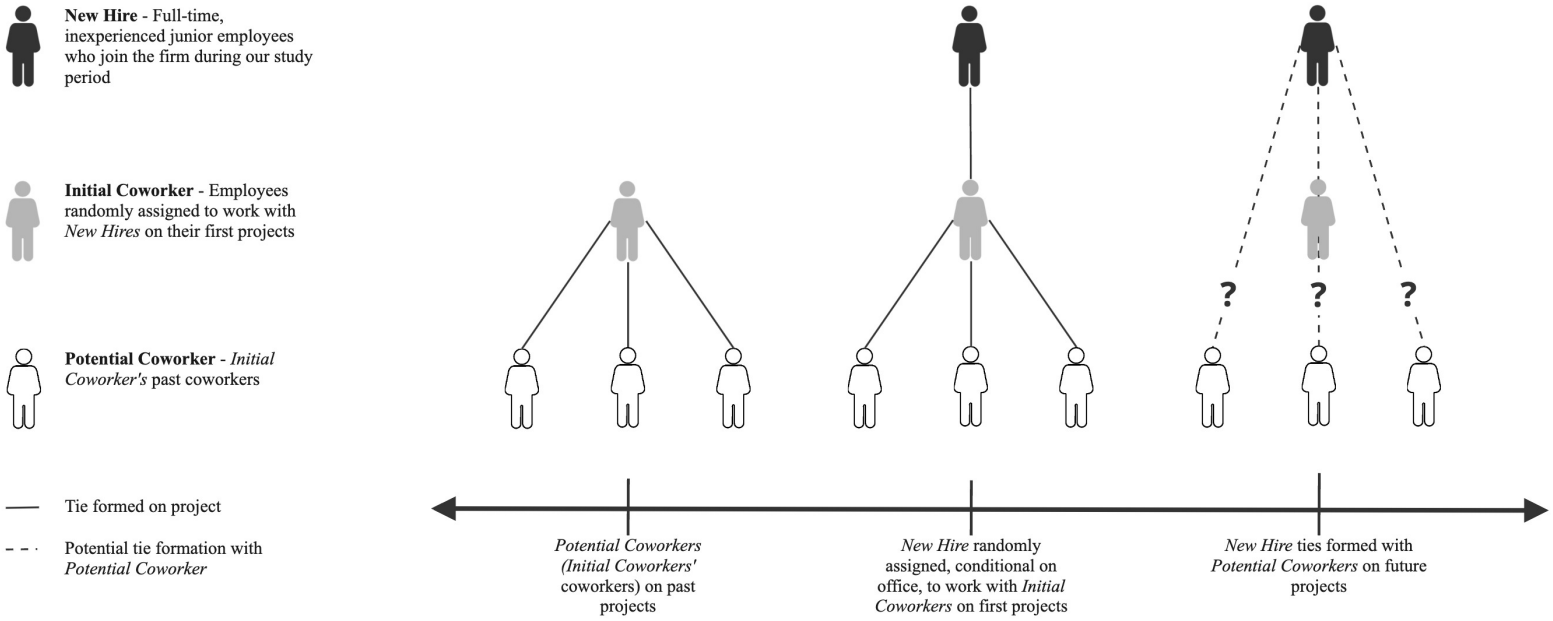
Notes. **Panel A** of this table displays the number of employees, the number of new hires, and the time span of the data. **Panel B** displays new hires' age and education characteristics. Age is estimated over our sample of 2,984 new hires; share in Top 20, Top 21-100, Top 101-1,000, and 1,001+ U.S. Schools are estimated over 2,668 new hires for whom we have school ranking data; share with a Master's Degree and Technical Master's are estimated over 2,754 new hires for whom we have degree data. **Panel C** displays (monthly) statistics about the projects assigned to new hires in their first three months. **Panel D** displays the same (monthly) statistics about projects new hires worked on in the subsequent nine-month period concluding their first year of employment. *Number of projects* corresponds to the number of distinct projects the new hire worked on each month in that period. *Project team size* is the average project team size per month in that period. *The share of client-facing hours* represents the share of hours that are billable to the client over the total hours that the new hire worked in that period.

Table 2: Descriptives for New Hires, Initial Coworkers, and Potential Coworkers

	New Hires	Initial Coworkers	Potential Coworkers
Nb. obs	2,984	49,397	172,417
% Women	48.7	41.7	40.3
% White	56.9	48.4	36.2
% Asian	21.8	23.5	21.1
% Black	10.7	5.0	4.4
% Hispanic	6.4	4.9	4.2
% Other	4.2	2.8	2.2
% Missing Race/Ethnicity	0.0	15.3	31.8
Med. Number of Ties	62	452	-

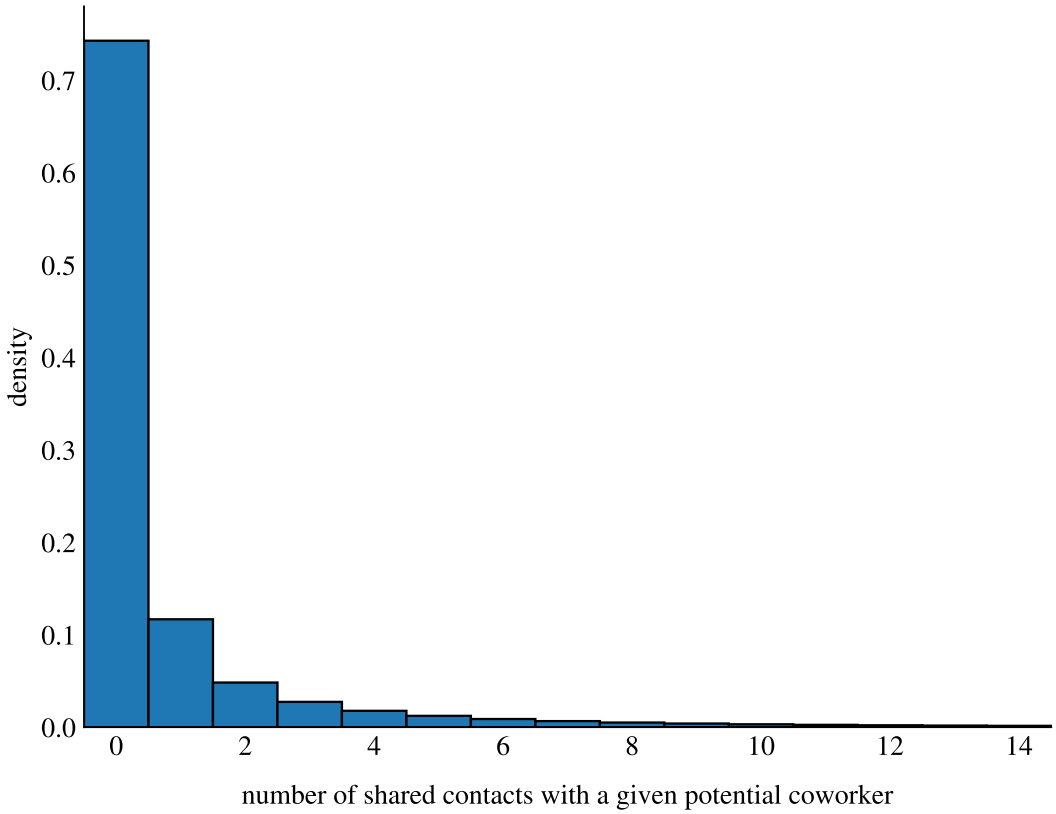
Notes. This table reports the demographic composition of new hires, their initial coworkers (who are contacts they share with potential coworkers), and their potential coworkers. Other includes non-Hispanic employees that identify as American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, Middle Eastern, North African, Near Eastern, Indigenous Mexican or Central American, or Two or More Races. For new hires, the median number of project ties indicates their median project ties to initial coworkers across the set of their initial project teams. For initial coworkers, the median number of project ties indicates their median number of project ties to their coworkers (who we term "potential coworkers") across their past project teams.

Figure 1: Illustration of Network Actors in Study



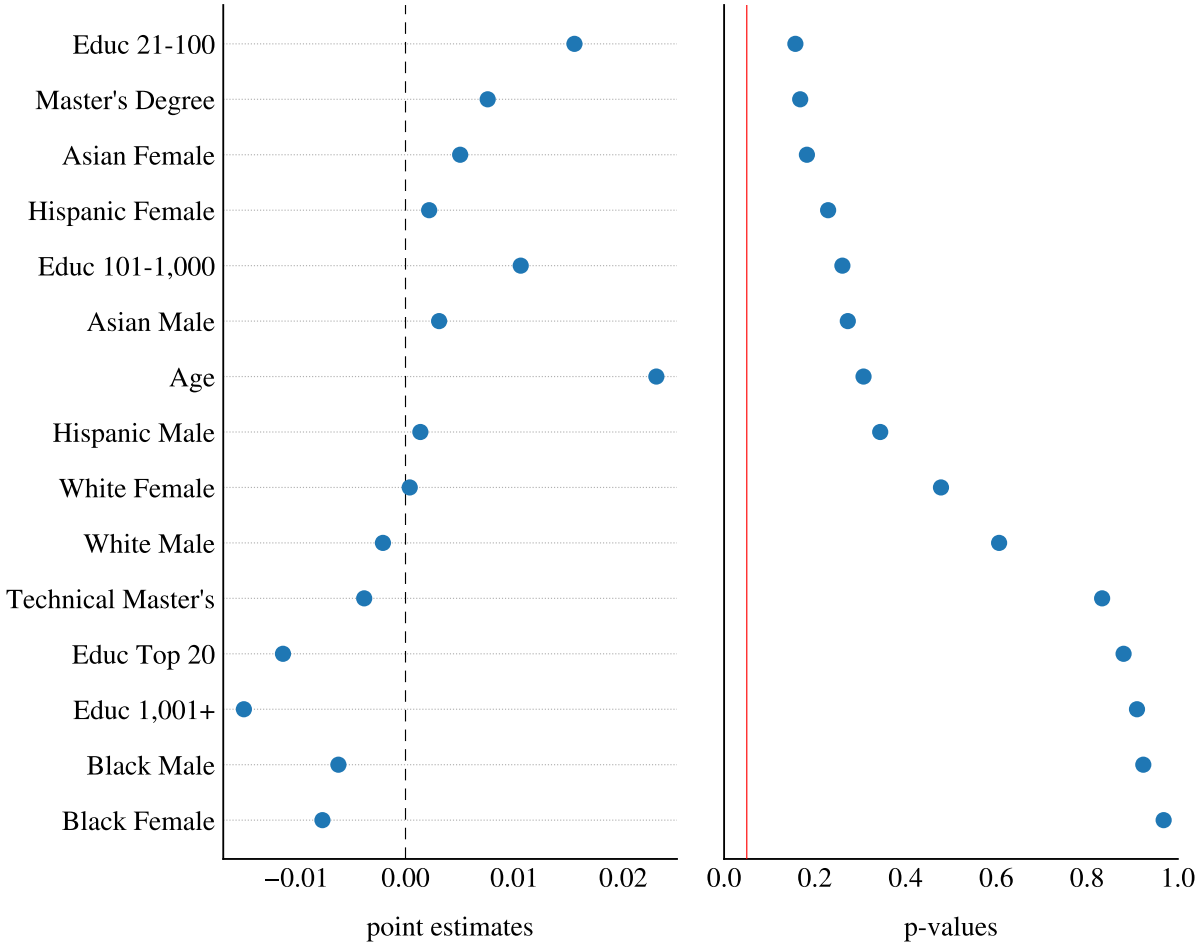
Notes. This figure illustrates the relationships between three types of employees in our study: new hires, initial coworkers (shared contacts), and potential coworkers. *New hires* are full-time, inexperienced junior employees who join the firm during our study period. *Initial coworkers* are the employees assigned to work with the new hires on their first projects, which we assume are randomly assigned, conditional on their office. *Potential coworkers* are past coworkers of the initial coworkers, representing the set of intraorganizational project ties that new hires could potentially work with via their initial coworkers.

Figure 2: Distribution of Shared Contacts to Potential Coworkers



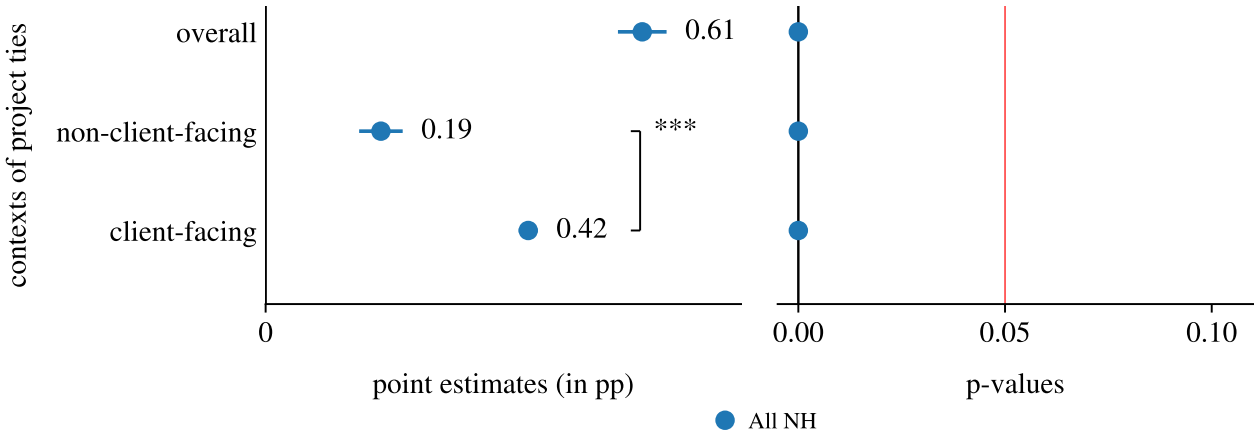
Notes. This figure depicts the distribution of the main independent variable, the number of initial coworkers who a new hire shared with other potential coworkers in the firm using our 2,984 new hire sample. The mean and median number of initial coworkers through which new hires are connected to potential coworkers is 1.12 and 0, respectively. Conditional on having at least one shared contact with a potential coworker, the mean and median of the number of initial coworkers connecting a new hire to a potential coworker is 4.21 and 2, respectively.

Figure 3: Placebo Tests of Random Assignment



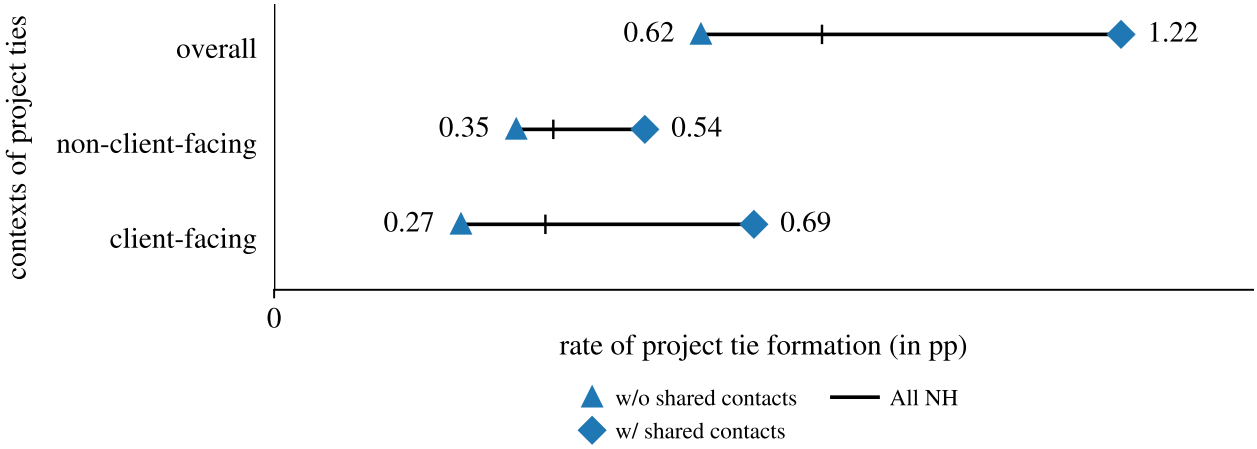
Notes. This figure reports the point estimates and p-values for a series of placebo tests. In each placebo test, we replaced our dependent variable with new hire characteristics that were determined prior to their entry to ConsultingCo—their racial/ethnic and gender identity, age, and education. As with our main model specification, we use randomization inference to test the null hypothesis. For the education variables (e.g., ranking, Master's Degree, and Technical Master's), values are missing for a subset of new hires. For these variables, we restrict attention to the subset of offices where at least two new hires have non-missing values.

Figure 4: Point Estimates of the Effect of Shared Contacts for All New Hires



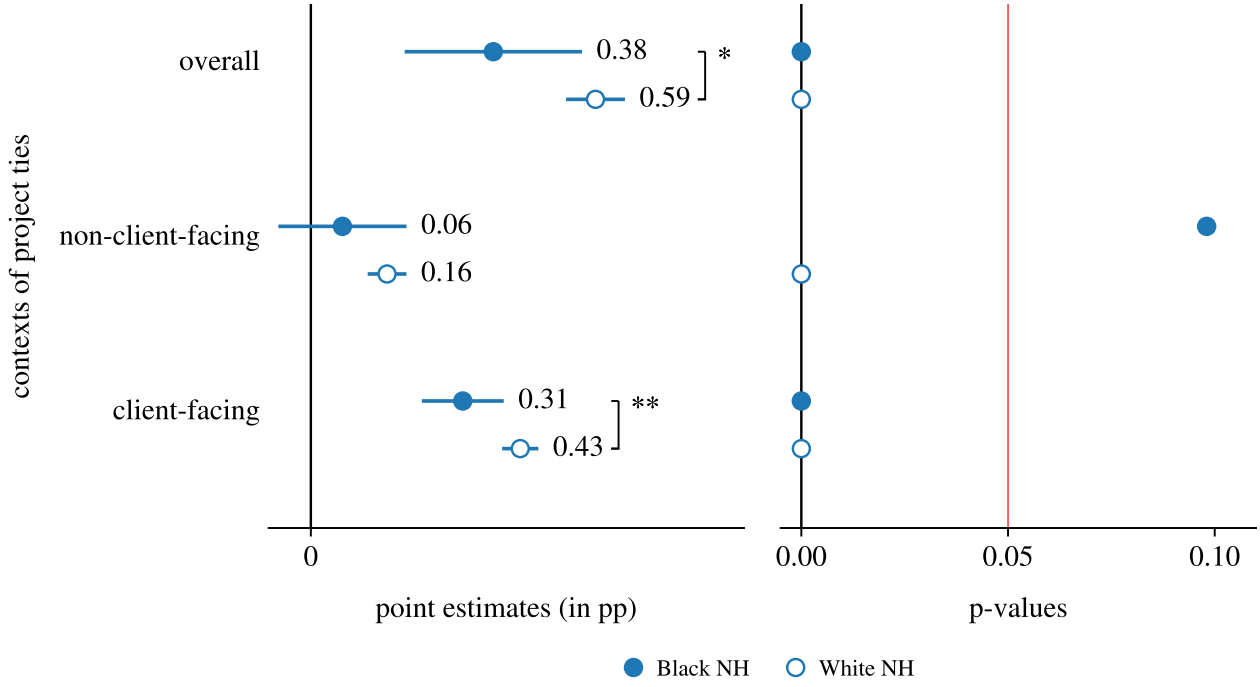
Notes. This figure reports the point estimates and p-values for the effect of shared contacts on subsequent project tie formation for all new hires across project contexts. Brackets denote significant differences in the effect of shared contacts on project tie formation between non-client-facing and client-facing project contexts for all new hires: * p < 0.1, ** p < 0.05, *** p < 0.01.

Figure 5: Predicted Project Tie Formation Rates for All New Hires



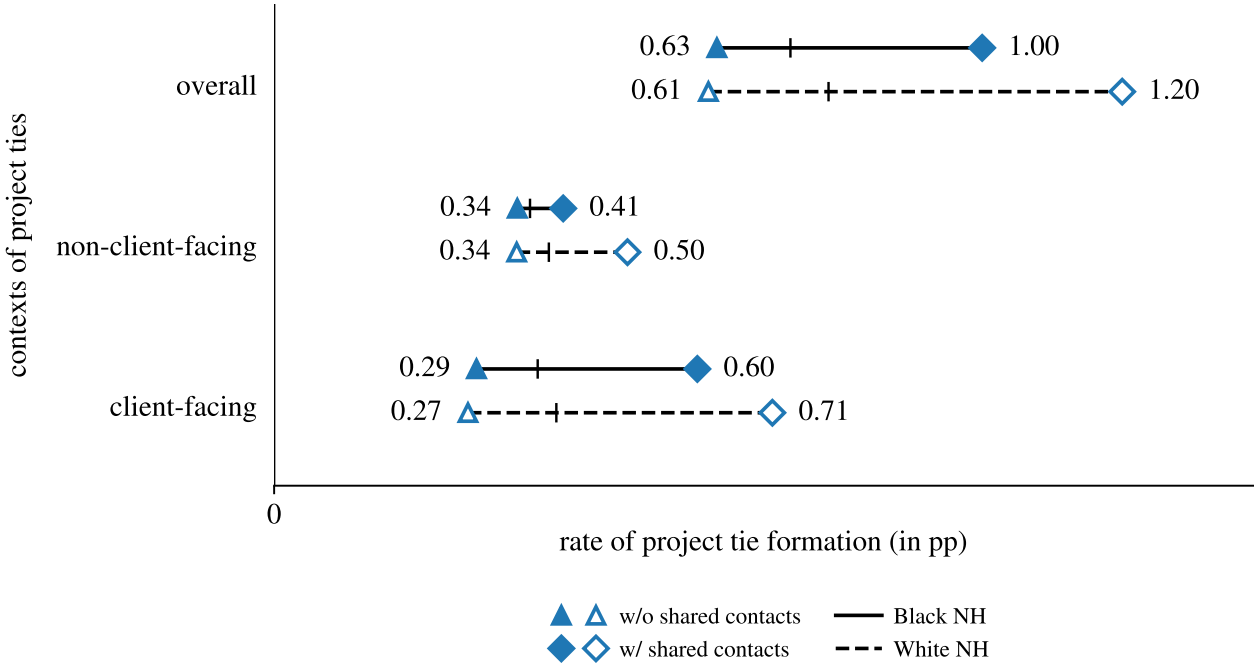
Notes. This figure illustrates two predicted project tie formation rates, as described in the Estimation section: without any shared contacts (r^0, left) and with shared contacts (r^1, right). The length of each line visually represents the corresponding point estimates of the effect of shared contacts on the subsequent probability of a new hire joining a project and forming new project ties. For reference, tick marks displayed in the middle of each line denote $\bar{Y}$, the average rate of project tie formation at the end of the first year within varying work contexts.

Figure 6: Point Estimates of the Effect of Shared Contacts by New Hire Race



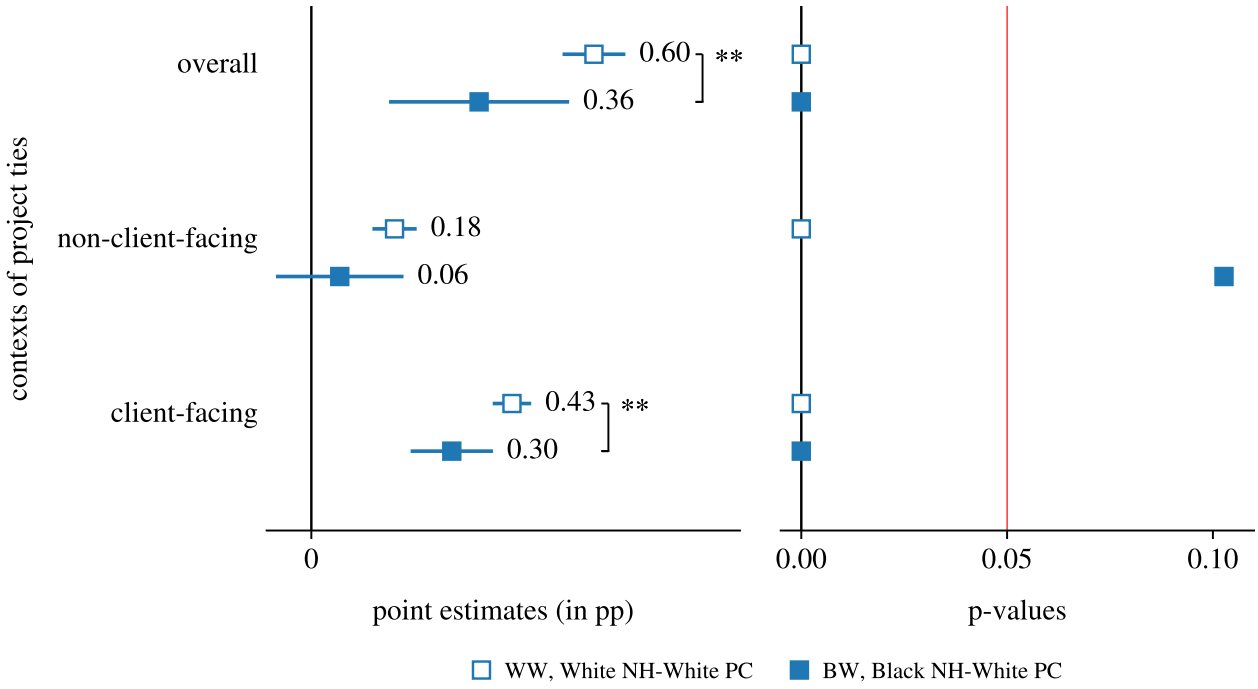
Notes. This figure reports the point estimates and p-values for the effect of shared contacts on subsequent project tie formation by race of new hires across project contexts. Brackets denote significant differences in the effect of shared contacts on project tie formation between Black and White new hires within each project tie formation context: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 7: Predicted Project Tie Formation Rates by New Hire Race



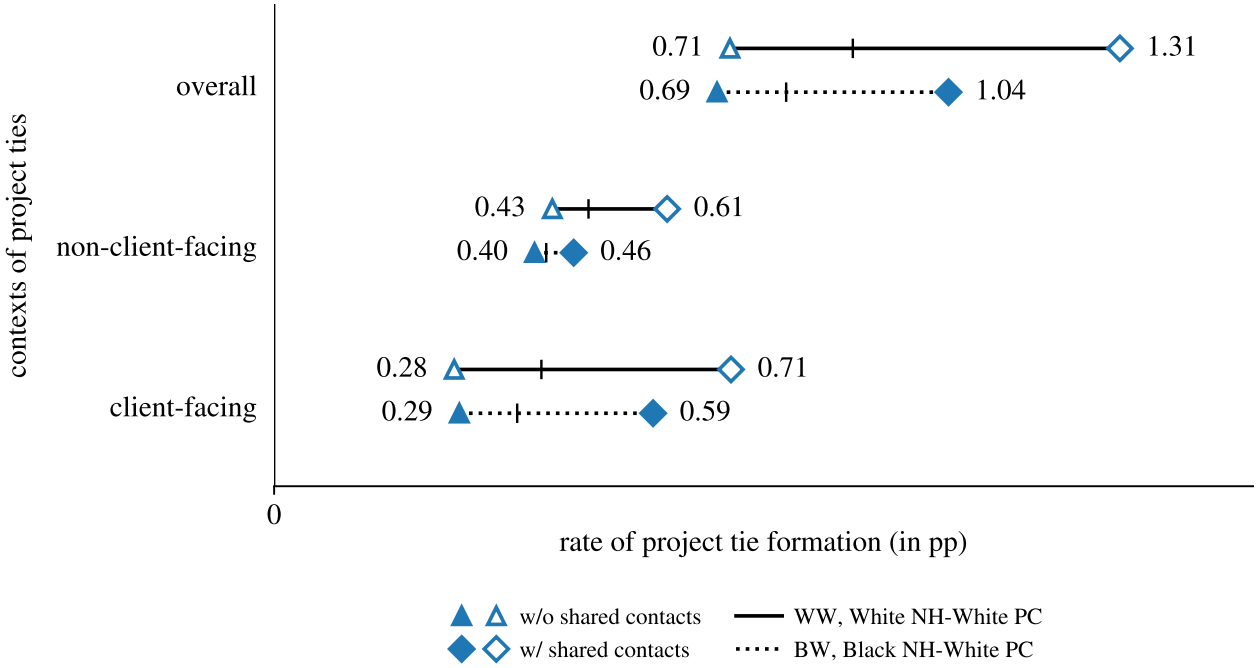
Notes. This figure illustrates two predicted project tie formation rates by race, as described in the Estimation section: without any shared contacts (r^0, left) and with shared contacts (r^1, right). The length of each line visually represents the corresponding point estimates of the effect of shared contacts on the subsequent probability of a new hire joining a project and forming new project ties. For reference, tick marks displayed in the middle of each line denote $\bar{Y}$, the average rate of project tie formation, for the corresponding new hire racial group and project tie formation context.

Figure 8: Point Estimates of the Effect of Shared Contacts on Forming New Project Ties with White Potential Coworkers for Black and White New Hires



Notes. This figure reports the point estimates and p-values for the effect of shared contacts on subsequent project tie formation with White potential coworkers for Black and White new hires. In other words, for two types of ties: (1) White new hires working with White potential coworkers, and (2) Black new hires working with those same White potential coworkers. Brackets denote significant differences in the effect of shared contacts on project tie formation with White potential coworkers between Black and White new hires within each project tie formation context: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Figure A2 depicts the estimated effect of shared contacts for all new hire-potential coworker race dyads across all project contexts.

Figure 9: Predicted Project Tie Formation Rates with White Potential Coworkers for Black and White New Hires



Notes. This figure illustrates two predicted project tie formation rates for Black and White new hires connecting with White potential coworkers, as described in the Estimation section: without any shared contacts (left) and with shared contacts (right). The length of each line visually represents the corresponding point estimates of the effect of shared contacts on the subsequent probability of a new hire joining a project and forming new project ties. For reference, tick marks displayed in the middle of each line denote $\bar{Y}$, the average rate of project tie formation, for the corresponding new hire-potential coworker race dyad group and project tie formation context.

APPENDIX

Appendix Methods

Approach for using causal bootstrap for standard errors. The idea of the causal bootstrap is to construct counterfactual outcomes, for each unit of observation ik, in a way that respects the observed marginal distribution of potential outcomes, but considers the worst-case joint distribution (i.e., copula). As shown in Menzel and Imbens (2021), in the context of conventional randomized experiments, the worst-case joint distribution is given by the so-called "isotonic copula," where potential outcomes are perfectly positively dependent. In our context, this suggests the following steps. We start by imputing counterfactual potential outcomes for each observation ik as follows:

1. If $X_{ik} = 1$, set $Y_{ik}^1 = Y_{ik}$, else set $Y_{ik}^0 = Y_{ik}$.

2. If $X_{ik} = 0$ and $Y_{ik} = 1$, set $Y_{ik}^1 = 1$.
   If $X_{ik} = 1$ and $Y_{ik} = 0$, set $Y_{ik}^0 = 0$.

3. If $X_{ik} = 0$ and $Y_{ik} = 0$, set $Y_{ik}^1 = 1$ with probability q_1.
   If $X_{ik} = 1$ and $Y_{ik} = 0$, set $Y_{ik}^0 = 1$ with probability q_0.

4. The probability q_1 is chosen such that the average of Y_{ik}^1 across all ik in the office equals the average of Y_{ik} across the observations such that $X_{ik} = 1$.
   The probability q_0 is chosen such that the average of Y_{ik}^0 across all ik in the office equals the average of Y_{ik} across the observations such that $X_{ik} = 0$.

Once these counterfactual outcomes are imputed, we can proceed as before: Choose a random permutation π of new hires in the office. Swap the treatment accordingly, so that the actual regressor X_{ik} is replaced by the counterfactual regressor $X_{\pi(i)k}$. Now (in contrast to randomization inference) replace the outcome Y_{ik} by the imputed counterfactual outcome $Y_{ik}^{X_{\pi(i)k}}$.

For these counterfactual values for the regressor and outcome, re-estimate the coefficient β. Repeating this procedure many times results in a distribution of estimates, the standard error of which provides a correct worst-case bound on the standard error of the estimator for β, under the randomization distribution.

Appendix Tables

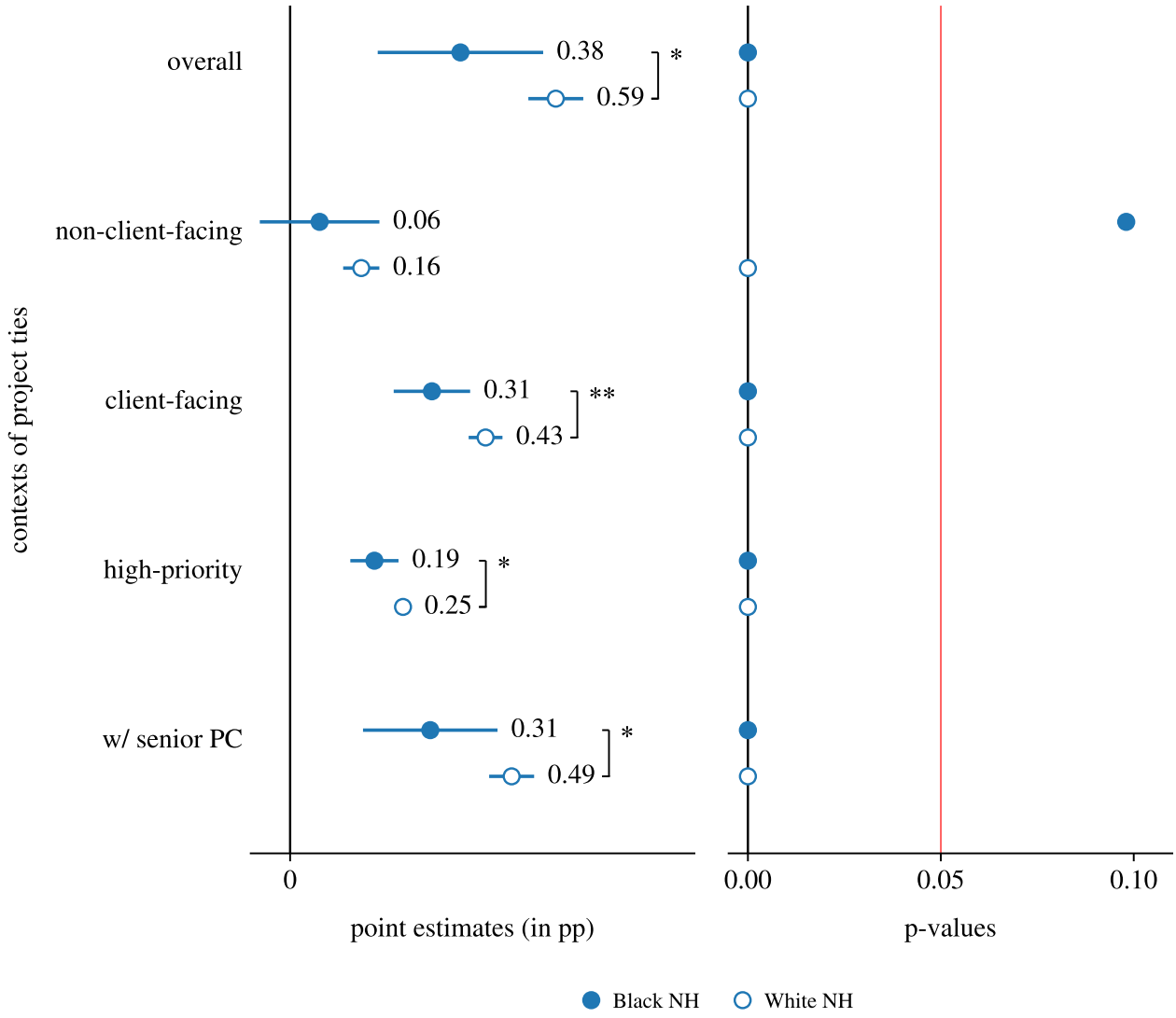
Table A1: Average Rates of Tie Formation

	B	W	WW	BW	BB	WB
Overall	0.731	0.785	0.896	0.793	0.954	0.864
W/ Senior PC	0.645	0.673	0.779	0.717	0.814	0.722
Non-Client-Facing	0.362	0.389	0.487	0.421	0.586	0.465
Client-Facing	0.373	0.399	0.414	0.376	0.374	0.403
High-Priority	0.140	0.152	0.171	0.159	0.172	0.180

Notes. This table reports $\bar{Y}$, the average rate of forming new ties on projects (as described in Estimation), for Black and White new hires and the new hire-potential coworker race dyads across different types of projects (project tie formation contexts).

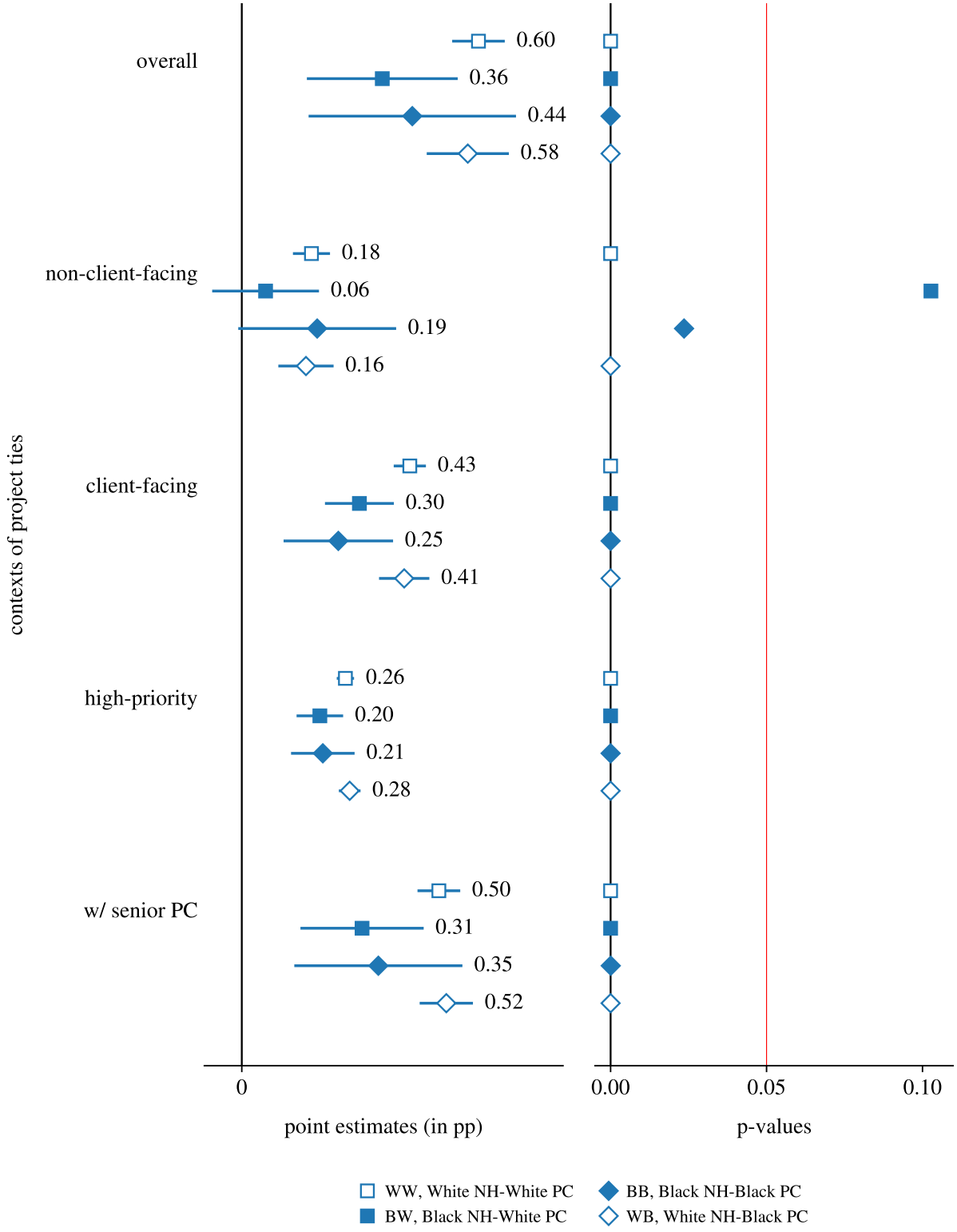
Appendix Figures

Figure A1: Point Estimates of the Effect of Shared Contacts by New Hire Race, All Contexts



Notes. This figure reports the point estimates and p-values for the effect of shared contacts on subsequent project tie formation by race of new hires. We note significant differences between Black and White new hires' point estimates within each project tie formation context: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A2: Point Estimates of the Effect of Shared Contacts by New Hire-Potential Coworker Race Dyad, All Contexts



Notes. This figure reports the point estimates and p-values for the effect of shared contacts on subsequent project tie formation by new hire-potential coworker race dyad.